Design of Interactive Skill-Transfer Agent From a Viewpoint of Ecological Psychology

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This article focuses on the design of an interactive skill-transfer agent for parameter tuning of an image sensor used to distinguish inferior goods from regular goods in a production line. The authors analyze the difficulty of transferring skills from a viewpoint of ecological psychology that takes into account the reciprocal relations between the participant and the environment. This article introduces an agent-based interactive skill-transferring system that stretches the meaning of this reciprocity as an interaction between an instructor and a successor. In concrete terms, an interactive agent system is proposed using an interactive learning classifier system with facial icons to enhance the human user's trust in the agent. The experimental results demonstrate the effectiveness of this system in transferring a human expert's skills.

1. INTRODUCTION

The purpose of this article is to develop an interactive skill-transfer agent. Recently, in Japanese industries, due to the prevailing advancement of automated systems, allowing next-generation workers to inherit skills from aged, experienced practitioners has become an urgent issue. That is, automation has cloaked the practitioners' proficient skills in a black box, and opportunities for human-to-human succession of these skills are becoming less frequent.

Thanks to Yasuhiro Nikaido for his invaluable help with experimental design and exciting discussions. Requests for reprints should be sent to Takayuki Shiose, Graduate School of Informatics, Kyoto University, Yoshida-Honmachi, Sakyo-ku, Kyoto, 606-8501 Japan. E-mail: shiose@i.kyoto-u.ac.jp
Despite the seriousness of this situation, systemization enabling and promoting such skill transfer has not been attempted so far. This is because most of the skills belong to a human and are thus difficult to share and reuse. Moreover, as compared with other engineering issues such as maintenance and automation, it is difficult to obtain explicit effects of improvements on production efficiency and financial return, so the task of skill transfer has been left only to individual, voluntary efforts.

In this study, we focus on skilled workers engaged in tuning an inspection image sensor that can automatically distinguish inferior goods on production lines. This is a very difficult task for apprentices or probationers, and they must perform this task frequently (i.e., not only when an image sensor is first introduced at the factory site, but also whenever the objects or goods of inspection are changed). At present, the service engineer of the sensor vendor is called on demand whenever tuning is needed, and this task is dependent on new skills. The know-how related to such skills is difficult to describe, which creates a bottleneck for skill succession and transfer mediated by Information Technology (IT) such as artificial intelligence. Currently, the only method of transfer is through human-to-human education similar to an apprenticeship and on the job training (Rogoff, 1990).

In this article, to develop an IT-based system supporting such education and training, we propose an apprenticeship system mediated by an interactive agent. First, we classify some difficulties of skill-transfer in the practical field and insist that it needs the viewpoint of ecological psychology as a logical consequence. Second, we analyze the difficulty of transferring skills from a viewpoint of ecological psychology that takes into account the reciprocal relations between the participant and environment, and stress that it is important to pay attention to the interaction between the instructor and the successor. Next, we demonstrate our interactive agent system implemented by an interactive learning classifier system (ILCS) based on such characteristics. We then present the results of experiments using our system. Finally, we discuss the effects of skill transfer and its contribution to reducing the time costs incurred in the skill transfer from experts to apprentices by summarizing opinions we obtained from actual users who interacted with the agent.

2. TARGETS FOR SKILL-TRANSFER STUDY

2.1. Human Skills in the Process of Tuning Parameters

In this study, we focus on skilled workers engaged in tuning an image sensor that automatically distinguishes inferior goods in the streams of production lines (see Figure 1). When such a sensor is introduced into a factory, it must be tuned appropriately so that it functions as desired. However, this is a complex task because there is a variety of inspected targets and several environmental factors to be considered, such as lighting conditions and the speed of the lined streams.

More concretely, the main part of this task is to find a sequence of operations (e.g., to specify a particular location or to change the size of an inspection frame) that enables the sensor to force inferior parts out of the entire image area so that the inspection frame can include only the essential image features that distinguish the
FIGURE 1  Skills in the process of tuning parameters.

inferior from the others. Once this frame is determined and a sensor is appropriately tuned, it can automatically distinguish inferior goods. Although the skills needed to perform this tuning are very difficult for apprentices or probationers to perform, skill transfer from skilled workers to probationers takes place within a system of apprenticeship.

2.2. End Condition for Tuning Parameters

Even an expert cannot decide the form of the desired inspection frame until the expert encounters the inspection target in practice. The expert must decide on a tentative form of the inspection frame and check how accurately the image sensor can distinguish inferior goods from the production line using the provisional frame. The validity of the inspection frame is calculated by the following process, and Figure 2 shows a conceptual image of the tuning process.

First, a correlation value between the image of the target product and the image of a regular product is calculated in the range of the provisional inspection frame

FIGURE 2  End conditions: Definition of barycentric and boundary-intervals.
that the user has temporarily chosen for the inspection of all objects registered in the process of tuning. Second, regular goods and inferior goods are marked differently for convenience. If the target product is categorized with the regular goods (we put a circle mark on the regular goods in Figure 2), the correlation value should be rated highly. On the other hand, the correlation value should achieve a low score when there is something wrong with the target product (we put a cross mark on the inferior goods in Figure 2). Third, the provisional inspection frame is validated in a visualized graph such as that in Figure 2. If the inspection frame is set up properly, the correlation values for the regular goods will show a higher value and those for the inferior goods will show a lower value. Here, to clarify the progression of the tuning processes, two indexes are introduced: the barycentric interval and the boundary interval. The former is defined as the interval between the barycentric coordinates of both groups, and the latter is defined as the interval between the lowest correlation value of the regular production group and the highest correlation value of the inferior goods group.

Tuning can be interpreted as a process of finding a sequence of operations that increases the values of both the barycentric interval and the boundary interval as much as possible.

2.3. **Difficulties in Skill-Transfer**

Generally speaking, difficulties in skill-transfer occur during the expert’s externalization of skills and the apprentice’s embodiment of the externalized skills. Many approaches for transferring expertise have been studied but have failed to obtain satisfactory results, despite using information technology that challenged the former difficulty (Boring & Harper, 1948; Clancey, 1983; Davis, 1979; Shortliffe, 1974, 1976). With regard to the latter difficulty, Ueno and Furukawa (1999) and Norris (1993) not only succeeded in quantifying advanced skills in sports and music to extract implicit knowledge from an ergonomic viewpoint, but also pointed out that the compulsion of such quantified skills may import bad habits to the successor without considering the individual differences of body and learning pace.

Here, the reason why an apprenticeship system between a human instructor and human successor practically succeeds in transferring the expert’s skill in our focus. The most important difference from common skill transfer mediated by information technology is the hypothesis with regard to the relationship between an expert and an apprentice. First, the expert is requested to externalize his or her own proficient skills by him or herself as usual, whereas the apprentice must discover the nuances of the skill actively by watching the expert in the apprenticeship system. Second, such discovered skills are not easily grasped by the apprentice, so that the apprentice needs the embodiment process of such skills.

We do not hypothesize that our system can transfer an expert’s skills in their entirety to an apprentice, because skills contain both verbally describable and tacit features that are difficult to encode. We believe that it is possible to encode the verbally describable features of skills by developing an appropriate learning algorithm, but for the tacit features, an approach of isolating and extracting skills from a
human and storing them in a machine is quite limited. Rather, we must develop another approach that can provide humans with the opportunities to exert their potential tacit skills and can let apprentices self-discover those skills.

In the next section, these approaches are explained and implemented from the viewpoint of ecological psychology.

3. SKILL-TRANSFER FROM A VIEWPOINT OF ECOLOGICAL PSYCHOLOGY

3.1. Viewpoint of Ecological Psychology

In ecological psychology, "to act" is regarded not as something static that is separated from the participant and the environment, but as something dynamic that emerges from interdependent relations between the participant and the environment. Brunswik (1956) was one of the founders of such ecological psychology. He proposed a lens model wherein relations between the judgment participant and the environment (distal) were explained by a symmetrical structure, placing cues (proximal) for the judgment at the center. Figure 3 shows an overview of the lens model, which is called a double system design in that it analyzes cues from two directions for the judgment and the environment.

An especially important point is that Brunswik distinguished "cue utilization validity" from "ecological validity." The former indicates the latent validity of how accurately cues specify the ecological criteria, and the latter indicates the individual validity of how efficiently cues reflect the acting participant's cognitive judgment (Cooksey, 1996, puts psychological meanings and details of the lens model together). As the logical conclusion of this distinction, the difficulties of skill-transfer are explained by introducing the validity, "cue utilization validity," and are classified into the following two processes: the expert's difficulty in externalizing his or

![FIGURE 3 A concept of lens model.](image-url)
her personal cues and the apprentice’s difficulty in embodying such acquired cues. The latter difficulty particularly emphasizes that we cannot adopt the existing simple skill-transferring approaches to force the expert’s skills to the apprentice or other target.

3.2. Skill-Transfer as an Interactive Activity

In the practice of an apprenticeship system composed of dyadic interaction between an expert and apprentices, the expert does not explicitly teach his or her skills to apprentices. This feature is called positive concealment, which encourages apprentices to acquire proficiency skills by self-training (Singleton, 1989). Here, a triple system design, which is one extension of the lens model, provides us with useful information for identifying the characteristics of this apprenticeship system (see Figure 4).

This method is called a triple system design because it analyzes cues from three directions for two judgments and the environment and is expected to explain that plural participants cooperatively judge by way of “interpersonal conflict” and “interpersonal learning” in the judgment processes between the two participants (see Figure 4). If one participant has a different ecological validity and cue utilization validity from another, the triple system design recognizes it as an interpersonal conflict and must solve this conflict through negotiations with mutual observations (this process of solving the conflicts is called interpersonal learning). Here, we need to change our focus from the reciprocal relations between the participant and the environment to the reciprocal relationships between both participants, because the interrelations of each participant’s utilization validities become more important in the case of interactions.

![Figure 4](image-url) Triple system design extended to explain plural participant’s judgment.
3.3. Skill-Transfer Depicted as the Triple System Design

In this section, we suggest that two difficulties of skill-transfer are expressed by two different interactions with the skill-transfer agent. The agent is requested to propose alternative tuning parameters to the user, and interactions between the agent and the user are depicted by the triple system design. The user (an expert in some cases and an apprentice in other cases) is requested to decide whether to accept the agent’s proposals with regard to the operation. Because the agent updates its proposing rules through interaction with the user, the role of the agent is different depending on the degree of proficiency of each user.

At first, the agent is requested to interact with an expert who is proficient in tuning the parameters of image sensors (see Figure 5a). This process corresponds to one of extracting skills from the expert. This does not present a severe burden for the expert compared to the work of everyday tuning, because all the expert has to do is decide whether he or she accepts the agent’s proposals.

Second, apprentices are assigned to the agent that has obtained proficient rules through interaction in the last phase (Figure 5b). What is important here is that it is assumed that the agent continues to update its own proposals even after the agent has already acquired tuning skills. As a result, the apprentice is expected to acquire his own individual utilization validities.

The detail mechanism of the interactive agent that achieves the previously mentioned two interactions is explained in the next section.

![Diagram of Skill-Transfer Depicted as the Triple System Design]

(a) Phase of extracting skills

(b) Phase of transferring skills

**FIGURE 5** Different interactions mediated by triple system design.
4. DESIGN OF INTERACTIVE SKILL-TRANSFER SYSTEM

4.1. Appearance of the Interface System

Figure 6 shows the appearance of our interface. This interface has four features: an image viewer showing an image of the inspection objects; an operation viewer showing the agent's proposal; buttons for receiving the user's responses (i.e., acceptance or rejection of the agent's proposals); and a facial icon representing the agent's confidence status.

4.2. Design of the Rules for the Agent

In this article, we adopt an interactive learning classifier system (ILCS) as the agent's learning method for the first type of skills (i.e., the describable skills). The learning classifier system (LCS) is a well-known architecture proposed by Holland (Holland, Holyoak, Nisbett, & Thagard, 1986), and each classifier rule is evaluated by an evaluation function provided by the system designer in advance. Different from an ordinary LCS, each classifier in the ILCS is evaluated by users who are requested to interact with the system (e.g., Katagami & Yamada, 2002). Our interactive agent monitors an object image taken by the image sensor and proposes alternative operations to change the location and size of the inspection frame within the image using classifier rules that are learned by observing the user's performance. Figure 7 shows an example image of various operations to change the location and size of the frame. Figure 8 shows the system flow of interaction with the agent.

1. The agent shows an image of the inspection objects.
2. The agent segments the image in the inspection frame into nine image parts and divides the brightness of these parts into three different levels (dark, middle, and bright).

![Image of interface system]

FIGURE 6 The interface system.
3. The agent decides the provisional proposal of the tuning parameters and shows this proposed through the operation viewer. It is depicted as one of 12 different operations (to move up, down, right, and left and to widen or narrow its size in each direction).

4. If the user agrees with the agent’s proposals, the agent increases the confidence in the related classifier rule by updating the numerical strength assigned to that rule.

5. The user and the agent repeat this cycle until the inspection frame satisfies the given end condition.

When the agent cannot find any classifier rules whose if-clause matches the situation, the agent is assumed to add a new classifier rule by abstracting the situation.
to the if-clause form and by combining it with new operations randomly (this process is a typical method of evolutional computation to create new rules, referred to as the Michigan approach by Holland, 1986).

4.3. Expression Using a Facial Icon

The agent is equipped with various icons of facial expression to present how confident it is in its proposals to human users. Such facial expressions allow the user to interact with the system more intuitively and interactively (Bisantz, Finger, & Llinas, 1999; Maes, 1994). Figure 9 shows the transition map from the past facial icon to the next facial icon. For instance, the agent reacts with the happy expression when the user accepts the agent's confident proposals. On the other hand, the agent reacts with the sad expression when the user rejects the agent's confident proposals. The effectiveness of using these facial icons is discussed in section 6.2.

It is important here that users need not always obey the agent's instructions. Rather, they can select alternative operations based on their own judgment or through attempts to see the responses of the agent to his or her temporal judgment. These intuitive reactions are expected not only to motivate the user to interact more with the agent him or herself, but also to enlighten the users themselves to explore their way of performing the tuning parameter tasks. We think this kind of continuous and reflective interaction effectively encourages users to demonstrate and actively self-discover the tacit aspects of human skills that cannot be captured by classifier rules.

4.4. Generalization of Classifier Rules

It is necessary to extend any learning rules acquired by the agent, because the quality of the tuning rules depends on both the quality and the quantity of the agent's experience in tuning various inferior goods with the user.

![Figure 9](#) Transition mapping of facial icons.
It is well known that conditional parts of classifier rules have the special attribute #, known as “don’t care,” which means that the rule can fire in any situation with regard to the concerned attribute. As a result, attribute # is expected to extend the scope of application for the classifier rule. Usually, this attribute is added into the conditional parts of the classifier rules at random and is ineffective because it evaluates the validity of the rules only as a result of an evolitional computation mechanism. In this study, ID3 (Quinlan, 1979), which is a famous machine learning architectures, is introduced to add attribute # arbitrarily into the conditional parts of the classifier rules. ID3 gives our proposing algorithm effective generalization that can add attribute # selectively to its conditional parts of the classifier rules.

Figure 10 shows the pre-experiment to confirm the effectiveness of the generalization by the ID3 algorithm. The user is requested to tune parameters with our proposing agent for a certain inspection object (to pick up inferior connectors with broken pins). The x axis represents each step of the tuning process and the y axis represents the transition of the barycentric interval and boundary interval. Figure 10a shows the transition of both intervals by rote learning, which memorizes the conditional part as experienced by the agent, and Figure 10b shows the transition by generalization with ID3. Comparison of the two approaches demonstrates that generalization with ID3 provides criteria that distinguish inferior goods from all goods more stably.

5. THE FIRST EXPERIMENT: DIFFERENCES BETWEEN EXPERT AND APPRENTICE

5.1. Different Participants and Target Objects

In this study, the following two types of participants with different skill levels were used.

The expert: A skilled worker who has been engaged in maintenance work for 15 years and is well versed in image processing.

![Graphs](image)

(a) Rote Learning  (b) Generalization Learning Mediated by ID3

FIGURE 10 Effectiveness of introducing ID3.
The apprentice: A bachelor student of our university at the time of the experiments. He is not familiar with an image processor, and only knows the objective of the image sensor.

The two participants were requested to regulate the parameters of the image sensor for distinguishing inferior goods from the following three objects: business cards, connectors, and Integrated Circuits (IC). Figure 11a and 11b shows example images of inferior goods for connectors with broken pins and ICs with broken pins. In all cases, it was difficult for the apprentice to regulate the image sensor sufficiently enough to appropriately detect inferior goods.

5.2. Tuning Parameters Mediated by the Interactive Agent

The expert and apprentices are first requested to regulate the parameters of the image sensors by interacting with the agent. The first target is assumed to be dirty business cards. Here, the user (sometimes the expert, sometimes the apprentice) is requested to continue selecting operations of tuning parameters until the system acquires the appropriate inspection frame. This set of tuning steps is called "a trial," and each user is requested to conduct 10 trials in each experiment.

Figure 12 shows an example transition of the agent's confidence in proposing alternative operations, and the transition of differences between the agent's proposal and the apprentice's choice. This transition is the 11th trial after the user (the user is the apprentice in Figure 12) interacts with the agent in 10 trials. Therefore, the agent's high confidence is because it has already experienced several interactions with the user. The x axis represents each step of the tuning process and the y axis represents the transition in each step.

Here, the differences between the agent's proposal and the user's selection are divided into four levels and are defined as follows. The value of zero indicates that the user accepts the agent's proposals as it is. On the other hand, the higher the number is, the more strongly the user rejects the agent's proposal.

What is interesting here is that the transition of the agent's confidence does not draw a simple learning curve, but rather a complex one, as shown in Figure 12. For instance, the A mark in Figure 12 indicates an interesting point where the transition of the agent's confidence fluctuates although the user agrees with the agent's pro-

(a) Connector with Broken Pins  
(b) ICs with Broken Pins

FIGURE 11 Example images of inferior goods.
FIGURE 12 The transition of the agent’s confidence and the difference between the agent’s proposals and the user’s choice.

proposals. This fluctuation mandates that the agent needs to produce new conditional parts of rules for situations where the agent is less experienced.

On the other hand, the B mark indicates the situation where the agent’s confidence drops off suddenly. This occurs when the user strictly rejects the agent’s proposals or the agent must produce a new rule. The C mark signifies that such a new rule has gradually gained confidence through the user’s acceptance. The D mark represents another situation where the confidence value decreases gradually. Such declination indicates that the user does not strongly reject the agent’s proposals.

5.3. Generalized Skills

When the target inspection object is changed, the transition of interaction between the agent and the user is expected to become more complex. The participants are requested to regulate the parameters of the image sensor when the target inspection objects are changed. The target inspection objects are therefore changed from the first object (business cards with dirty marks) to the second one (connectors with broken pins), and from the second one to the third one (ICs with broken pins).

Figure 13a and 13b shows the transition of the differences between the agent and the expert or apprentice, respectively (this graph indicates the transition of the 11th interaction). Comparing Figure 13a with that of 13b demonstrates that the expert requires a smaller number of steps to specify an appropriate inspection frame than the apprentice does. Additionally, the number of times the expert rejects the agent’s proposals is fewer than that of the apprentice although the target inspection objects are changed while tuning the parameters. This result suggests that the expert obtained more general rules of tuning the parameters of the image sensor than the apprentice did.
5.4. Coherency of Judgment: Consistency

Discussions of the lens model present two types of indexes to validate the appropriateness of a judgment: "consistency" and "cognitive control." Consistency indicates how coherently the user can judge from the same sets of cues (Cooksey, 1996). On the other hand, cognitive control indicates how faithfully the user can judge against his or her own policy. Here, the "policy" is akin to the principles for the user to judge according to his or her experiences. These indexes distinguish the expert's works from the apprentice's.

Here, we can predict the agent's decision along with his or her consistency if we pay attention to the average confidence value of the total classifier rules, because the reinforcement value of the classifier rules remains low when the user cannot choose coherent operations from the agent's proposals. Figure 14 shows the transi-

FIGURE 13 Effectiveness of skill-transfer mediated by interactive agent.

FIGURE 14 Transition of confidence (comparison of the expert with that of the apprentice).
tion of the agent’s confidence in proposing operations during interaction with the expert and with the apprentice, respectively. Table 1 shows an average value of the agent’s confidence in proposing operations through a series of interactions.

With Cooksey’s (1996) discussions, these results hint that agent interaction with the expert achieves a higher consistency than that of the apprentice. Thus, introducing ILCS instead of the usual linear analysis model does not eliminate the difference between the expert and the apprentice.

5.5. Matching Property of Judgment: Cognitive control

The experiment in section 5.3 shows “cognitive control,” which means how faithfully the expert and apprentice can judge against their own policy. Table 2 shows that the average confidence in proposing operations and the average number of acquired rules is arranged around the agent who formed it with the expert and the agent who formed it with the apprentice, respectively.

Because the user was requested to tune parameters for different inspection objects, it can be easily assumed that a new rule will be formed for each inspection object. Contrary to the usual conjecture, the agent who had interaction with the expert acquired only 26 rules. This is less than one fifth the number of rules acquired when the apprentice had interaction with the agent. If the sets of rules that the agent acquired by interacting with the user are general and independent from the superficial features of each inspection object, the number of rules should be small and the confidence level of proposing operations should be large. Comparison of the number of consequent rules provides possibilities for guessing how faithfully the expert judges along with his or her conviction, since consequent numbers of rules represent how comprehensively those rules were used in the evolitional computation.

Drawing from these discussions of consistency and cognitive control, the ILCS can be used to explain the features of proficiency skills that are addressed in the lens model studies. Although the ILCS was introduced instead of the linear analysis model because (a) environmental criteria cannot be obtained one at a time and (b) a phased change of the processes of acquiring skills cannot be expressed by the

| Table 1: Difference Between the Expert and the Apprentice by Paying Attention to Consistency |
|-----------------------------------------------|-------------------|
| Interaction With the Expert                  | Interaction With the Apprentice |
| Average value of confidence                  | 79.634            | 63.5 |

| Table 2: Difference Between the Expert and the Apprentice by Paying Attention to Cognitive Control |
|-----------------------------------------------|-------------------|
| Interaction With the Expert                  | Interaction With the Apprentice |
| Average value of confidence                  | 76.032            | 61.026 |
| Average number of rules                      | 26                | 136    |
usual linear analysis model, the ILCS can substitute for the lens model’s expressiveness as regards proficiency skills.

6. THE SECOND EXPERIMENT: SKILL-TRANSFER

6.1. Results of Skill Transfer

In the second experiment, the expert tries to transfer his skills to the apprentice using our interactive agent system. At first, the expert interacts with the agent five times to inspect three types of work in turn. Then, the apprentice interacts five times with the agent to inspect the same set of three works in turn. Figure 13c shows the difference between the user’s choice and the agent’s proposal: (a) difference between the expert’s choice and an inexperienced agent’s proposals; (b) difference between the apprentice’s choice and an inexperienced agent’s proposals; (c) difference between the apprentice’s choice and the experienced agent’s proposals.

Figure 13a shows that the expert hardly rejects the agent’s proposals through inspecting Work C, though the agent acquires classifier rules through inspecting other works (A and B). On the other hand, the apprentice could not help rejecting the agent’s proposals during the inspection of Work C (see Figure 13b). These results mean that the agent that interacted with the expert could have acquired general rules independent from the difference in work, while the agent that interacted with the apprentice acquired only skills peculiar to each object. The fact that the agent that was educated by the apprentice has five times more rules than the agent educated by the expert supports this conclusion. Finally, Figure 13c illustrates the difference of the operations between the apprentice’s choice and the experienced agent’s proposal. As a result of this interaction, the frequency of the apprentice’s rejection and the number of steps needed to finish the tuning decreases.

These results can be also verified by paying attention to the transition of the barycentric interval and the boundary-interval. Figure 15 shows the transition of the barycentric intervals for Figure 13b and 13c, respectively (the transition of the boundary interval is omitted because it is similar to the transition of the barycentric

![FIGURE 15 Improvements in learning rules by skill-transfer.](image)
interval). Here, the end condition for completing the regulation of the parameters for the image sensor is set into 10 or more of the correlation values. Figure 15 clearly shows that the agent who had interaction with the expert finished regulating the parameters in a smaller number of steps than the agent who had interaction with the apprentice. The previously mentioned results demonstrate that our proposal system can improve apprentice performance mediated by an interactive agent.

6.2. Discussion

After the experiments, we asked the apprentice to fill out a questionnaire describing his impressions of interacting with the agent and of his own task performance. The following is a summary of the representative comments.

I had expected interactions with the agent to be amazing and might have put excessive confidence in the agent’s proposals, because I had known that the agent had been educated by the expert. However, I could not understand the experienced agent’s proposals at the beginning of the session, because I did not know what parts the agent was paying attention to. Especially in the final steps of the session, I often favored choices different from the agent’s, because I did not know what the sub-goal for the agent to finish inspecting was. That is, the goals sought by the agent were invisible to the human user.

The previous examinations illustrate that the typical difference between the expert and the apprentice is related to the method of changing the size of the inspection frame. The apprentice is apt to proceed with tuning by changing the size of the inspection frame, whereas the expert pays more attention to the movements of the inspection frame and a decision on the size of the frame is made at an early stage. This decision does not change during the session. Additionally, the apprentice’s impression, “I was urged to pay attention to relations among operations by that system,” supports this finding. The expert glances at the presented image less frequently than the apprentice does, which means that the expert pays more attention to the earlier steps of the operation.

7. CONCLUSIONS

In this article, we analyzed the difficulties of skill transfer from an ecological psychology viewpoint and designed an interactive skill transfer agent based on the apprenticeship system. Both the expert who engaged in image processing and the apprentice inspected objects in practice by interacting with the agent. According to the answers to our questionnaires, the interactions with the agent were so naturalistic that both the expert and the apprentice were not conscious of being engaged in a task of skill transfer. Answers to the questionnaires also showed that the apprentice obtained skills that are independent from the objects of the inspection. We can conclude that our system succeeded in solving the earlier mentioned two difficul-
ties: low-cost extraction of skills from the expert and autonomy for apprentices to learn skills by themselves.

In this article, we introduced the viewpoint of ecological psychology that regards reciprocal relations between a participant and an environment as important. It should be noted that skills that should be transferred are defined not by only the instructor but by the reciprocal relationships between the instructor and the successor. In future work, we expect to specify how such reciprocal relationships are constructed through interaction between the instructor and the successor.

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