Chapter 4

Modeling a Human's Learning Processes toward Continuous Learning Support System

This chapter describes the learning support system for a human to achieve continuous learning. The objective of this research is to make a prototype system on the basis of a learning process model to guide a human to achieve continuous learning.

First, the need for continuous learning in mechatronics engineering is described, and then we give an introduction to research on learning support systems for a human. We point out the importance of support for awareness and understanding of learning processes. Second, requirements for modeling a learning process to achieve continuous learning are discussed. The main issue is "who generates a learning goal of a learner?" When the learner accomplishes the learning goal, he/she stops learning.

The main problem is how to keep supplying new goals to a learner for achieving continuous learning. A useful suggestion is from research in metalearning in education. To encourage the sense of continuous awareness towards goal discovery, we propose an idea to provide a human learner with invisible goals. Then, this chapter formalizes the continuous learning by a simple maze model with *invisible goals* and designs *the maze sweeping task*

Chapter written by Tomohiro YAMAGUCHI, Kouki TAKEMORI and Keiki TAKADAMA.

that involves *multiple solutions* and *goals*. Under *the maze sweeping task* to collect as many optimal solutions as possible, we perform the experiment to make a comparison between *under invisible goals* condition and under visible goals condition. Experimental results showed that our continuous learning support system is effective, besides *the invisible goals* are more effective to assist a greater understanding in a learning process than the visible goals. Finally, several issues to develop our approach are discussed.

4.1. Introduction

4.1.1. *The need for continuous learning in mechatronics engineering*

In recent years, a new design approach for human and a mechatronics system that considers a human's intelligent behaviors such as skill level going up or learning has been studied [HAB 06, HAB 08, SUZ 10]. Human adaptive mechatronics (HAM) [SUZ 10] is the new mechatronics concept: the HAM system changes its mechanism and/or operating mode according to an operator's skill level to support the operator appropriately. By virtue of a human's adaptation ability, the operator may not only achieve his/her tasks but also up one's skill level.

To design HAM for humans to up their skill level, there are several research targets on humans' intelligent and mental processes such as individual learning, team-based learning or creative thinking [HAB 08]. This chapter focuses on the design method for an individual human's continuous learning support system toward open-ending learning.

4.1.2. *Learning support systems for a human*

Since the 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 [SKL 10]: (1) to replicate human behavior, (2) to model human behavior or (3) to augment human behavior. The goal of the first class of system is to approximate the outcomes of human behavior such as expert systems and some robotic systems. The goal of the second class of system is to imitate the processes underlying human behavior. The purpose behind modeling of humans is in order to better understand how and perhaps why humans act as they do. Research in this area comes under social science, particularly psychology, so that there is no computer model. The goal of the third class of systems, such as an agent-based system, is to facilitate the acquisition of knowledge or help the learner to become proficient. The aim is to provide artificial partners for joint human activity. As discussed above, the position of our research is based on the second class toward the third class.

A learning process has been focused on several research areas, man–machine systems, education and management in business. The first learning process is operation learning in man–machine systems [RAU 96]. In that, to estimate the degree of the learning process level, the complexity of observed behaviors is calculated by one of the standard metrics in graph theory. The second learning process is computer-mediated education through a virtual learning environment or through online learning support such as e-learning. In that, the role of educators can change toward facilitating and guiding students instead of transmission of knowledge. Since it is important to support the awareness and understanding of learning processes, several visualization methods such as activity visualization [HAR 99] or visualizing the students' communication activities in a Web-based system [MAY 11] has been proposed. However, there is a basic problem in that these previous methods commonly depend on observable behaviors or activities. On the other hand, observing the learning process of a human is very difficult since it is a mental process. So, it is necessary to add a new criterion to observe the learning process of a human.

4.1.3. *Modeling a learning process to achieve continuous learning*

In the field of business management, psychological research on human motivation comes to the fore. Pink [PIN 09] examines the three elements of true motivation – autonomy, mastery and purpose. Since an organization needs to be successful in today's rapidly changing environment, there is a great need to facilitate continuous improvement and innovation in business processes. Therefore, a learning process model to achieve continuous improvement has been proposed [BUC 96]. In this section, we summarize the Buckler's learning process model.

A learning process is defined as a process that results in changed behavior [BUC 96]. There are three elements for this process to be effective: the hows, the whys and the whats of learning. The "hows" of learning is a technique to help the learning process. Table 4.1 shows the summary of two kinds of major learning methods from [BUC 96]. Our approach is mainly based on the discovery model and it is a learner-centered approach. Our system empowers a learner to achieve the goal, and to challenge under risk of failure. Thereby, the sense of autonomy enhances intrinsic motivation toward creativity.

Model	Taught model	Discovery model
Focus	Teacher-centered	Learner-centered
Motivation	Extrinsic	Intrinsic
Culture	Controlled	Empowered/Autonomous
Advantages	Consistency	Creativity
Disadvantages	Create barriers to change	Higher risk of failure

Table 4.1. *Two kinds of major learning methods*

The "whys" of learning creates an environment that provides meaning. The "whats" of learning enables a focus on goals or tasks. Figure 4.1 shows an overview of a learning process model for the positioning of the whats and whys of learning. These are the input of the learning process. The output of the learning process is a learning result, it is observed as a change of behavior of a learner.

The learning process consists of several stages. Table 4.2 shows the stages of the learning process with the role of leadership [BUC 96]. This chapter focuses on the stages of awareness, understanding and commitment as shown in Figure 4.1.

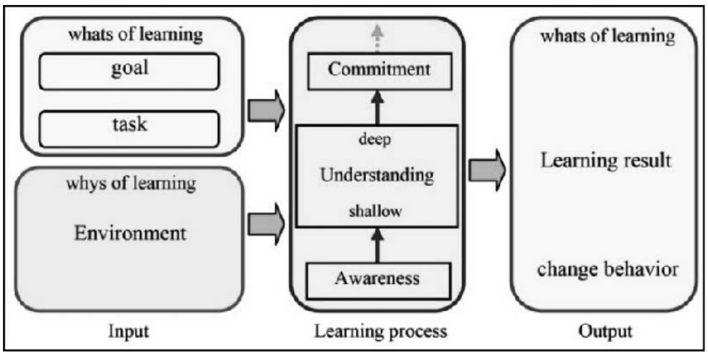

Figure 4.1. *Overview of a learning process model*

Stage	Meaning	The role of leadership
6 Reflection	"What have we learned?" "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.

Table 4.2. *The stages of learning process*

Then, we discuss requirements for modeling a learning process to achieve continuous learning. The main issue is "who generates the learning goals of a learner?" Almost all previous research in machine learning assumes that a learning goal is an external input of a learning agent or system, and it is fixed and given by the human designer [RUS 95, RUS 09]. Thus, when the learner accomplishes the learning goal, it stops learning. The same can be said for human learning. To avoid a learner stopping to learn, the leader assumes the role of leadership to guide the learning of the learner as shown in Table 4.2. Therefore, to realize the learning support system for a human to achieve continuous learning, it is necessary to automate the role of leadership, particularly to generate adequate goals as "whats" of learning.

4.1.4. *How to keep supplying new goals to achieve continuous learning*

As pointed out above, the main problem is how to keep supplying new goals to a learner for achieving continuous learning. A useful suggestion is from research in metalearning in education. The definition of metalearning is the state of "being aware of and taking control of one's own learning" [BIG 85]. In other words, it is the monitoring and control of learning [AND 07].

To solve this problem, we propose an idea to provide a human learner with *invisible goals* to encourage the sense of continuous awareness towards goal discovery. Figure 4.2 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 stimulus* enters the state of being aware of something different. There are two points to consider. The first point is that the *invisible stimulus* effects a continuous feeling in the learner's mind. The second point is that the *understanding* process of feeling something *invisible* is exposed to view. So that the output of *understanding* is a change in vision that causes a change behavior.

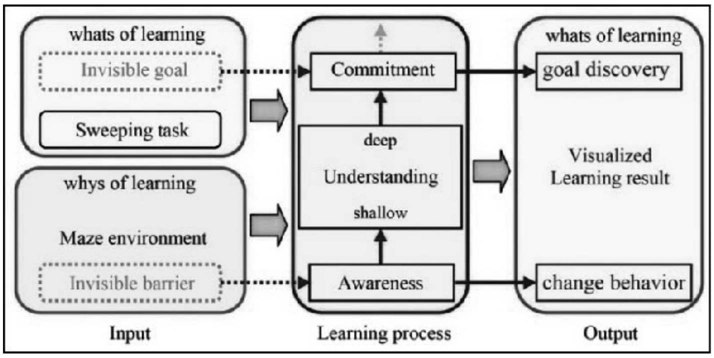

Figure 4.2. *Modeling a learning process by invisible stimulus*

We design two kinds of *invisible stimulus*, *invisible barrier* and *invisible goal* as shown in Figure 4.2. An *invisible barrier* makes the learner feel *awareness*, something that causes a failure of the performed action. When the learner intends to change his/her action to avoid the failure, it will be observed as a change in behavior. The *awareness* that results from the change in behavior is one of *shallow understanding*, called single-loop learning that consists of normal level learning with a fixed goal. Section 4.5 describes one of the effective usages of *invisible barriers* to guide the learner's shallow thinking or his/her trial and error to collect all solutions by a systematic search.

On the other hand, an *invisible goal* provides the learner with the 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 the one of *deep understanding*, called double-loop learning that consists of two kinds of learning level: normal level (change behavior) and metalevel (goal discovery). This chapter focuses on goal discovery for continuous learning by *invisible goals.*

4.1.5. *The concept to formalize the continuous learning by a maze model*

For modeling the major stages of a learning process as shown in Figure 4.2, this chapter formalizes the continuous learning by a simple maze model with *invisible goals* and designs *the maze sweeping task* that involves *multiple solutions* and *goals*. This section summarizes the design concepts of them. First, we describe the concept for designing the "whys" of learning to create a learning environment as a grid maze model, and then we describe the concept for designing the "whats" of learning as *the maze sweeping task*.

Designing a learning environment for a human learner, we adopt a grid maze model from start to goal since it is a familiar example for finding the path through a trial and error process. Figure 4.3 shows an example of a two-dimensional (2D) grid maze model. Figure 4.3(a) shows an example of the problem of a grid maze. S is the start state of the maze and G is the goal state of the maze. The details are given in the following section. For designing a learning environment, there are two points as follows:

– easy to monitor a learning process;

– capture the essential features of continuous learning.

In the first point, there are two kinds of advantages. For a learner, self-monitoring the learning processes assists in the awareness to improve them. For the system, observing the learner's learning processes enables it to evaluate the effect of the learning support system. In the second point, to evaluate a discovery learning task through the experiment with subjects within minutes, it is important to pass on easily the meaning of the experimental task to a human learner.

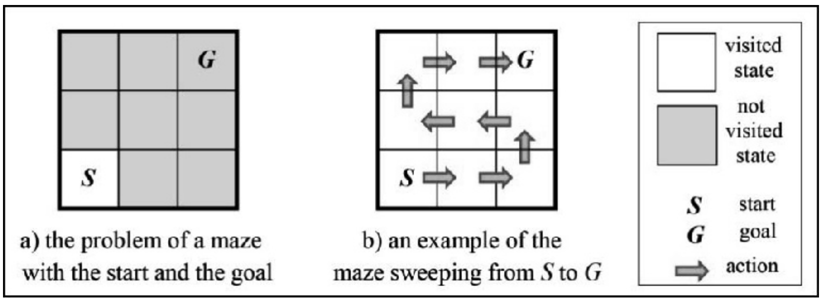

Figure 4.3. *An illustrated example of a grid maze model*

Next, we describe the concept for designing the "whats" of learning in a maze model. As the task: we employ *the maze sweeping* problem. *The maze sweeping* is to find the shortest path from S to G in a maze that visits all states only once. Figure 4.3(b) shows an example of the solution of the maze sweeping. For designing *the maze sweeping task* to encourage the process of continuous learning for a human learner, there are two points which are as follows:

– To drive single-loop continuous learning, *the maze sweeping task* is requested to collect all optimal solutions for each goal.

– To drive double-loop continuous learning, the goal aspects of *invisible and multiple goals* are designed.

4.2. 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 shown. After designing the thinking level, we introduce the layout design of mazes for the continuous learning task.

4.2.1. *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.* First, we describe the structure of a 2D grid maze, and then each of the five elements is defined.

4.2.1.1. *The structure of a 2D grid maze*

The $n \times m$ grid maze consists of the $n \times m$ number of 1×1 squares. It is surrounded by walls. Figure 4.4 shows the structure of a 2D grid maze. Figure 4.4(a) shows a 4×3 grid maze with the start and a goal. In a grid maze, every square that touches one of their edges is connected. Figure 4.4(b) shows the X-Y coordinate of the grid maze. Each square in a maze model is called a state. Each state is distinguished by a coordinate value as (x, y). S is the start state of a maze model that is fixed in origin (0, 0). In Figure 4.4(a), G is a goal state of the maze located at (3, 2).

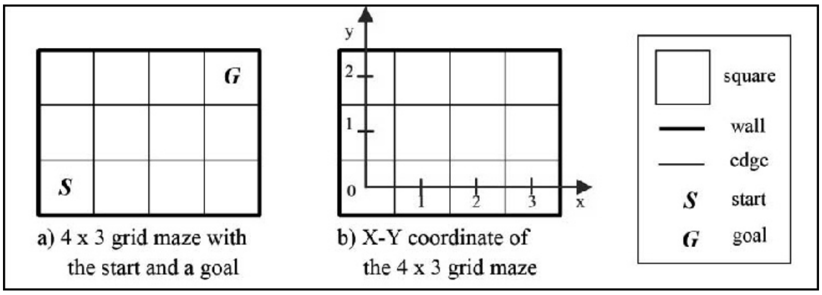

Figure 4.4. *The structure of a 2D grid maze*

4.2.1.2. *The definition of state set*

A maze model has a state set that corresponds to the structure of squares in the grid maze. Each state has several state variables as follows:

– (x, y): X-Y coordinate value.

– Flags: they consist of S flag, G flag, invisible G flag and discovered G flag.

– The number of visits: the number of occurrences in the path from S to G.

Figure 4.5 shows an example of a maze model with invisible goals. Figure 4.5(a) shows the 3 × 3 maze. In each state, whether visited or not, it is distinguished by the background color of the square. A state visited just once in the path is displayed as a white square and a not visited state is displayed as a gray square.

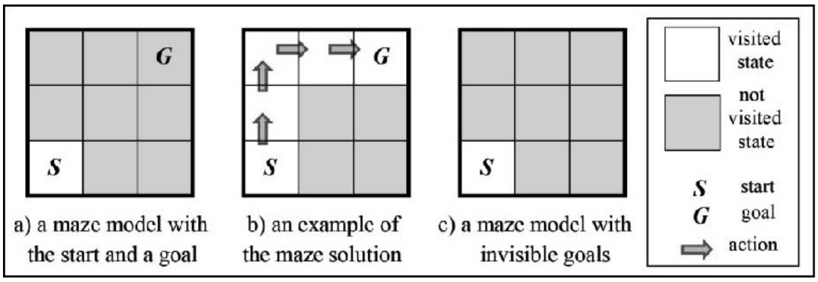

Figure 4.5. *A maze model with invisible goals*

4.2.1.3. *The definition of transitions and action set*

Transitions between states in a maze model is defined as whether the corresponding square are with four neighbors, {up, down, left, right} except for walls connected or not. They are represented as the labeled directed graph. The *action set* is defined as a set of labels to distinguish the possible transitions of a state. In a grid maze model with four neighbors, the *action set* is {*up, down, left, right*}, and each *action* of the action set is defined as follows:

– *up*: a transition to increase coordinate value of y to $y + 1$.

– *down*: a transition to decrease coordinate value of y to $y - 1$.

– *left*: a transition to decrease coordinate value of x to $x - 1$.

– *right*: a transition to increase coordinate value of x to $x + 1$.

4.2.1.4. *The definition of a maze task with its solution*

A maze task is defined to find the shortest path from S to G and is called a *solution* in the maze model. This task is easy since all (optimal) solutions are able to generate procedurally from relative coordinate values between S and G. A *solution* is described as the action sequence from S to G. Figure 4.5(b) shows one of the *solutions* of the maze task from S to G, and its action sequence is (*up, up, right, right*).

4.2.1.5. *The definition of an invisible goal*

An invisible goal is defined as the undiscovered goal state of a maze sweeping task. Figure 4.5(c) shows an example of the maze model with *invisible goals*. In this maze, the G state is hidden until a learner commits the *invisible goal* state. In this case, all states except S are possible *invisible goals*.

4.2.2. ***The maze sweeping task that involves multiple goals***

4.2.2.1. *The definition of the continuous learning task*

The continuous learning task is defined so as to collect all *solutions* [SAT 06, YAM 11] of the task. The *optimality* of a maze task is defined as the minimum length of a path from S to G.

4.2.2.2. *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 so as to find the (shortest) paths from *S* to *G* that visits all states only at once in the maze model. Note that *S* is the fixed position as shown in Figure 4.4.

An *achievement* is defined as the *continuous learning task* of a *maze sweeping* with a fixed goal. Figure 4.6 shows an example of *an achievement of a 3 × 3 maze sweeping task*. Figure 4.6(a) shows an initial situation of an example of *an achievement* of a 3 × 3 maze model. Figure 4.6(b) shows all *solutions* of *the achievement* as shown in Figure 4.6(a). *An achievement* is harder than the maze task described in section 4.2.1.4 since it needs a systematic search method to collect all *solutions*. So, it is suitable to make an acceptable difficulty of *the continuous learning task* for a human learner in a reduced size of the maze model.

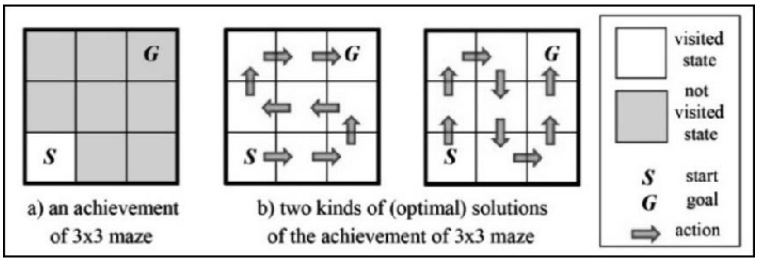

Figure 4.6. *An example of an achievement of a 3 × 3 maze sweeping task*

4.2.2.3. *The definition of a stage of the maze sweeping task*

In this section, 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* that visits all states only once in the maze model, note that *G* is the last state in the path.

A stage is defined as the continuous learning task of a maze sweeping with multiple goals. Figure 4.7 shows an example of the stage of a 3 × 3 maze sweeping task *under invisible goals* condition. Figure 4.7(a) shows an initial situation of the stage of a 3 × 3 maze *under invisible goals* condition. There are three kinds of goals in a stage of the maze model that are as follows:

– visible goal;

– invisible goal;

– dummy goal.

The first type of goal is displayed for a learner as shown in Figure 4.6(a). The second type of goal is not displayed for a learner in the beginning as shown in Figure 4.7(a). After all solutions of the corresponding invisible goal are found, it is displayed as a discovered goal (DG) as shown in Figure 4.7(b). The third type of goal is not displayed for a learner in the beginning just like an invisible goal. However, there is no solution corresponding to a dummy goal. A dummy achievement is defined as an achievement that has no solution. Each dummy goal corresponds to a dummy achievement.

As previously described in section 4.2.1.5, *invisible goals* are possible and undiscovered goal states of the *solution* of *a maze sweeping task*. In this stage of a 3 × 3 maze, there are four *invisible goal* states displayed as DG within eight states as shown in Figure 4.7(b), and other states are *dummy goal* states of this stage.

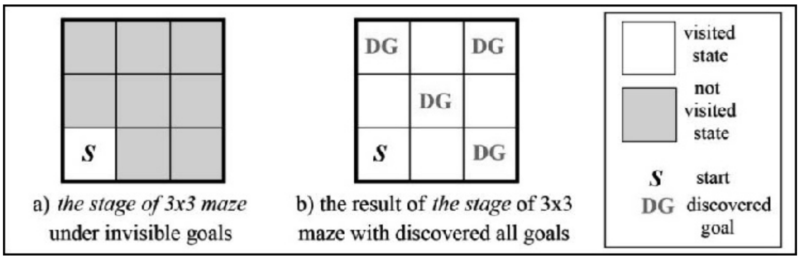

Figure 4.7. *An illustrated example of the stage of a 3 × 3 maze sweeping task*

4.2.2.4. *The hierarchical structure between a stage and the achievements*

Now, we describe the hierarchical structure between *a stage* and *the achievements*. Since *every stage* with more than a 2 × 2 maze has multiple goals, *the stage* has multiple *achievements* corresponding to the goals. Then, we show an example of the hierarchical structure between *a stage* and *the achievements*. In the case of *the stage* of a 3 × 3 maze *under invisible goals* condition as shown in Figure 4.7(a), the stage has eight states with gray except start state *S* with white. Within them, there are four *achievements* and four *dummy achievements.* Figure 4.8 shows four *achievements* of *the stage* of a 3 × 3 maze.

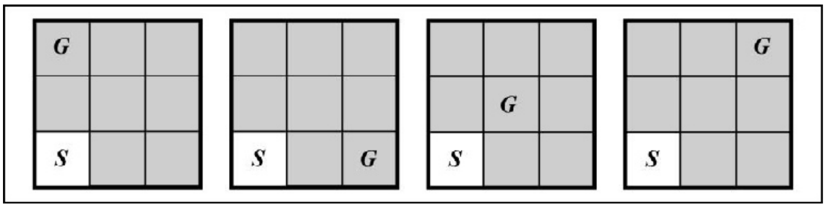

Figure 4.8. *All achievements of the stage of a 3 × 3 maze sweeping task*

4.2.3. *Designing the thinking level*

4.2.3.1. *Objective for designing the thinking level*

The objective for designing the thinking level is to keep maintaining the flow state of the human learner according to the learner's skill development. Flow is the mental state of an operation in which a person performing an activity is fully immersed in a feeling of energized focus, full involvement and enjoyment in the process of the activity [CSI 05]. We design the thinking level to reconstitute the stages of the learning process as shown in Table 4.2, in order of increasing difficulty of thinking for a human learner.

4.2.3.2. *Designing the thinking level by depth and width*

The thinking level is the difficulty of thinking in a learning process. Our idea is to estimate it as the number of candidates to be considered. We focus on both the constraints on learning goals and the number of solutions. Figure 4.9 shows the formalization of the thinking level space by two kinds of axis as follows:

– the width of thinking;

– the depth of thinking.

The objective of the width of thinking is to prepare alternatives for the change of the learning environment in future. It is defined by the number of solutions per achievement. We classify it whether unique or multiple. The case of multiple solutions needs a broader level of thinking to collect all of them than the case of unique solution. The objective of the width of thinking is to find goals to achieve toward continuous learning. It is defined by the condition of goals, that is whether goals are visible or *invisible*. The case of *invisible goals* is a deeper level of thinking than the case of visible goals. As described in section 4.1.3, a learner thinks by shallow understanding (single-loop learning) under visible goals condition since the goals are given and known. On the other hand, *under invisible goals* condition, the learner thinks by deep understanding (double-loop learning) since the goals must be discovered.

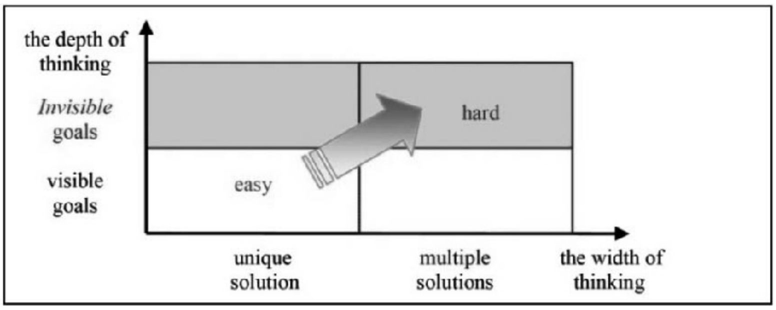

Figure 4.9. *The formalization of the thinking level space by depth and width*

4.3. The layout design of mazes for the continuous learning task

4.3.1. *Overview of the continuous learning support system*

Our system consists of three layers as follows:

– top level;

– maze level;

– achievement level.

Figure 4.10 shows the overview of the top level of the system for a learner. A user can opt to start or exit the experiment, select the current maze to challenge and can verify the state of progress of continuous learning by the display of several measurements described in section 4.4.1.3.

In the maze level, the user can select an achievement to challenge by clicking one of states in the current maze displayed in the center of the maze-level window. If he/she finds all the solutions in the achievement, the goal state in the achievement is displayed as DG as shown in Figure 4.7(b), and then it becomes non-selective.

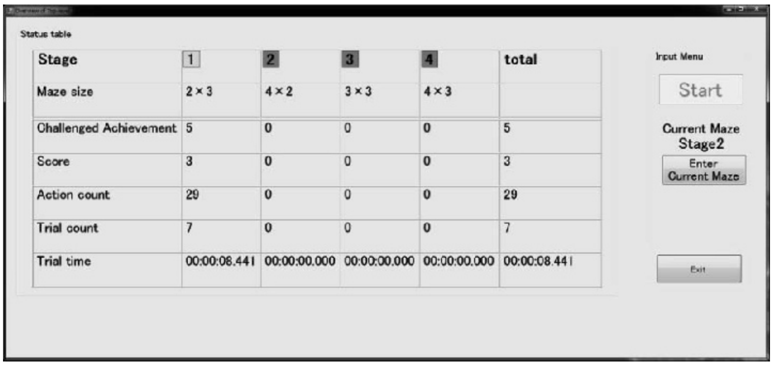

Figure 4.10. *Graphical User Interface for a learner – top level of the system*

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

4.3.2. *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 4.11 shows the layout design of mazes for the continuous learning task. It is composed of four stages.

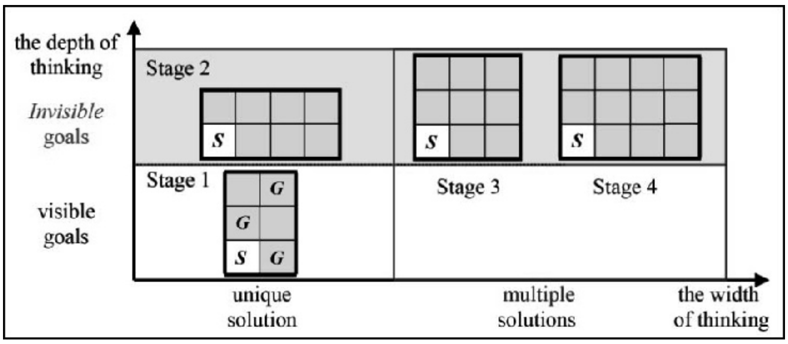

Figure 4.11. *The layout design of mazes for the continuous learning task*

4.3.2.1. *Stage 1: visible goals under unique solution*

This consists of a 2 × 3 maze model with three visible goals and two *dummy goals*. Each goal is linked with an achievement of the 2 × 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.

4.3.2.2. *Stage 2: invisible goals under unique solution*

This consists of a 4 × 2 maze model with four *invisible goals* and three *dummy goals*. Figure 4.12 shows an overview of stage 2 *under invisible goals* condition. Figure 4.12(a) shows maze level of stage 2. Each *invisible* goal is linked with an achievement of the 4 × 2 maze with the corresponding *invisible goal*. The rest of each state is linked with a *dummy achievement* of the 4 × 2 maze with a *dummy goal*. Figure 4.12(b) shows the achievement level of stage 2. Note that for a learner, showing 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.

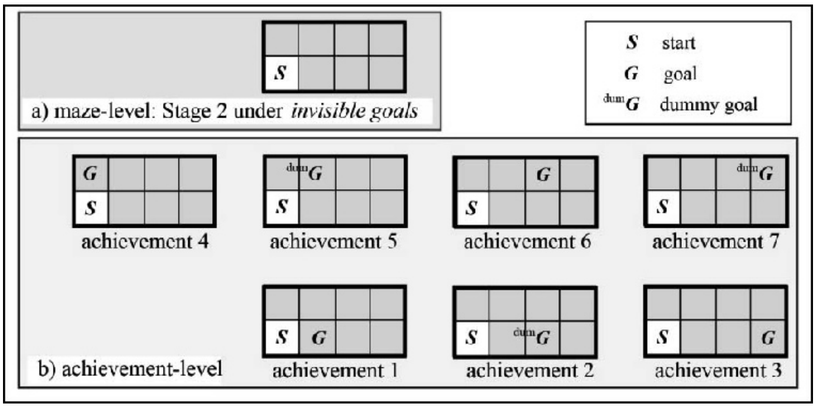

Figure 4.12. *Overview of stage 2 under invisible goals condition*

4.3.2.3. *Stage 3: invisible goals under multiple solutions*

This consists of a 3 × 3 maze model with four *invisible goals* as shown in Figure 4.7(b) and four *dummy goals*. As is the case with stage 2, each *invisible goal* is linked with an achievement of the 3 × 3 maze with the corresponding *invisible goal* as shown in Figure 4.8. Each achievement with an invisible goal has two solutions; on the other hand, a dummy achievement has no solution. In Stage 3, there are a total of eight solutions.

4.3.2.4. *Stage 4: invisible goals under many solutions*

This consists of a 4 × 3 maze model with six *invisible goals* and five dummy goals. In this stage, there are a total of 17 solutions, much more than the number of solutions in stage 3. Within the six goals, three goals have four solutions each, two goals have two solutions each and the last goal has one solution.

4.4. Experiment

4.4.1. *Experimental setup*

To examine the effects of our continuous learning support system, we perform the experiment in which a total of 12 subjects are divided into two groups for comparative conditions. There are two objectives. The first one is "does our system support the continuous learning for a human?" The 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.

4.4.1.1. *The experimental task and the instruction*

The experimental task explained to the subjects is to collect as many as possible of the solutions of the maze sweeping task as described in section 4.2.2. To examine the degree to work through the continuous learning for the maze sweeping task, we prepare four stages as described in section 4.3.2. All subjects are instructed as follows:

– Stage 1 is the practice maze so as to get used to the maze sweeping task.

– Stage 2 and 3 are the real part and the collection of as many solutions as possible.

– Stage 4 is a bonus maze; if you want to continue this experiment, you can challenge this stage as long as you can.

4.4.1.2. *Comparative conditions*

Figure 4.13 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 4.13(a) shows the condition of mazes *under invisible goals* condition. In this condition, all goals in the maze are *invisible*. Figure 4.13(b) shows the condition of mazes under visible goals condition. In this condition, all goals in the maze are visible.

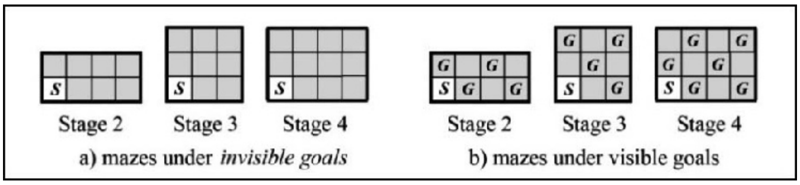

Figure 4.13. *Comparison of invisible goals with visible goals*

4.4.1.3. *Assumptions and measurements*

In this experiment, deep thinking mainly occurs at the learning stage of commitment to achieve a goal as shown in Table 4.2. It is harder to commit to a goal under invisible goals condition than to commit to a goal under visible goals condition. To measure and evaluate the continuous learning for a human, we make the following assumptions:

– The degree of continuous learning depends on the degree of depth of thinking.

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

– The degree of shallow understanding (single-loop learning) can be estimated by the playing time in the achievement level.

Next, we describe the measurements of the experiment as follows:

1) the number of challenged achievements;

2) the number of collected solutions (displayed as the score in Figure 4.10);

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 level;

6) the playing time in the maze level;

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 4.10. The fifth measurement is to estimate the degree of shallow understanding (single-loop learning). The last two measurements are to estimate the degree of deep understanding (double-loop learning) as described in section 4.3.2.

4.4.1.4. *The hypothesis*

The condition of invisible goals is expected to take deeper thinking as described in section 4.2.3, then we make a hypothesis as follows:

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

4.4.2. *Experimental results*

4.4.2.1. *Does our system support the continuous learning for a human?*

This section evaluates the effectiveness of our continuous learning support system. All 12 subjects performed the bonus stage 4, and each four subjects of both conditions collected all 17 solutions of stage 4. The data of Table 4.3 and Table 4.4 is the averaged value of six subjects for each condition, and (data) is the standard deviation of six subjects for each condition. Table 4.3 shows the experimental result of the total results of stages 1, 2, 3 and 4. The seven measurements are described in section 4.4.1.3. As shown in Table 4.3 (2), about 87% of solutions (28 solutions among a total 32 solutions) are collected in both conditions.

Measurements	(1) [times]	(2) [times]	(3) [times]	(4) [times]	(5) [sec]	(6) [sec]	(7) [lines]
Conditions							
Invisible goals	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	18.0	27.8	340	42.0	245	527	4.50
	(1.27)	(7.06)	(114)	(9.19)	(140)	(250)	(4.04)

Table 4.3. *The experimental result: total results of stages 1–4*

4.4.2.2. *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 4.3, there is no significant difference in the first five measurements (1), (2), (3), (4) and (5) between both conditions. However, the last two measurements (6) and (7) that are relevant to the degree of depth of thinking (double-loop learning) seem to be different. Analyzing the ratio of (6) divided by (5), four of six subjects are over four times under *invisible goals* condition, compared to one of six subjects over four times under visible goals condition.

Next, we analyze the measurements in stage 4 to evaluate the degree of continuous learning in a straightforward way. Table 4.4 shows the experimental result of stage 4. The six measurements are the same as in Table 4.3. In Table 4.4, 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), both of the results under *invisible goals* condition are longer than the results under visible goals condition. Therefore, these results suggest that the *invisible goals* condition is more effective to assist the deep understanding in a learning process than the visible goals condition.

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

Table 4.4. *The experimental result of stage 4*

4.5. Discussions

4.5.1. *The role of motivations to drive the continuous learning*

To begin with, we discuss the role of motivations to drive the continuous learning. In the experiment, all 12 subjects performed the bonus stage 4, and 8 of 12 subjects collected all 17 solutions of stage 4. The reason may be the display effect of DG in the maze level when all solutions corresponding to G state are collected as described in section 4.3.1. Figure 4.14 shows the hierarchical model of achievement motivation [ELL 97, ELL 06]. According to this model, the display of DG positively effects competence expectancy since he/she accomplished the achievement. As a result, it increases the intrinsic motivation to the task.

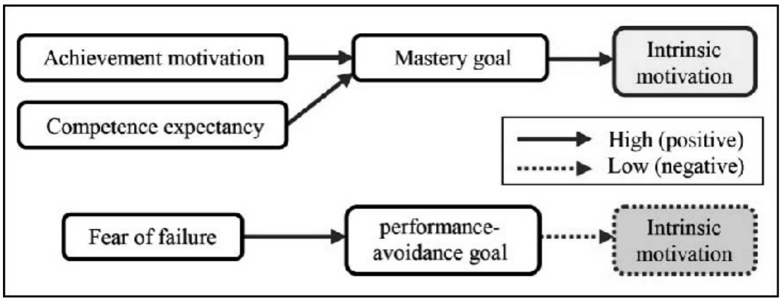

Figure 4.14. *Hierarchical model of achievement motivation*

4.5.2. *Why is it important to collect all solutions for continuous learning?*

We discuss the reason why to collect all solutions for continuous learning. A useful idea is from the economic complexity index [HID 09, HAU 11]. They present the measures of complexity of countries on economic growth as the productivity of a country resides in the diversity of its available non-tradable capabilities in that country. They also show that the measures of complexity are correlated with a country's level of income (GDP), and that deviations from this relationship are predictive of future growth.

What is interesting about this is that they take it as an analogy of "Lego® theory" [HID 09]. In that, economic growth is like assembling many hundreds of different Lego® pieces. In other words, a child who has various lego pieces in his/her bucket is able to make more complex Lego® model. We can say the same for the continuous learning. A learner who has various solutions in his/her learning experience is able to make more complex solution according to the growth of his/her continuous learning process.

Figure 4.15 shows the example of reusing previous solutions to solve a 4×3 maze sweeping task. Figure 4.15(a) shows the 4×3 maze *under invisible goals* condition as described in section 4.3.2. The solution of this is classified into five cases according to the beginning of the action sequence as shown in Figures 4.15(b)–(f) as follows:

(b) (up, up, right): there are four DGs and the number of solutions is eight by reusing the learning result (solutions) of a 3 × 3 maze.

(c) (up, right): there is no solution.

(d) (right, up): there are four DGs and the number of solutions is four.

(e) (right, right, up): there is one DG and one solution.

(f) (right, right, right, up): there are four DGs and the number of solutions is four by reusing the learning result (solutions) of the 4 × 2 maze.

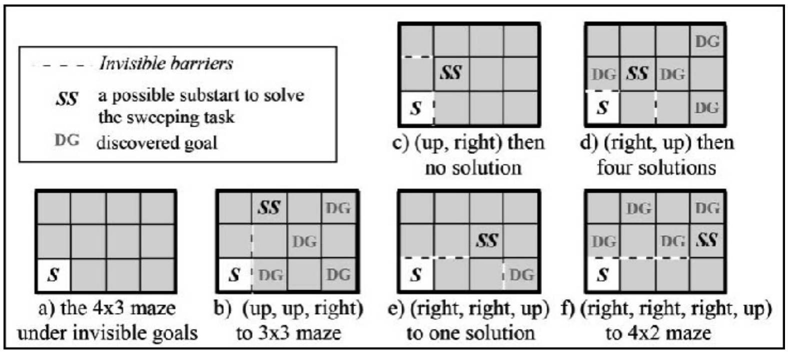

Figure 4.15. *Solving the 4 × 3 maze by reusing previous solutions*

Next, we show an idea of the effective usage of i*nvisible barriers* to guide the learner's shallow thinking or his/her trial and error to collect all solutions by systematic search. In Figure 4.14, the dotted line is the *invisible barriers* in order to guide the beginning of the action sequence of a learner. It is expected to result in the awareness for shallow thinking or learning through trial and error. As part of our future work, we are planning to examine this effective usage of *invisible barriers.*

4.5.3. *Toward an application of a maze model and invisible goals*

This section discusses the meaning of *invisible goals* toward the application of a maze model. Regarding the X-Y coordinate of the maze model as shown in Figure 4.4(b), we look at the *x*-axis as the previous values and the y-axis as the new values, and then we discuss the *invisible goals* on the development of an adhesive as typical discovery episode.

First, we begin with the development history of the Post-it note [ROB 89]. In 1968, a researcher of 3M was attempting to develop a superstrong adhesive, but instead he accidentally created a "low-tack", reusable, pressure-sensitive adhesive. Figure 4.16 shows the simple functional map of adhesive in 1968. In this single axis of values, a state without "(a) development goal" is regarded as a failure as shown in "(b) product failure". However, he focused on the reusable function of the weak adhesive. Figure 4.17 shows the extended functional map of the adhesive, in which the x-axis shows the previous values as the function of the adhesion force and y-axis shows a new value as the function of reusability.

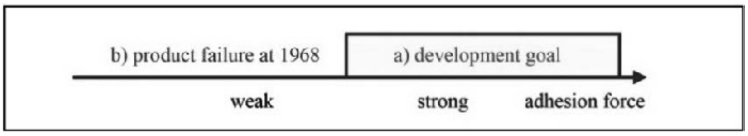

Figure 4.16. *The simple functional map on adhesive*

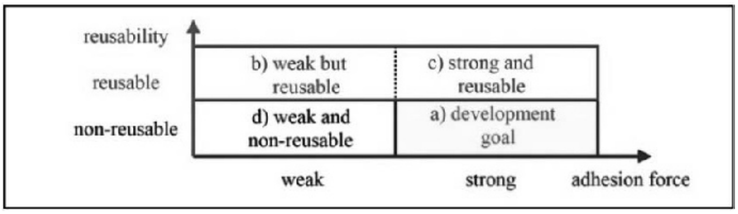

Figure 4.17. *Extended functional map on adhesive*

Second, we discuss the transition from focusing on a new function to discovering an unknown usage. The key point is "how to discover the potential needs behind the new function?" In 1974, a colleague of the researcher who created a "low-tack", reusable adhesive came up with the idea of using the adhesive to anchor his bookmark in his hymnbook. At this time, about "(b) weak but reusable" as shown in Figure 4.17, a new usage for temporarily attaching is discovered. In 1978, 3M issued free samples designed for temporarily attaching notes to documents and other surfaces and in 1980, the product debuted in US stores as "Post-it notes". Now, this episode suggests that an *invisible goal* in this case is revealed by the discovery of a different usage from previously known goals.

Then, look at the rest states of (c) and (d) in Figure 4.17, what kind of invisible goals are hidden? Table 4.5 summarizes the R&D process of the adhesive materials from extended function map to discovering an unknown usage. In Table 4.5, (c) is a adhesive material with strong and reusable functions. In 2012, a new adhesive material with these functions is presented [AKI 12]. The idea is that the new material becomes liquid under ultraviolet light and it becomes solid under visible light. The usage of (c) is not found yet, it is an interesting continuous discovery with Post-it notes.

Function map	A new material with new functions	The discovery of a new usage
(b) Weak but reusable	Accidentally created in 1968	1974: Temporally attachment 1980: Post-it notes
(c) Strong and reusable	R&D in 2012	
(d) Weak and non-reusable	(Difficult to determine bonding strength objectively)	

Table 4.5. *The R&D process from extended function map to discovering an unknown usage*

4.6. Conclusions

We described the learning support system based on a learning process model to guide a human to achieve continuous learning. To support the awareness and understanding of learning processes, we proposed to provide a human learner with *invisible goals* to encourage the sense of continuous awareness toward goal discovery. Then, we formalized the continuous learning by a simple maze model with *invisible goals* and designed *the maze sweeping task* that involves *multiple solutions* and *goals*. The experimental results showed that our continuous learning support system is effective. Moreover, besides *the invisible goals* is more effective to assist deep understanding in a learning process than the visible goals.

As part of our future work, we are planning to quantitate the degree of difficulty of continuous learning as the complexity of maze model and action sequences of a learner for maintaining the flow state of the human learner according to the learner's skill up.

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