Ambiguity-Driven Interaction in Robot-to-Human Teaching

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ABSTRACT
The transfer of task knowledge is ubiquitous in our daily lives, where various types of interaction occur. Such an interactive task knowledge transfer, however, requires that an instructor and a learner to be at the same place and time. If we use a robot to mediate between them, such limitations can be eliminated. This paper focuses on human-to-robot teaching, in which a robot instructor interactively teaches a human learner how to achieve a task. We develop an ambiguity-driven formulation of interactive teaching based on the Dempster-Shafer theory. We implemented an experimental system for blocks world tasks as a proof-of-concept and show our preliminary results.

ACM Classification Keywords
H.1.2. MODELS AND PRINCIPLES: User/Machine Systems

Author Keywords
interactive teaching; robot instructor; ambiguity-driven interaction; Dempster-Shafer theory

INTRODUCTION
Transfer of task knowledge is ubiquitous. At production sites, skilled workers teach novices various pieces of knowledge such as how to manipulate objects, how to operate tools, and how to organize production schedules. At home, parents teach children, for example, how to use toys and how to cook. Transferring such task knowledge requires an instructor and learner to exist at the same place and time in order to use various modalities including gestures and actions. Using a robot as a mediator, we could remove this limitation.

Robot-mediated task knowledge transfer is divided into two stages: (1) a person teaches a robot; and (2) the robot teaches another person. The first step is so-called *robot teaching* and is one of the important research areas in robotics and human-robot interaction (HRI). One promising approach is *programming by demonstration* (PbD) or *teaching by showing*, in which a human instructor demonstrates a task and a robot observes it to make a task model [2]. second step has not been significantly researched in robotics, although several works discusses the affective communication strategy (e.g., [7, 5]) and/or physical presence of the teacher (e.g., [3]).

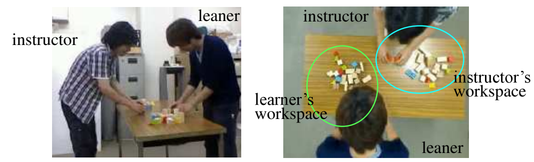

Figure 1. Human-to-human teaching by mutual demonstration.

This paper deals with robot-to-human teaching of assembly tasks through *mutual demonstration*. An instructor robot first demonstrates an assembly step and a human leaner then demonstrates what he/she has just understood (i.e., tries to copy the same step). Fig. 1 shows an example teaching scene among humans.

By mutual demonstration, an instructor transfers knowledge of the task to a leaner. If transfer is not complete (e.g., the learner misses some details), the learner could issue a query to make it clearer. The instructor could provide an additional explanation/demonstration when he/she thinks the learner does not understand the task completely. Instructions are thus considered to arise when knowledge transfer by teaching is incomplete, or trasferred knowledge is *ambiguous*. We would like to develop a mechanism of such an *ambiguity-driven* interaction with a robot. Moreover, the ambiguity is assessed by estimating a learner's internal model. We use the Dempster-Shafer theory (DST) to formulate the model because DST can express ambiguities explicitly.

MODELING INTERACTION PROCESS IN ROBOT-TO-HUMAN TEACHING OF ASSEMBLY TASKS

Necessary models in interactive teaching
The instructor has a description of a task to teach, by following which the task is achieved. We call the description a *task model*. The model includes descriptions such as objects involved in the task and geometrical relations between objects. An assembly task is defined by a sequence of assembly steps, and each step is described by a set of relations added (or removed) by that step.

Models of others are for representing the internal state of others, and can be used for predicting and recognizing their behaviors. Such a model is definitely important in developing human-machine interaction systems such as intelligent tutoring systems (e.g., [8]).

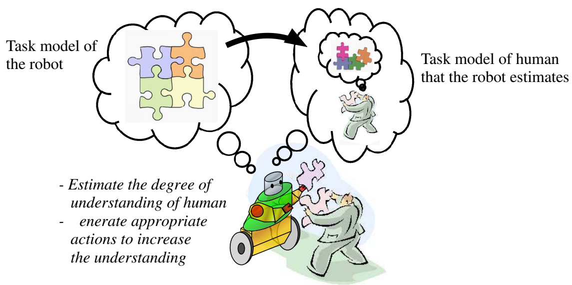

Figure 2. Robot teaches human.

The goal of instructor, who has a complete task model, is to make the learner construct the same model in his/her mind. To check this, the instructor must estimate the learner's degree of understanding of the task. For this estimation, it is further needed to know how the learner behavrs depending on his/her internal state. Fig. 2 illustrates such a model-based interaction; the robot will give appropriate (additional) instructions based on the learner's model under estimation.

Modeling the interaction process

The process of teaching can be viewed as the one that the set of possible task models (of an assembly step), or *ambiguity of task model*, in the learner's mind are gradually reduced demonstrations/explanations by the instructor, and it finishes when the instructor robot recognizes the complete transfer of task knowledge.

Another important model of interaction is the relationship between the learner's task model and his/her behavior. The learner may pose a question depending on what is ambiguous about the task. For example, if which object to pick up is not clear, he/she will ask about the identity of the object. Since the robot instructor cannot directly see the learner's internal state, it is necessary to assess it from his/her behaviors.

Dempster-Shafer theory

We adopt the Dempster-Shafer theory (DST) [6] to represent both parts of interaction modeling because *ambiguity* is a key concept in both types of modeling and DST is very suitable for representing ambiguities (or *ignorance*) [1]. In DST, a set of possible (discrete) states Θ is called a *frame of discernment* (FOD), and a degree of belief (called *basic probability*) is assigned to each subset A_i of FOD such that the sum of the basic probabilities becomes one. There are two quantities: belief function $Bel(A_i)$ and plausibility $Pla(A_i)$, which represent the lower and the upper bound, respectively.

By assigning a probability to each subset, we can represent "ignorance" explicitly; we can represent the case where we know the answer is one of the two candidates, a and b, but do not know which is more probable at all, by assigning the entire probability mass to subset $\{a,b\}$. This way of assigning probabilities is quite suitable for representing ambiguities in possible task models.

Fusion of two independent source is performed by several combination rules. We here use the Dempster's combination rule and denoted as $\oplus$.

Formulation of the interaction process

We formulate the interaction process as gradually refining the basic probability assignment (bpa). The process is divided into the following steps:

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1. Demonstration and Initialization: demonstrate an assembly step to the human, enumerate a set of possible models as an FOD, and calculate bpa (i.e., assign basic probabilities to its subsets).
2. Observation: observe the human's behavior. Example behaviors are: *execute the step perfectly*, *execute the step differently*, and *make a query to the robot instructor*.
3. Estimation: calculate a bpa for this observation and combine it with the current bpa for update.
4. Judgement: assess the degree of task knowledge transfer.
   a) Check if task knowledge of this assembly step is considered to be sufficiently transferred. This is done by judging if only the subset with the correct relation set (we call it the *correct subset*) as a single element has a high basic probability. If this is the case, move to the teaching of the next assembly step.
   b) Otherwise, proceeds to interaction planning.
5. Planning: select and execute the best interactive action, and then go to 2.

Interaction planning

Step 5 determines the robot's best interactive action for transferring the task knowledge. We take a similar approach to sensing planning under an uncertainty in which an action is chosen that maximizes the expected utility with a prediction of possible future states [4].

In the current context, prediction is about what the human will perceive (or understand) by a robot action such as gesture or verbal instruction. We would therefore like to maximize the predicted belief on the correct subset A^*. The predicted belief is the combination of the current belief m_c and the belief m_u to be obtained by a robot interactive action u. The best action u^* is then given by:

$$u^* = \arg\max_u \{Bel(A^*) \text{ given by } (m_c \oplus m_u)(A)\}. \qquad (1)$$

Calculation of basic probability assignment

Steps 1, 3, and 4 require the calculation of basic probability assignments (bpa's). We have not devised a general procedure for that. We here show some ideas for this calculation and will show examples in the experiments.

In steps 1 and 4, a bpa represents how the robot's demonstration is perceived by the human. Apparent knowledge (e.g., whether to put an object on another or put an object aside another) is easier to perceive, while a subtle difference (e.g., whether two planes should be coplanar) is more difficult. A voice message could carry more information when teaching an object's identity, while a gesture would be better when

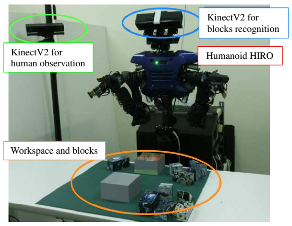


Figure 3. The experimental setting.

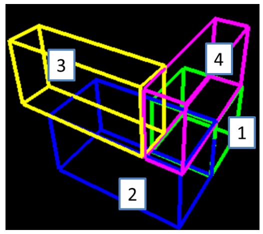


Figure 4. A blocks world task.

Table 1. Geometrical relations to achieve in the task shown in Fig. 4. Alphabets indicate suface id's.

step	relations
1	$Coplanar(1\text{-}C,2\text{-}D)$, $Against(1\text{-}E,2\text{-}F)$
2	$On(4\text{-}C,2\text{-}A)$, $On(4\text{-}C,1\text{-}B)$, $Coplanar(4\text{-}A,2\text{-}D)$, $Coplanar(4\text{-}B,2\text{-}C)$
3	$On(3\text{-}C,2\text{-}A)$, $Coplanar(3\text{-}A,4\text{-}B)$, $Against(3\text{-}D,4\text{-}E)$

teaching gemeotrical relations. The bpa to each subset should be calculated considering such factors.

In step 3, the leaner's state is estimated from his/her behavior. We suppose that the learner's behavior highly depends on the state; if the learner thinks to have a firm knowledge, for example, he/she will execute the current assembly step quickly without any hesitation. If not, he/she may take a longer time for execution or explicitly issue a query. We consider the ambiguity in the learner's model is almost directly related to his/her behaviors.

EXPERIMENTAL RESULTS

The robot and the task

Fig. 3 shows the experimental setting. The robot (HIRO by Kawada Co.) recognizes the workspace and human actions using two Kinects and a camera. Verbal communication with a designated set of words is also used. Fig. 4 shows an example task in which four blocks are assembled in three steps: put blocks 1 and 2, put block 4 on blocks 1 and 2, and put block 3 on block 2. Table 1 shows the geometrical relations to be achieved in each step.

Examples of robot-to-human interactive teaching

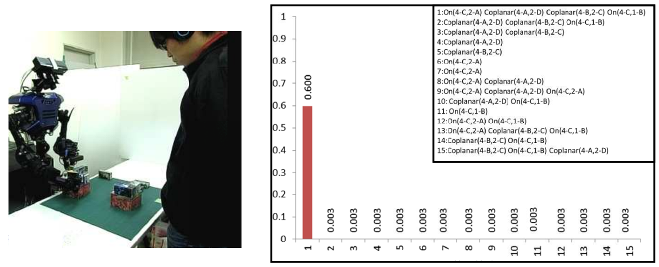
We conducted three trials of robot-to-human interactive teaching. In one case, the transfer is completed without additional interactions because the human learner was able to achieve the correct assembly steps only from the robot demonstrations. In the other cases shown below, additional interactions were necessary.

Case 1: Query from the learner

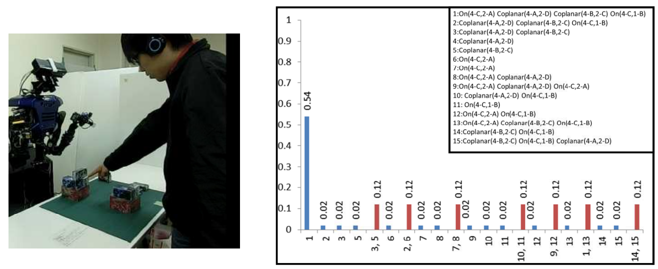
When the robot teaches step 2, the human learner asks if a coplanar relation is necessary. The robot replies it is necessary and the learner correctly reproduces the step. Fig. 5 shows this process.

Case 2: Incomplete knowledge acquisition of the learner

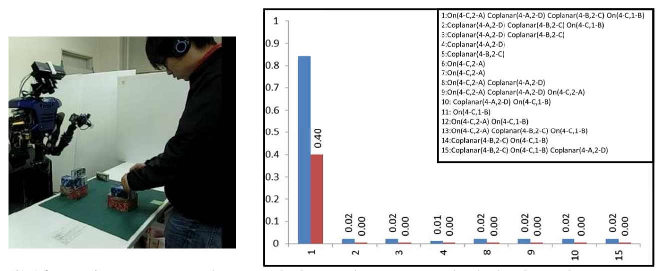
When the robot teaches step 3, the human learner receives an incomplete set of knowledge, which is found in his demonstration. The robot then gives an additional advice to clarify



(1) Robot demonstrates step 2, which achieves four relationships as shown in Table 1. There are 15 possible consequences. Some of the bpa's are shown on the right. The correct subset is 1 and given 0.6. The set including all consequences is given 0.3 but is not shown in the graph.



(2) Human asks if blocks 2 and 4 are aligned [i.e., relation *coplanar*(4-*B*, 2-*C*)]. From this query, the robot supposes that the human is ambiguous in this relationship, and calculates the bpa shown in red. Subsets that include consequences with and without that relationship have higher probabilities. Combining this and the bpa above, the bpa in blue is obtained. Since the belief of the correct subset, 0.54, is less than the threshold, the robot plans an interactive action of answering yes , and this makes the probability of the correct subset higher.



(3) After getting an answer to the query, the learner demonstrates what he has learned. From a combination of prior knowledge with knowledge gained from newly observed demonstrations (in red), the robot gets the blue bpa on the right. Since the belief of the correct subset is higher than the threshold, the robot considers that the learner obtained enough knowledge of this assembly step, and moves to the teaching of the next step.

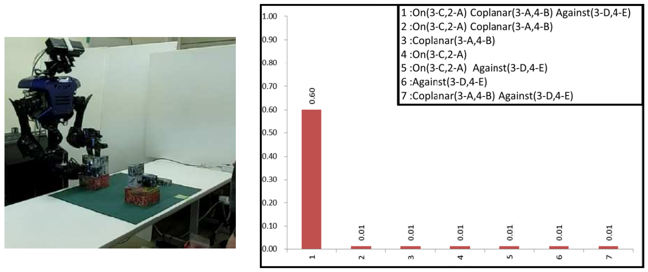
Figure 5. Interaction example 1: query from the learner.

an ambiguous point and the learner corrects his knowledge to complete the step. Fig. 6 shows this process.

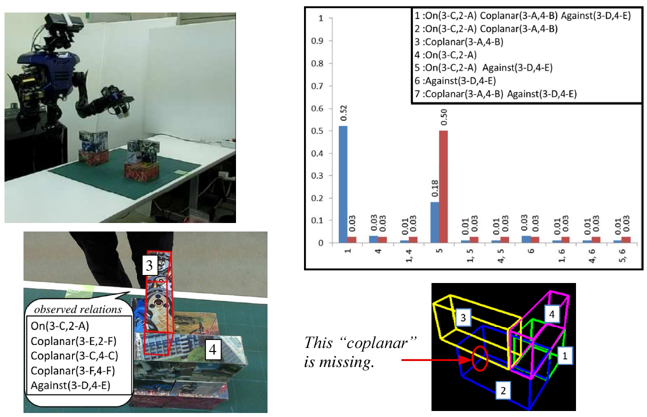
CONCLUSIONS AND DISCUSSION

We have developed a formulation for robot-to-human interactive teaching of assembly tasks. It is ambiguity-driven and based on the Dempster-Shafer theory (DST). The interaction process during teaching is viewed as the one of choosing interactive actions which reduce ambiguities in the human learner's estimated knowledge. This process is well modelled by DST. As proof of concept, we implemented and tested a robot system that can teach blocks assemblies to a human.

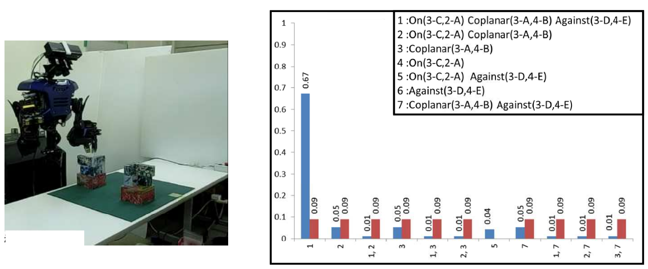
A key to realizing a smooth interaction is to properly determine basic probability assignments (bpa's). Currently, bpa's are set manually considering the degree of knowledge transfer for each demonstrations and instructions. As stated above, this would depend on many factors such as the learner's past experiences and the complexity of the task, and should also change as the teaching proceeds. Investigating a reasonable



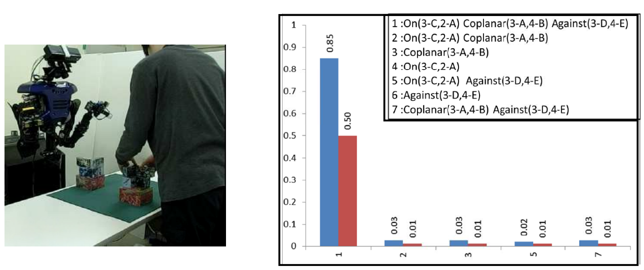
(1) Robot demonstrates step 3, which achieves three relationships as shown in Table 1. Some of the bpa's are shown on the right. The correct subset is 1 and given 0.6.



(2) The robot observed the human demonstration and found that one geometrical relation [*coplanar*(3-*A*,4-*B*)] is missing. Combined with the newly obtained bpa (in red), the updated bpa (in blue) is obtained.



(3) Since the belief of the correct subset is less than the threshold, the robot generates and executes a pointing gesture-based additional advice. The predicted bpa is updated and, as a result, the correct subset has a sufficient probability.



(4) After the advice, the robot asks the learner to demonstrate again. This time, he does it correctly and the belief becomes above the threshold. The robot then judges that the knowledge of this assembly step is correctly transferred.

Figure 6. Interaction example 2: incomplete knowledge transfer.

way to determine bpa's and a mechanism for learning them is a very challenging work. For this purpose, we also need to seek various cues that will appear in human behaviors and will be effective in estimating the degree of the human's understanding.

It is also necessary to enhance the robot's ability. The robot can teach what it can do. Implementing various robot skills is necessary for applying the proposed framework to more complex tasks.

Our ultimate goal is to develop a robot mediator, which gets knowledge from a human expert and gives it to a human novice. We could apply programming by demonstration (PbD) research works in the former step. As a robot leaner, it is necessary to actively asks the human instructor for uncertain/missing pieces of knowledge. An interaction planning perspective, which has been introduced in robot-to-human teaching in this paper, will also be necessary in human-to-robot teaching.

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