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PREFACE

This volume contains the papers that were presented at the Third Workshop on Algorithmic Learning Theory (ALT'92), which was held at the CSK Information Education Center in Tokyo from October 20 to 22, 1992. In addition to 3 invited papers, this volume contains 19 papers accepted for presentation at the workshop.

The contributions in the proceedings were selected from 29 extended abstracts submitted in response to the call for papers, at the final selection meeting of the program committee held in Tokyo on June 19, 1992. The volume contains three invited papers: "Discovery Learning in Intelligent Tutoring Systems" (by S. Otsuki), "From Inductive Inference to Algorithmic Learning Theory" (by R. Wiehagen), and "A Stochastic Approach to Genetic Information Processing" (by A. Konagaya).

By now the importance of machine learning to the success of the next generation of AI systems has been widely recognized and accepted. At the same time, decades of theoretical research in inductive inference and its complexity-theoretic analogue have led to the emergence of algorithmic respectively computational learning theory. ALT is the Japanese series of international workshops focusing on these learning-theoretical issues. The ALT workshops have been held annually since 1990, and are organized and sponsored by the Japanese Society for Artificial Intelligence (JSAI). The main objective of these workshops is to provide an open forum for discussions and exchanges of ideas between researchers from various backgrounds in this emerging, interdisciplinary field of learning theory.

There are two concurrent series, AII initiated in 1986 in Europe, and COLT started in 1988 in the USA. It is our intention to integrate the international community of scientists interested in algorithmic respectively computational learning theory. A first step towards such an integration is to exchange all available information. We are grateful to Springer-Verlag for providing an opportunity to present the proceedings of ALT'92 to a wider international community. A further step may be to integrate even learning theory conferences for a higher concentration of scientific discussions and more efficient transfer of ideas between disciplines.

The editors are deeply grateful to all the program committee members and referees who took part in the evaluation and the selection of submitted papers. In particular, we wish to thank M. Numao, T. Shinohara, and Y. Takada for their excellent work. The program committee thanks all three invited lecturers for having accepted the invitation.

We thank all those who made this workshop possible, especially K. Miura, T. Nishino, and A. Sakurai. Finally, we also wish to express our gratitude to CSK for the assistance and support with local arrangements.

Tokyo, September 1993

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INVITED PAPERS

Discovery Learning in Intelligent Tutoring Systems

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Abstract

A brief history of Intelligent Tutoring Systems and their necessary educational functions which have already been realized and not yet been realized are presented separately, then problems to be solved within the framework of ITS and problems that transcend the framework of ITS are discussed. Lastly, it is indicated that the problems will be solved by an amalgamation of an open-end system like a micro world and a discovery system with direct manipulation into ITS and that the central problem to realize the amalgamation is a discovery learning by a machine itself.

1 Introduction

The first generation of CAI was made public in the 1950's and presently it is called traditional CAI. It is widely known that the traditional CAI has often been criticized as a mere electronic page-turning machine[1], because the traditional CAI has no ability to answer student's questions, and its only means of evaluating student's responses and selecting the next presentation is a pre-defined selection tree, whose forks are designed in great detail to correspond with all the pre-supposed students' good and wrong answers to an imbedded problems. It was supposed that all of these mooted points stemmed from inability of the traditional CAI to solve given problems.

The first development of the second generation of CAI, (alias Intelligent tutoring system, ITS in abbr.), was done by J. R. Carbonell in 1970[2] in order to remove the inability of problem solving by introducing an inferential function based on a knowledge representation, in place of the procedural representation of the traditional CAI. One of the most remarkable contributions of the work was the proposition of necessity to develop the following four elementary techniques.

1) Inferential technique for problem solving.
2) Student modeling by diagnosing error origins.
3) Representation method for teaching expertise.
4) Mixed initiative knowledge communication.

For more than ten ensuing years, his proposition had influenced ITS researches continuously. In fact, most papers published during these ten years were researches on either one of the four elementary techniques or on systems composed of the four elementary techniques[3]. These publications are roughly divided into two parts; basic researches in the 1970's[4] and its development in the first half of the 1980's[5].

1) The 1970's.
- Aims: To remove the defects of traditional CAI.
- Methods: Problem solving by computers, Student modeling, Teaching expertise, Mixed initiative dialogue.
- Elementary techniques: Knowledge representation method, Overlay student modeling, Buggy student modeling, Coaching, Natural language dialogue , Qualitative reasoning.

2) The first half of the 1980's
- Aims: Development of the elementary techniques
- Method: Identification of error origin, Cognitive modeling of human understanding
- Elementary techniques: Introducing structures into knowledge representation, Hypothetical inference, MIS, Adaptive guiding, Qualitative reasoning, Usage of student model, Truth maintenance.

In the middle period of the 1980's, as the whole aspect of ITS became gradually clear, demands for a breakthrough in the ITS methodology increased from the viewpoints of both tractability and educational cognitive science[6,7]. Issues on this problem will be treated in section 4. The problem has been strongly influenced by GUI techniques, and a new generation of CAI has been gradually revealed since the latter half in the 1980's[7].

3) The latter half of the 1980's
- Aims: Discovery environment by student initiative, Multiformity in CAI.
- Method: Micro world, Open-end, High individualization
- Elementary techniques: GUI, Multimedia, Hypermedia, Direct manipulation, Navigation, Natural language understanding.

In the latter half of the 1980's, although multifarious CAIs have emerged for practical use, AI techniques developed in ITS have not been applied. Hence it is impossible for these CAIs to give a student deep understanding. Recently, It seems to me that amalgamation of the third generation techniques into ITS becomes more and more important, but concrete techniques have not been established yet .

In section 2 what has been done and not yet been done in ITS are described and mooted points will be discussed in section 3. In section 4 the significance of so called discovery system is described from the stand point of deep understandings and in section 5 necessity of amalgamation of two methodology to realize the discovery system is described.

2 What has been done and not yet been don in ITS

2.1 What has been don in ITS

As described above, ITS has been equipped with various powerful architectures for mixed initiative and highly individualized knowledge communication. The following list shows what ITS has achieved.

1) ITS is able to solve problems by using suitably composed knowledge base to the domain.
2) A subset of sentences in natural language which corresponds to knowledge representation is able to be understood and generated.
3) As a result of 1) and 2), ITS is able to explain students a problem solving process, and able to answer students' questions.
4) ITS is able to identify the correct knowledge used in student's problem solving processes.
5) ITS is equipped with identification methods of student's error origins, though they are not complete.
6) As a result of 4) and 5) ITS is able to construct student models which correspond to each individual student's knowledge.
7) By using a student model, ITS is able to predict the student's problem solving process. Hence it is able to judge the suitability of the problem to be presented to the student.
8) Thus ITS is able to provide the most suitable learning material to each individual student or able to select the most adaptable teaching strategy to each student's comprehension level.

2.2 What has been left over in ITS.

To put the other way around, the above list suggests that ITS includes the following unsolved problems, which will be divided into two portions; problems within the framework of ITS and problems which transcend the framework of ITS.

(1) Problems within the framework of ITS

1) Completeness of the error origin identification

A variety of the identification methods has been developed, but non of them satisfies generality, tractability and completeness at the same time.

2) Completeness of student models

An important prerequisite of a student model is the complete representation of problem solving knowledge which the student has presently acquired in the domain. But the incompleteness of error origin identification described in 1) prevents ITS from constructing a complete student model.

(2) Problems that transcend the framework of ITS

1) Techniques which have been developed in ITS are confined to apply to a limited form of tutoring, that is, they are confined to support student's learning effectively by error identification techniques in the problem solving. It is difficult for ITS to step out of the frame of the problem solving.

2) As a result of 1), It is difficult for a student to acquire a fundamental comprehension about a concept, an axiom, a theorem or a procedure that the student has first encountered.

3) In general, it is impossible to grasp the student's state entirely within the problem solving frame. Hence, even if a student answers correctly it is impossible for ITS to distinguish whether the answer is a result of student's fundamental comprehension or a result of mere memorization of only solving procedure.

4) As a result, ITS has not been equipped with an effective architecture of supporting a student to acquire a new knowledge by discovery, which the cognitive and educational science esteem the most important form of human learning because the discovery learning provides students a base to find how to behave when they encounter inexperienced situations.

The above issues have played a big role of bringing a variety of the 3rd generation CAI. Although at present their state of architecture still remains within the applications of GUI or hypermedia , it is well recognized that both the architecture and cognitive meanings of the 3rd generation CAI have a complementary importance to ITS. The problem will be discussed in section 4 and 5.

3 Problems within the framework of ITS: error diagnosis and error origin diagnosis

3.1 Importance of error origin diagnosis

Supposing that a system derives all the correct answers of a problem, a student's answer to the problem must fall one of the following two cases; the answer coincides with one of the derived answers or not. If the student's answer doesn't coincide, we can decide that it is an erroneous answer. However, if the knowledge base used for the problem solving is not complete, that is, if there is no guarantee that the system derives all the correct answers of the problem, the disagreement of the answers between the system and the student does not mean that the student answered incorrectly.

If the system has special knowledge that derives incorrect answers and is distinguished from ordinary domain knowledge, it is able to derive the correct answers by using ordinary domain knowledge only and incorrect answers by using both special and ordinary domain knowledge. Hence, the system is able to identify the student's incorrect knowledge (we call the incorrect rule a "Buggy rule") used in the problem solving process, together with the correctly used knowledge so long as the student's answer coincides with the derived answer regardless of their correctness. In general, buggy rules have a character of strong domain dependence, hence at the authoring, time consuming works of collecting and analyzing the buggy rules are required for each domain. On the other hand, if the system has knowledge about student's error origins which derives buggy rules, the knowledge is not only able to identify the student's buggy rule, but also able to be applied to broad domains, because the error origins are divided into two parts; a domain independent part and a domain dependent part, hence they have characteristic of more domain independence than the buggy rule has. The problem of domain independence becomes important for authoring new systems.

Besides the characteristic of domain independence, identifying the error origin and storing it in the student model makes ITS possible to predict a student's error in the use of even an inexperienced rule .

3.2 Means to identify students' errors

(1) Methods to generate buggy rules

The following four methods identify a student's correct or incorrect rule according to their correct or incorrect answers, respectively.

1) Error identification by buggy rule.

At the authoring ITS, collecting as many kinds of error instances as possible in the real student 's answers, classifying them according to the error origins and representing the results as buggy rules are the main task of the method.

As mentioned above, the defect of the method is the characteristic of strong domain dependence.

2) Error identification by perturbation method

There have been many research works published concerning student's errors and their causes in the fields of both cognitive science and pedagogy[4),5)]. Analysis of these works has revealed the causes of student's erroneous behavior. For instance, students often neglect or confuse the constraints when they apply already acquired rules to a different situation, students often drop a part of subgoals when they substitute subgoals for a goal, thus they encounter an impasse, moreover in order to dissolve the impasse students often behave inconsistently to their previous answers, etc. The facts suggest that by formulating operators by using the results from these analysis of the real errors and applying them to correct rules, buggy rules are able to be constructed.

The perturbation method[10)] reconstructs student's errors by applying the cognitively probable operators to the correct rule. The problem of how widely the perturbation method can cover the student's error depends on the breadth and details of the analysis in the real instances. The defect of the method is the problem of operator combinations, which will be discussed later.

3) Unification of perturbation method with buggy method

If buggy rules which are generated by perturbation method are stored in a buggy catalogue pool, as shown in Fig.1, they can be used directly for identifying student's errors so that a computing time for generating buggy rules may be saved. Buggy rules collected by human experts are used as the initial state of the buggy catalogue pool.

4) Error identification by truth maintenance

This method is a different approach from the above three methods which recognize the

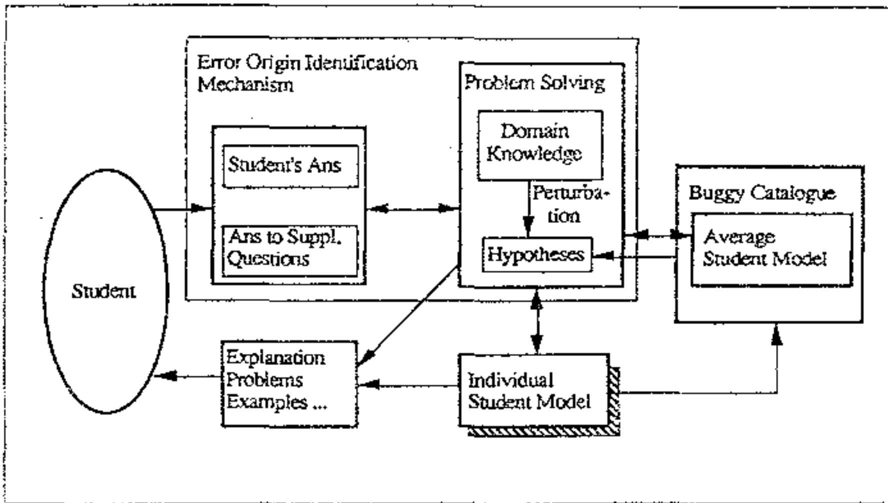

Fig.1 Student Modeling Mechnism

existence of a student's error first, then infer a student's erroneous rule by identifying the error origin. On the contrary, the fourth method infers a rule used by student first from a series of student's answers regardless of the correctness or incorrectness of the student's answer, then a truth maintenance system determines if the inferred rule is consistent with the domain rules or not.

Generating a student's rule from a series of student's answers means to make some kind of inductive inference. At present, the typical method uses MIS[11] (Model Inference System) for constructing student's rules and then ATMS[12] (Assumption Based Truth Maintenance System) for detecting the error candidate[13].

The defect of the method is susceptibility to influence from input noise which often occurs according to the change of student's comprehension and from pre-supposed terminology concerning the student's errors. In order to apply the method to the real system, tractability may cause another difficulty, which will be discussed later.

(2) Methods which do not construct the error rules

1) overlay method

So long as a student's answer coincides with one of the answers derived by the system, rules used for the derivation are considered to be acquired correctly by the student. Thus the method gathers the correctly acquired rules only. The defect point is that the method has no awareness of student's error.

2) Error identification by a classification tree

This method is the same as the medical diagnosing tree. Errors are analyzed by experts of education and an unique phenomenon to each error is selected to organize a fork in a diagnosing tree. This method depends strongly on the domain.

3.3 Criteria of error identification methods

The following four items are often used for assessment of error identification methods.

1) Generality (or independence of the domain)

Generality is an criterion of facilities in authoring ITSs.

2) Covering rate

Covering rate indicates the extent of the error range to which the system can identify student's errors. It is quite difficult to work out the precise rate because the whole kinds of human errors can not be detected even if the domain is limited. The covering rate is often used in comparison between different systems within a definite set of student's errors.

3) Tractability

One of the classification methods of error identification is whether real instances of human errors are taken into consideration or not. If instances are used, it is necessary to collect and analyze the instances, which needs almost the same time as or even more time than that of describing the domain knowledge, and yet it is impossible to guarantee the complete covering rate. In the case of perturbation method an overhead time of operator combinations is added to the execution time. To avoid the overhead a teaching sequence is introduced according to the relationship between a goal and subgoals of the rule, and a problem concerning a goal is not presented to the student until all of its subgoals have been correctly comprehended by the student. This method prevents a student from learning a new goal by using subgoals which have not yet been comprehended.

On the other hand although real instances of human errors are not taken into consideration, a student's rule is able to be inferred by using MIS if all the predicate names and arities which will appear in the student's erroneous answers are suitably determined beforehand. This strong verbal dependence causes to decrease the covering rate. Besides, it is necessary for MIS to employ a method like ATMS for detecting inconsistency of the derived rule to the domain knowledge, which requires a further computation and consumes considerable computing time because of the complexity of the time-space structure and the label computation.

4) Accuracy

Whether the obtained error origin hits the true student's error origin is also an important problem. This problem should be examined in each system separately.

4 Open-end educational systems

4.1 Micro world for supporting discovery learning

An open-end educational system like a micro world or a hyper media system with direct manipulation and visualization of internal states has a possibility of realizing a third generation CAI because of the following new features.

1) A student is allowed to observe invisible phenomena like force, gravity, velocity, sound waves, etc. schematically by manipulating objects directly.
2) As a result, it is possible for a student reorganize his/her mental model about the functions and the behavior of the objects by repeating a trial and error cycle of hypothesizing, experimenting and verifying. Thus, the system has the possibility of supporting discovery learning.
3) Visualization function which allows students observe a state and its transitions makes students understand the internal structure of the world, if suitable explanations are added by qualitative simulation.

Thus, the open-end system arouses a student interest in the objective world, establishes student's independence and supports student's discovery learning. In spite of these excellent features, the system has not yet obviated the following defects.

1) It is impossible for open-end system to answer student's questions concerning his/her trial and error operation.
2) There is no means to support a student when he/she impasses or loses the way in the experiment because the system has no means to infer the student's intention in the trial and error operation.
3) Highly individualized coaching is impossible because the system has no means to model a student.

The above discussion, together with the discussion in 2.2, shows the complementary characteristics of the open-end system and ITS.

4.2 Discussion on human learning from the epistemological view point

A learning process through which the human is conscious of the existence of an unknown rule, understands it and applies it by him/herself to a new problem is described by the following three steps.

The first step is an inductive knowledge acquisition from an instance based on trial and error. In this step, the obtained rule may be strongly influenced by the model of the world. It is the most important thing in the first step that the student should has already acquired all the premise knowledge of the target rule.

In the second step plural instances are employed to formulate a rule by generalizing rules obtained in the first step. The over specifica-

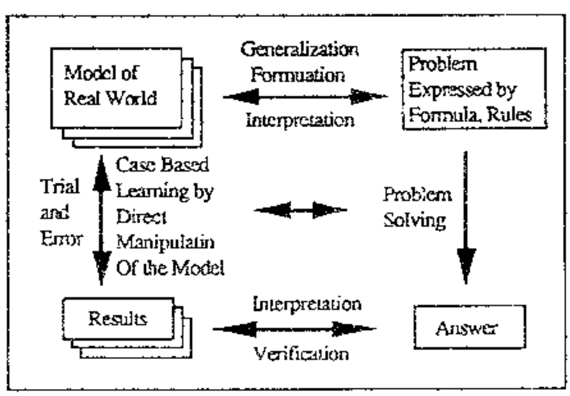

Fig. 2 A model of human learning

tion that may occur in the previous step should be reformulated in the second step.

The third step fixes the rule acquired in the previous step by applying the rule deductively to a variety of new problems so that the rule may be assimilated to his/her background knowledge. Thus it becomes unnecessary for students to think back to the premises or fundamentals of the rule every time they solve a problem.

Fig.2 explains the process schematically. The squares represent concepts and the arrows represent mental or concrete operations. Hence, experiments in a laboratory or natural phenomena in the real word are replaced by models of the upper-left squares in this figure.

An open-end educational system like a micro world or a hyper media system with direct manipulation and visualization of the internal states corresponds to the first step learning, while ITS corresponds to the thirds step, and a new method should be introduced to amalgamate these two methodology through the second step.

5 Discussion and conclusions

In order to solve problems described above, researches on amalgamating ITS to the open-end system are now proceeding[14),15),16)]. Our approach to solve the problem bases on the following ideas.

1) In order to grasp the student's intention in the open-end system, it is necessary for the system to have an ability of discovery learning through internal experiments of the micro world by using back ground knowledge base. The internal experimentation[17)], shown in Fig. 3, is one of the solutions.

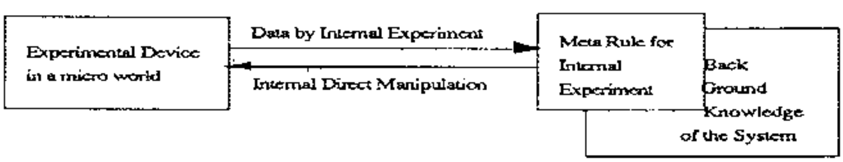

Fig. 3 Discovery learning through internal experiment

2) Premises of a target rule of an instance in the discovery environment, must be well-formed in the student's back ground knowledge. Suitability is able to be determined by a student model and well-formed domain knowledge. In this case, the well-formed relation is derived from the consistency between goal and sub goal relation.
3) System's support for student's discovery learning consists of the following two steps. Firstly, the knowledge region used for trial and error is gradually decreased from whole back ground knowledge to the premises of the target rule, and secondly, through meta-procedures for discovery learning which includes internal experiments the system acquires knowledge to support a student to organize a correct mental model.
4) ITS is used for deductive learning by using the already acquired knowledge, where if counter

examples are needed the instances used in the inductive learning of the first step is the most effective. The reason is that they are the common examples between the student and the system and that the student's comprehension level of generalization of the rule has been recorded in the student model.

5) In ITS only, if a student answers correctly it is impossible to determine whether the student has the fundamental comprehension or used the merely remembered procedures only. In amalgamated system the difference is obtained if a student model keeps records of processes for acquiring rules.

In the long run, all the problems discussed here resolve into the common problem of AI, machine learning in the big knowledge base.

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