Modeling a Human's Learning Processes to Support Continuous Learning on Human Computer Interaction

Kouki Takemori[1], Tomohiro Yamaguchi[1], Kazuki Sasaji[1], and Keiki Takadama[2]

[1] Nara National College of Technology
Nara, Japan
{Takemori,yamaguch,sasaji}@info.nara-k.ac.jp
[2] The University of Electro-Communications
Tokyo, Japan
keiki@inf.uec.ac.jp

Abstract. This paper presents the way to design the continuous learning support system for a human to achieve continuous learning. The objective of this research is to make a prototype system based on a learning process model to guide a human to achieve continuous learning. The main problem is how to keep supplying new goals to a learner for achieving continuous learning. To encourage the sense of continuous awareness toward goal discovery, we propose an idea to provide a human learner with invisible goals. This paper formalizes the continuous learning by a simple maze model with invisible goals and designs the maze sweeping task which involves multiple solutions and goals.

Keywords: continuous learning, invisible goals, maze sweeping task.

1 Introduction

Since 1980s, computer systems have been used in many different ways to assist in human learning. Computer-based systems have been applied in the field of human learning for three different purposes [1]: (1) to replicate human behavior, (2) to model human behavior, or (3) to augment human behavior. Described above, the position of our research is based on the second class toward the third class. However, there is a basic problem that these previous methods commonly depend on observable behaviors or activities. On the other hand, a learning process of a human has a major difficulty in observing since it is a mental process. So it is necessary to add a new twist to observe the learning process of a human.

In the field of management in business, psychological research on human motivation comes to the frontline. While, there is a great need to facilitate continuous improvement and innovation in business processes since an organization is to be successful in today's rapidly changing environment. And so, a learning process model to achieve continuous improvement has been proposed, it is defined as a process that results in changed behavior [2]. There are three elements for this process to be effective: the hows, whys, and whats of learning. The "hows" of learning is a technique to

S. Yamamoto (Ed.): HIMI/HCII 2013, Part I, LNCS 8016, pp. 555–564, 2013.

help the learning process. The "whys" of learning creates an environment and a task which provides meaning. The "whats" of learning enables a focus on goals or tasks. Learning process is consists of several learning-stages. Table 1 shows the stages of learning process [2]. This paper focuses on the learning-stages of awareness, understanding and commitment as shown in table 1.

Table 1. The Learning-stages of Learning process

Learning-stage	Meaning	The role of leadership
6 Reflection	"What/How have we learned?"	
5 Enactment	"I want to try this"	Allow risk taking
4 Commitment	"I want to know about this"	Remove barriers
3 Understanding	"I need to know about this"	Develop shared vision "whys"
2 Awareness	"I ought to know about this"	Develop shared vision "whats"
1 Ignorance	"I do not know and do not care"	Question

The main problem is how to keep supplying new goals to a learner for achieving continuous learning. To solve this problem, we propose an idea to provide a human learner with invisible goals to encourage the sense of continuous awareness toward goal discovery. Figure 1 shows modeling a learning process by invisible stimulus. Invisible stimulus means that it has no impact on sensory perception before action, but the response of the action differs from the past. Thus a human learner who encounters an invisible barrier becomes the state of being aware of something different. Awareness that results in change behavior is one of the shallow understandings, called *single-loop learning* that consists of normal level learning with fixed goal. In figure 1, the blocks with broken line mean that they are not given explicitly to a learner. The learner is expected to aware them, goals, barriers and rule of the learning task by understanding the maze sweeping learning task.

An invisible goal provides the learner with unforeseen success of goal discovery. It is expected to enhance the need for discovering unknown goals, then it results in a goal commitment of the learner. Commitment that results in goal discovery is one of the deep understanding, called *double-loop learning* that consists of two kinds of learning level: normal level (change behavior) and meta level (goal discovery). This paper focuses on goal discovery for continuous learning by invisible goals. For modeling the major learning-stages of a learning process as shown in figure 1, this paper formalizes the continuous learning by a simple maze model with invisible goals and designs the maze sweeping task which involves multiple solutions and goals.

For designing a learning environment, there are two points as follows:

(i) easy to monitor a learning process.
For a learner, self-monitoring the learning processes assists the awareness to improve them. For the system, observing the learner's learning processes enables to evaluate the effect of the learning support system.

(ii) capture the essential features of continuous learning.
To evaluate a discovery learning task by the experiment with subjects within minutes, it is important to be easy to pass on meaning of the experimental task to a human learner.

Next, we describe the concept for designing the "whats" of learning in a maze model. For designing the maze sweeping task to encourage the process of continuous learning for a human learner, there are two points as follows:

(i) to drive single-loop continuous learning, the maze sweeping task is requested to collect all optimal solutions for each goal.
(ii) to drive double-loop continuous learning, the goal aspects of invisible and multiple goals are designed.

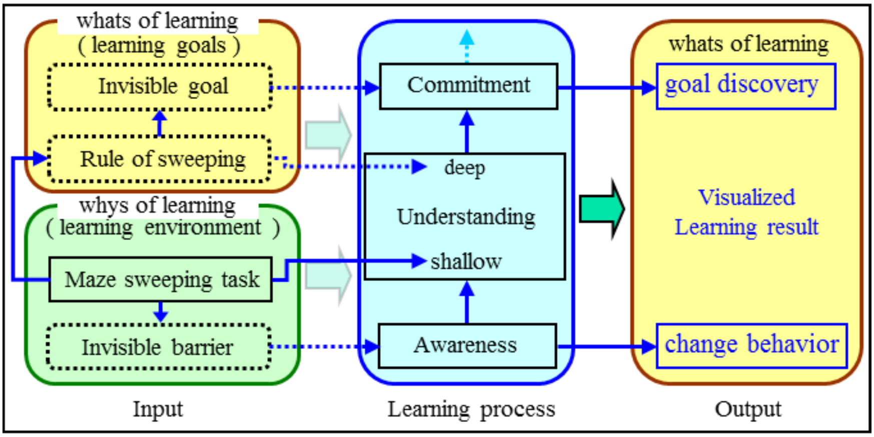

Fig. 1. Modeling a learning process by invisible stimulus

2 Designing the Continuous Learning by a Maze Model

First we describe designing the "whys" of learning to create a learning environment as a grid maze model, second, designing the "whats" of learning as the maze sweeping task is illustrated. For detail, please refer [3].

2.1 A Learning Environment by a Maze Model with Invisible Goals

As a learning environment, a maze model is defined by five elements, state set, transitions, action set, a maze task with its solution, and invisible goals. An invisible goal is defined as the undiscovered goal state of a maze sweeping task. In a 2D grid maze model, S is the start state of the maze, and G is the goal state of the maze.

2.2 The Maze Sweeping Task That Involves Multiple Goals

2.2.1 The Definition of an Achievement of the Maze Sweeping Task

To begin with, we describe a *maze sweeping task* with a fixed goal. It is defined as to find (shortest) paths from S to G which visits all states only at once in the maze model. Note that S is the fixed position. The *continuous learning task* is defined as to collect all solutions [4] of the task. The optimality of a maze task is defined as the minimum length of a path from S to G. An *achievement* is defined as the single-loop continuous learning of a maze sweeping with a fixed goal. Inputs of the learning are a maze environment and two kinds of states, a start state S and a goal state G in it. Note that a goal state G maybe a dummy goal. The *single-loop learning goal* is to find all optimal maze sweeping paths from S to G in a given maze.

Figure 2 shows an illustrated example of an achievement of 3x3 maze sweeping task. Figure 2 (a) shows an initial situation of an example an achievement of 3x3 maze model. Figure 2 (b) shows all solutions of the achievement as shown in figure 2 (a). An achievement is harder than a maze task since it needs a systematic search method to collect all solutions. So that it is suitable to make an adequate difficulty of the continuous learning task for a human learner in a small size of the maze model.

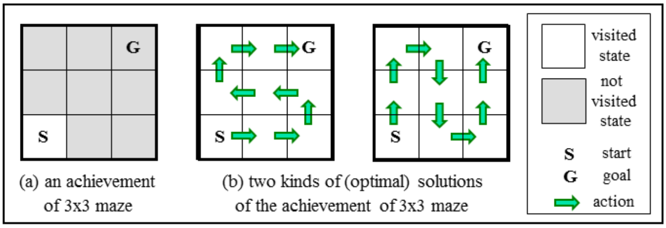

Fig. 2. An example of an achievement of 3x3 maze sweeping task

2.2.2 The Definition of a Stage of the Maze Sweeping Task

Next, we introduce a maze sweeping task that involves multiple goals. A maze sweeping task with multiple goals is defined as to find the paths from S which visits all states only at once in the maze model, note that G is the last state in the path.

A *stage* is defined as the double-loop continuous learning of a maze sweeping with multiple achievements. Inputs of the learning are a maze environment and a start state S. Note that a goal state G is normally invisible. The *double-loop learning goal* is to find all achievements in the given maze by discovering corresponding invisible goal state for each achievement. Figure 3 shows an illustrated example of the stage of 3x3 maze sweeping task invisible goals condition. Figure 3 (a) shows an initial situation of the stage of 3x3 maze invisible goals condition. There are three kinds of goals in a stage of the maze model as follows:

(i) visible goal
This type of goal is displayed for a learner as shown in figure 3

(ii) *invisible goal*
This type of goal is not displayed for a learner in the beginning. After all solutions of the corresponding invisible goal are found, it is displayed as a discovered goal DG as shown in figure 3 (b).

(iii) dummy goal
This type of goal is not displayed for a learner in the beginning just like an invisible goal, and it has no solution associated with the dummy goal. A dummy achievement is defined as an achievement which has no solution.

In this stage of 3x3 maze, there are four invisible goal states displayed as DG within eight states as shown in figure 3 (b), and other states are dummy goal states of this stage.

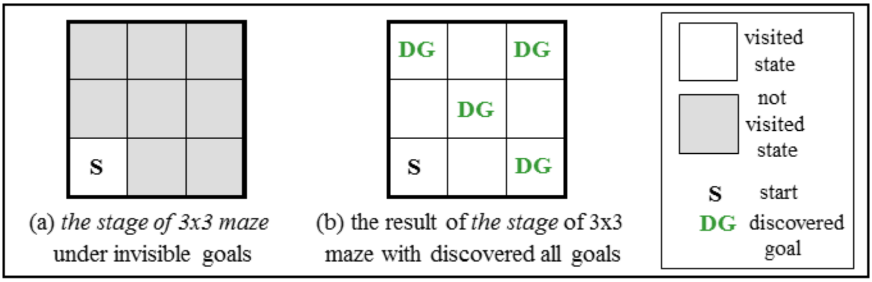

Fig. 3. An illustrated example of the stage of 3x3 maze sweeping task

3 The Layout Design of Mazes for the Continuous Learning Task

3.1 Overview of the Continuous Learning Support System

Our system consists of three layers, top-layer, maze-layer and achievement-layer. The main function of top-layer for a learner is to select a stage associated with the maze-layer to proceed continuous learning according to the difficulty. The main function of maze-layer for the learner is to discover all achievements to learn.

(i) top-layer
Figure 4 shows the overview of the top-layer of the system for a learner. A user can operate to start or exit the experiment, select the current maze (current stage) to challenge, and can verify the state of progress of continuous learning by the display of several measurements described below at section 4.1.

(ii) maze-layer
In this layer, the user can select an achievement to challenge by clicking one of states in the current maze displayed in the center of the maze-layer window. If he/she find all solutions in the achievement, the goal state in the achievement is displayed as DG as shown in figure 3 (b), then it becomes to non-selective.

(iii) achievement-layer

In this layer, the user can challenge the maze sweeping task of the achievement selected at the maze-layer. If the user finds a solution of the achievement, it is registered, then the system goes back to the maze-layer. If he/she visits G without finding a solution, the small window appears to notice failure, then he/she can restart this achievement.

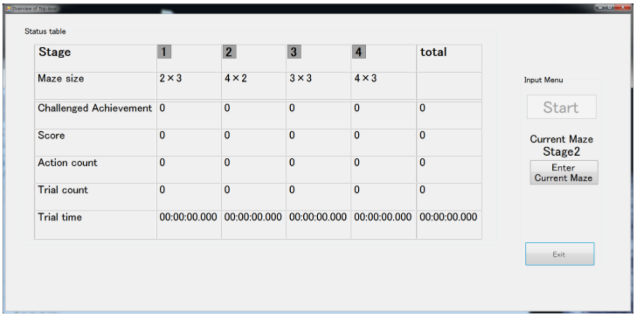

Fig. 4. Graphical User Interface for a learner - top-layer of the system

3.2 The Layout Design of Mazes on the Thinking Level Space

Now we coordinate the layout design of mazes on the thinking level space for designing the continuous learning task. Figure 5 shows the layout design of mazes for the continuous learning task. It is composed of four stages.

stage 1: visible goals under unique solution.

It consists of 2 x 3 maze model with three visible goals and two dummy goals. Each goal is linked with an achievement of the 2 x 3 maze with a fixed goal. The solution of each achievement with a visible goal is unique, on the other hand, each dummy achievement with a dummy goal has no solution.

stage 2: invisible goals under unique solution

It consists of 4 x 2 maze model with four invisible goals and three dummy goals. Note that for a learner, showing of both goal and dummy goal is the same until the learner finds a solution on an achievement with an invisible goal. The solution of each achievement with an invisible goal is unique, on the other hand, a dummy achievement has no solution.

stage 3: *invisible goals* under multiple solutions

It consists of 3 x 3 maze model with four invisible goals as shown in figure 3 (b) and four dummy goals. Each achievement with an invisible goal has two solutions, on the other hand, a dummy achievement has no solution. In stage 3, there are total eight solutions.

stage 4: *invisible goals* under many solutions

It consists of 4 x 3 maze model with six invisible goals and five dummy goals. In this stage, there are total seventeen solutions much more than the number of solutions in stage 3. Within six goals, three goals have four solutions each, another two goals have two solutions each, and the rest of a goal has one solution.

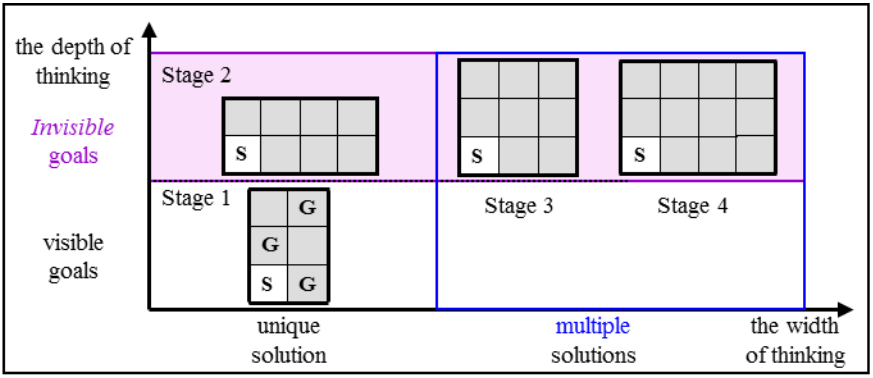

Fig. 5. The layout design of mazes for the continuous learning task

4 Experiment

4.1 Experimental Setup

To examine the effects our continuous learning support system, we perform the experiment in which total of twelve subjects are divided into two groups for comparative conditions. There are two objectives. First one is "dose our system support the continuous learning for a human?" Second question is "does the condition of invisible goals work so well to assist the continuous learning for a human?" Then, we describe the experimental task and the instruction for subjects, comparative conditions, assumptions and measurements, and the hypothesis. The experimental task explained to the subjects is to collect solutions of the maze sweeping task as many as possible as we described at section 2.2. To examine the degree to work through the continuous learning for the maze sweeping task, we prepare four stages as we described at section 3.2.

All subjects are instructed as follows:

(i) Stage 1 is the practice maze to get used to the maze sweeping task.
(ii) Stage 2 and 3 are the real part, collect solutions as many as possible.
(iii) Stage 4 is a bonus maze, if you want to continue this experiment, you can challenge this stage as long as you can.

Figure 6 shows the experimental condition whether goals of each maze are invisible or not. Note that Stage 1 is the common condition that all goals are visible. Figure 6

(a) shows the condition of mazes invisible goals condition. In this condition, all goals in the maze are invisible. Figure 6 (b) shows the condition of mazes visible goals condition. In this condition, all goals in the maze are visible.

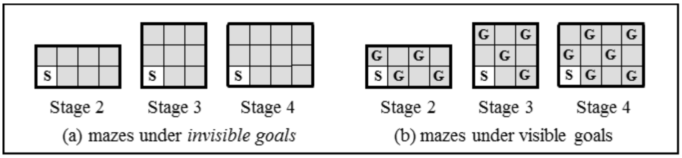

Fig. 6. Comparison of invisible goals with visible goals

To measure and evaluate the continuous learning for a human, we make an assumption as follows:

The degree of depth of thinking (double-loop learning) can be estimated by the playing time in the maze-layer and by the number of lines of free comments relevant to a subject's learning process in the questionnaire after the experiment.

Next we describe the measurements of the experiment as follows:

(1) the number of challenged achievements
(2) the number of collected solutions (displayed as Score in figure 4)
(3) the number of actions of the challenged achievements
(4) the number of trials of the challenged achievements
(5) the playing time in the achievement-layer
(6) the playing time in the maze-layer
(7) the number of lines of free comments relevant to a subject's learning process in the questionnaire after the experiment

First four measurements are counted on each stage as shown in figure 4. Fifth measurement is to estimate the degree of shallow understanding (single-loop learning), The last two measurements are to estimate the degree of depth of thinking (double-loop learning). Note that these measurements except (7) include the play data in dummy achievements.

Then we make a hypothesis as follows:

The condition of invisible goals encourages the deep thinking in the maze layer, and it results in the longer continuous learning than the condition of visible goals.

4.2 Experimental Results

4.2.1 Dose Our System Support the Continuous Learning for a Human?

This section evaluates the effectiveness of our continuous learning support system. All twelve subjects performed the bonus stage 4, and each four subjects of both conditions collected all 17 solutions of stage 4. The data of table 2 and table 3 is the averaged value of six subjects for each condition, and (data) is the standard deviation of six subjects for each condition. Table 2 shows the experimental result of the total results of stage 1, 2, 3 and 4. The seven measurements are described at section 4.1. As shown in table 2 (2), about 87 percent solutions (28 solutions among total 32 solutions) are collected in both conditions. Therefore, these results suggest that our continuous learning support system is effective for both conditions.

4.2.2 Does the Condition of Invisible Goals Work So Well to Assist the Continuous Learning for a Human?

This section evaluates the effectiveness of the condition of invisible goals compared to the condition of visible goals. In table 2, there is no significant difference in first five measurements (1), (2), (3), (4) and (5) between both conditions. However, the last two measurements (6) and (7) which are relevant to the degree of depth of thinking (double-loop learning) seems to be different. Analyzing the ratio of (6) divided by (5) the playing time in the achievement-layer, 4 out of 6 subjects are over 4 times invisible goals condition, relative to 1 out of 6 subjects is over 4 times visible goals condition.

Next, we analyze the measurements in stage 4 to evaluate the degree of continuous learning in straightforward way. Table 3 shows the experimental result of stage 4. The six measurements are same as table 2. In table 3, there is no significant difference in first four measurements (1), (2), (3), and (4) between both conditions. However, the last two measurements (5) and (6) the playing time in the maze-layer, both of the results invisible goals condition are longer than the results visible goals condition. The reason is that most subjects tend to find correct path at the maze-layer before select a goal state associated with the achievement in order to avoid failure at the achievement-layer. Therefore, these results suggest that the invisible goals condition is more effective to assist deep thinking of the maze sweeping task than the visible goals condition.

Table 2. The experimental result: total results of stage 1, 2, 3 and 4

measurements	(1) [times]	(2) [times]	(3) [times]	(4) [times]	(5) [sec]	(6) [sec]	(7) [lines]
Invisible goals conditions	17.6	28.0	341	39.8	270	1080	9.00
	(3.67)	(6.33)	(63.0)	(6.11)	(240)	(1230)	(4.00)
Visible goals conditions	18.0	27.8	340	42.0	245	527	4.50
	(1.27)	(7.06)	(114)	(9.19)	(140)	(250)	(4.04)

Table 3. The experimental result of stage 4

measurements	(1) [times]	(2) [times]	(3) [times]	(4) [times]	(5) [sec]	(6) [sec]
Invisible goals conditions	6.50	14.0	214	21.3	201	648
	(2.95)	(5.62)	(67.9)	(6.74)	(243)	(1045)
Visible goals conditions	6.00	14.0	219	21.7	112	199
	(0.63)	(5.29)	(112)	(10.4)	(65.0)	(172)

5 Discussions

The objective of the depth of thinking is to find learning goals to achieve toward continuous learning. It is defined by the condition of goals, that is whether goal states are visible (for single-loop learning) or invisible (for double-loop learning). The case of invisible goals is deeper level of thinking than the case of visible goals. A learner thinks by shallow understanding (single-loop learning) under visible goals condition since the goal states are given and known. On the other hand, under invisible goals condition, the learner thinks by deep understanding (double-loop learning) since the goal states must be discovered.

Then we discuss the awareness of learning objectives by a learner. Minimum requirements for double-loop learning are to find all goal states of a given maze sweeping task. However, the objective of "whys" of learning is to understand the rule of maze sweeping deeply. (For example, the regularity of the positions of DG in figure 3 (b).) Since "Reflection" is a sort of an interpretation of learning results by the learner, it is essential to aware various reflections (interpretation of learning results) in order to discover various learning goals for continuous learning.

6 Conclusions

We described the way to design the continuous learning support system based on a learning process model to guide a human to achieve continuous learning. Experimental results suggest that the invisible goals are more effective to assist deep understanding in a learning process than the visible goals. As one of the future works, we are planning to quantitate degree of difficulty of continuous learning as the complexity of maze model and action sequences of a learner, to keep maintaining the flow state of the human learner according to the learner's skill up.

Acknowledgement. The authors would like to thank Prof. Habib and Prof. Shimohara for offering a good opportunity to present this research. We also thank the reviewer for important comments. This work was supported by JSPS KAKENHI (Grant-in-Aid for Scientific Research (C)) Grant Number 23500197.

References

1. Sklar, E., Richards, D.: Agent-based systems for human learners. The Knowledge Engineering Review 25(02), 111–135 (2010)
2. Buckler, B.: A learning process model to achieve continuous improvement. The Learning Organization 3(3), 31–39 (1996)
3. Yamaguchi, T., Takemori, K., Takadama, K.: Modeling a human's learning processes toward continuous learning support system. In: Habib, M.K., Paulo Davim, J. (eds.) Mechatronics Engineering. Wiley-ISTE (to be appeared June 2013)
4. Yamaguchi, T., Nishimura, T., Sato, K.: How to recommend preferable solutions of a user in interactive reinforcement learning? In: Mellouk, A. (ed.) Advances in Reinforcement Learning, pp. 137–156. InTech Open Access Publisher (2011)