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Proof of Concept for a User-Centered System for Sharing Cooperative Plan Knowledge Over Extended Periods and Crew Changes in Space-Flight Operations

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Abstract—With the Robonaut-2 humanoid robot now permanently flying on the ISS, the potential role for robots participating in cooperative activity in space is becoming a reality. Recent research has demonstrated that cooperation in the joint achievement of shared goals is a promising framework for human interaction with robots, with application in space. Perhaps more importantly, with the turn-over of crew members, robots could play an important role in maintaining and transferring expertise between outgoing and incoming crews. In this context, the current research builds on our experience in systems for cooperative human-robot interaction, introducing novel interface and interaction modalities that exploit the long-term experience of the robot. We implement a system where the human agent can teach the Nao humanoid new actions by physical demonstration, visual imitation, and spoken command. These actions can then be composed into joint action plans that coordinate the cooperation between agent and human. We also implement algorithms for an Autobiographical Memory (ABM) that provides access to of all of the robots interaction experience. These functions are assembled in a novel interaction paradigm for the capture, maintenance and transfer of knowledge in a five-tiered structure. The five tiers allow the robot to 1) learn simple behaviors, 2) learn shared plans composed from the learned behaviors, 3) execute the learned shared plans efficiently, 4) teach shared plans to new humans, and 5) answer questions from the human to better understand the origin of the shared plan. Our results demonstrate the feasibility of this system and indicate that such humanoid robot systems will provide a potential mechanism for the accumulation and transfer of knowledge, between humans who are not co-present. Applications to space flight operations as a target scenario are discussed.

Index Terms—human-robot interaction, shared-plan, behavior learning, robotic teaching, space-flight operations.

I. INTRODUCTION

Humanoid robots will play an increasingly important role in interaction with human crews in modern space-flight operations [1], and thus a major goal is to render these robots as useful as possible. Research in human social interaction has demonstrated that one of the unique abilities that provides the basis for human social interaction is cooperation [2]. Inspired by this, we have developed a methodology for cooperative human-robot interaction systems with language playing an important role [3-7]. We believe that if humanoid robots are to engage with humans in useful, timely and cooperative activities, they must be able to learn from their experience with humans, and importantly, to share their knowledge in a suitable way.
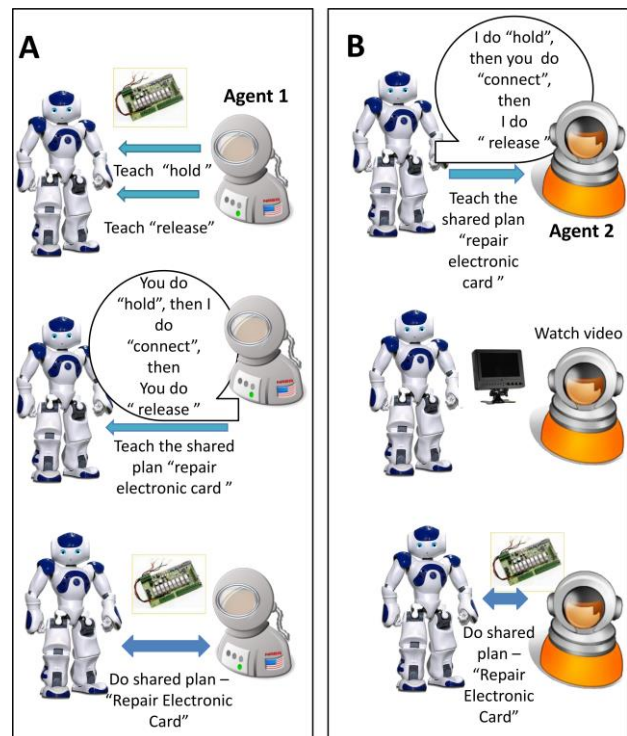

Figure 1. Robot as Learner and Teacher. Column A. Agent 1 teaches the Nao composite actions "hold" and "release", and then combines these in the shared plan "repair electronic card, which they perform together. Column B. Later, Nao teaches the shared plan to Agent 2, invites him to watch the training video, then they perform the shared plan together.

Learning by imitation or/and demonstration provide methods for humans to transmit desired behavior to robots [8, 9] and such learning can then provide the basis for building cooperative shared plans, in which the robot and human work together to achieve a shared goal. In the current research, we implemented these modalities by allowing the robot to learn simple behaviors and then to compose more complex shared plans by integrating these named learned behaviors, illustrated in Figure 1.

Using these behaviors as building blocks, the humans can teach the robot new shared plans - goal directed action plans achieved by two cooperating agents, in order to achieve a common goal that could otherwise not have been achieved individually [2]. Part of the uniquely human ability to cooperate is to change roles – to take the place of the other in the cooperative activity [9]. Thus, part of the novelty of the current research is to reverse the roles in teaching-learning shared plans. We implement this capacity in our cognitive system, such that the robot is no longer only learning from humans, but now takes on the role of teacher. Using the robot as a means for transmitting expert shared-task knowledge can be of particular use in cases where human crews are replaced, and robots remain in place to potentially transmit acquired knowledge, such as in space-flight operations [10].

II. A SCENARIO FOR HUMAN-ROBOT COOPERATION

Figure 1 illustrates the Human-Robot Interaction (HRI) scenario that we developed in this research which involves two humans (Agent1 and Agent2) and the robot Nao. In the first part of the scenario, Agent1 teaches Nao, whereas in the second part Nao becomes the teacher and Agent2 is the learner. The interest here is to demonstrate that the robot can thus serve as a platform for interactive sharing of accumulated knowledge between humans, though the humans do not directly interact. During spaceflight operations on the International Space Station (ISS), crew renewal could require mechanisms for transmitting information between crew members who are not simultaneously present [10]. Astronauts in one crew would teach the robot new shared plan procedures. The robot could then transmit this knowledge to new members of the next crew, thus providing continuity in the maintenance and transfer of knowledge. The Robonaut 2 humanoid is currently flying on the ISS [1], so such situations have a realistic future possibility.

The shared goal in our example cooperation scenario is to repair a electronic board/card that has become broken. The card should be removed and then held, and a defective part replaced. Thus, the card cannot be repaired by a single agent alone. Agent1 needs help from Nao to hold the card while it is being repaired. Agent1 starts by teaching Nao first how to *hold* and then to *release* the card, by physical demonstration, and then he teaches the shared plan by vocally describing the different steps. Finally, he executes the shared plan while Nao records with video what it is seeing. Later, Agent2 arrives, and does not know how to repair the electronic card. Agent2 asks Nao how to do it, watches the video recorded in part one and then executes the shared plan with the robot.
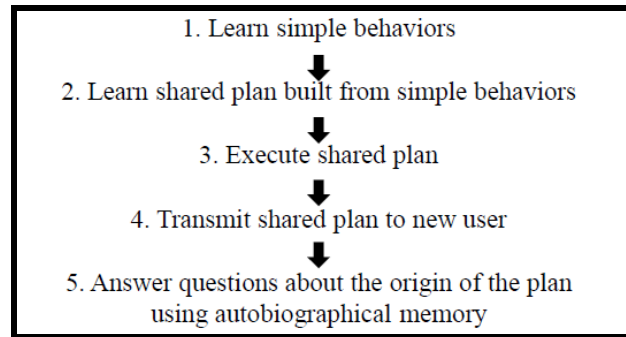

Figure 2. Five tiers of Knowledge Transmission

III. IMPLEMENTATION OF THE SYSTEM

A. The Nao humanoid

The current study is performed with the Nao humanoid robot which is a 25 degree of freedom humanoid robot (Aldebaran). Nao is a medium size (57 cm) entertainment robot that includes an on-board CPU x86 AMD Z530 processor with 1.66 GHz and 2Gb Flash memory, WiFi (802.11g) and Ethernet, two 640x480 cameras with up to 30 frames per second, inertial measurement unit (2 gyro meters and 3 accelerometers), 2 bumper sensors and 2 ultrasonic distance sensors. Its open, programmable and evolving platform can handle multiple applications. The on-board processor can run the YARP server (described below) and can be accessed over the internet via cable and WiFi.

We extend the perceptual system of the Nao to include a 3D motion capture capability implemented with the Kinect™ sensor. The OpenNI library using the color + depth data delivered by the Kinect sensor recognizes a human body image in a configuration posture, and then continuously tracks the human for the learning modality "Kinect", described below.

B. Inter-Process Communications via YARP

Functional processes implemented in different software modules are interconnected using YARP, an open source middleware developed to support software development in robotics [11, 12]. YARP provides an intercommunication layer that allows processes running on different machines to exchange data. Data travels through named connection points called ports. Communication is platform and transport independent: processes are not aware of the details of the underlying operating system or protocol and can be relocated at will across the available machines on the network. Interface between modules is specified in terms of YARP ports (i.e., port names) and the type of data these ports receive or send (respectively for input or output ports) is specified in the "bottle". This modular approach allows minimizing the dependency between algorithm and the underlying hardware/robot; different hardware devices become interchangeable as long as they export the same interface.

C. System architecture

The system behavior is coordinated by the Supervisor, and spoken language interaction with the human is realized by the SpeechRecognizer, developed using the Microsoft speech recognizer SAPI5.1. We use a simple, task-specific grammar and vocabulary that allows the recognizer to label each word or group of words according to its semantic role in the sentence. The structure of the interaction commands are specified in section IV. For example, in the commands *"Learn stop"* or *"Replay start"*, the first word will be labeled as the action and the second as the start/stop modality. Working with grammars and vocabularies has the advantages of binding the semantic role of each word directly, and generating less recognition errors due to the specific limited vocabulary specified for the task.
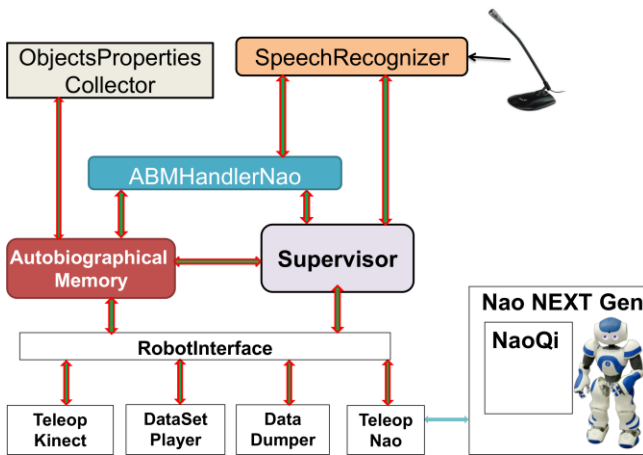

Figure 2 – System architecture. The architecture is organized in functional modules that provide sensory-motor input and output to the robot, storage and recall of learned behavior, and coordination of the interactions via spoken language. See text for details.

The recognized sentences are sent to the Supervisor that packages the extracted meaning into commands for RobotInterface. The RobotInterface interacts with the robot via TeleopNao, which manages the interface between the system level representation of action (in the Kinect human format) and the Nao. The RobotInterface also manages storage of behaviors, and shared plans and their execution. This includes a function for learned behavioral trajectories based on shifted mean angle values and angle derivation that smooths the motion and removes beginning and end of the learning where robot is not moving.

For learning by demonstration or imitation, the RobotInterface also controls the activation of dataDumper that stores, with a timestamp, Yarp bottles sent to teleopNao. These contain human joints angles <roll, pitch, yaw> for the the following segments: head, torso, both arms: shoulder, elbow, and wrist and finally <left_hand,right_hand> for the hands (from 0, hand closed, to 1 hand opened). For replaying learned actions, RobotInterface uses

DataSetPlayer (developed with YARP) to simulate the sending of stored bottles during a behavior replaying process.

Learning a behavior can be made in two different modalities. The first, called *"Kinect,"* is based on visual imitation of the user's actions through Kinect (teleopKinect converts Kinect data to human joints, it is based on the SWOOZ platform [13] open source code: https://github.com/GuillaumeGibert/swooz), the second modality, called *"Demo,"* consists in manually moving the Nao's joints (teleopNao converts Nao joints to human joints).

The Objects Properties Collector (OPC) serves as a working memory, and represents the state of the world at a given time. The OPC encodes the contextual data from the different sensors which will be stored in the autobiographical memory (ABM) [14]. This memory provides a continuous log of all interactions which can later be interrogated, and also is used, to identify the user in order to allow the system to adapt to the user's experience level. The robot will provide more explicit instruction to beginners, and will avoid this with more experienced users.

IV. INTERACTION

The system should allow the user to manage behaviors, that is, to teach new behaviors in different modalities, and then to use these behaviors. We thus implemented a set of corresponding behavior management commands (listed in Table 1). We also provide commands allowing the user to access some of the native functions of the Nao (Table 2). These are available for use with a set of commands for the creation and use of shared plans (Table 3).

Vocal command	Correspondence
Learn demo <behavior_name> Learn kinect <behavior_name>	Launch learning process with the label <behavior_name> and the modality physical demonstration or Kinect demonstration
Learn demo more (by erasing)	Modify last loaded behavior by inserting or erasing movements (if "by erasing" pronounced) where behavior replaying was stopped.
Learn stop	Stop learning process and stored data
Replay load <behavior_name>	Load the behavior
Replay start	Launch replaying process of the last behavior loaded
Replay <behavior_name>	Load the behavior, if existing launch the replaying process
Replay stop	Stop replaying process
Video replay <behavior_name>	Launch video with the label <behavior_name> on a screen
Video record <behavior_name>	Nao records what it is seeing in a video labeled with a behavior or shared plan name
Delete <behavior_name>	Delete the behavior
List behavior	Nao lists all the behaviors it knows

Table 1 - Behavior management commands

A. General commands for behaviors

The SpeechRecognizer uses a simple grammar to recognize speech commands in different interaction modes. Commands concerning behaviors and their consequences are presented in Table 1.

These commands allow for a full set of behavior management functions including the learning of new simple behaviors such as grasping or releasing the electronic card; allowing the user to indicate whether learning will be by Kinect, or physical demonstration; to indicate that the robot should film what it is doing for future knowledge transmission; and to list the set of learned behaviors. This corresponds to tier 1 of knowledge transmission.

B. Specific commands

In addition to the behavior commands, the user should also have access to native functions of the robot, including opening and closing the hands, and different modes of locomotion. These are specified in Table 2.

Vocal command	Correspondence
Open/close left/right/both hand(s)	Apply the corresponding action to the hands
Go to posture init	Nao goes to initial posture
Go to sleep	Nao goes to a safety posture and the system shuts down
Walk forward/backward	Nao walks in the stipulated direction
Turn left/right	Nao pivots in the stipulated direction
Walk stop	Nao stops any walking/turning action
Follow red <object>	Nao tracks any visible red object by walking

Table 2 - Specific commands

C. General commands for shared plans

Table 3 identifies commands that allow the user to compose shared plans from the component actions that have been learned, or that are native to the robot. This corresponds to Tier 2 interaction – learning shared plans, where the user indicates who does what actions in the shared plan. Tier 3 interactions – executing shared plans, allow the user to replay the shared plans, and to have the robot describe the shared plan verbally. Finally, in tier 4 interactions, a newly arrived user can access previously learned shared plans in order to him/herself learn those shared plans.

D. Commands for accessing Autobiographical memory

The Tier 5 interactions provide the user access to the accumulated knowledge and "experience" of the robot, encoded in the autobiographical memory. Table 4 specifies commands that allow the user to pose questions to the robot, related to its accumulated experience as encoded in the ABM. In actual operations, this can allow the new user of a shared plan to better understand the needs for, and origin of the shared plan.

Vocal command	Correspondence
Learn shared plan <plan_name>	Launch shared plan learning process with the label <plan_name>
I/You do <behavior_name>	Describe a shared plan step
Learn stop	Stop learning process and stored shared plan
Replay <plan_name> (but we change role)	Launch shared plan replaying process (role inversion if "but we change role pronounced)
Replay next	Pass the shared plan to next step
Replay stop	Stop replaying process
Explain me how to <plan_name>	Nao describes the shared plan steps
Video replay <plan_name>	Launch video with the label <plan_name> on a screen
Video record <plan_name>	Nao records what it is seeing in a video labeled with a behavior or shared plan name

Table 3 - Shared plan management commands

Vocal command	Correspondence
When was the <first, last> time you <learned, did> <plan_name, behavior_name>?	Return information about when this event occurred
How many times did this happen?	For the current action, reply with how many times
Who was present?	Say who was there
What did you do?	Report on all actions performed with the person at that meeting
Do you want to talk more about it?	Continue or not on the same person or event

Table 4 – Autobiographical memory management commands

V. PROOF OF CONCEPT

A. Interaction enhancements

We used a standard set of interaction enhancements including (1) Speech verification (e.g. "Did you say learn demo hold?") so speech recognition errors were reduced. (2) To avoid subjects having difficulty knowing what they could say to the robot at different periods in the interaction, we defined a beginner/expert mode distinction (>10 interactions for a beginner). In beginner mode, the system explains the current possibilities to the user. (3) We used the colors of the LEDs in the eyes to communicate which of the three states (waiting for instructions, learning, or executing a learned behavior) the robot was in at all times, which aided subjects in keeping track of the stages of the interaction.
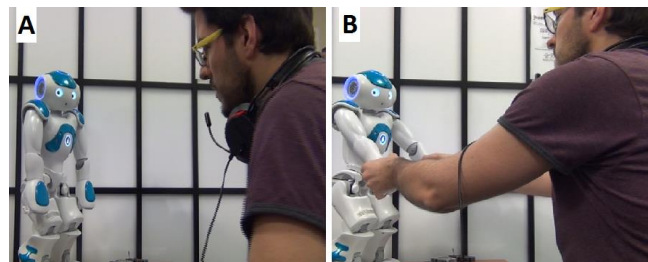

Figure 3 – Naïve subject teaching robot to hold. A. Nao in initial posture. B. User teaching hold to Nao

B. Five-Level System Validation

In order to evaluate the system, we tested naive subjects (who had never used the system before) in the Figure 1A scenario. Subjects have to teach "hold card" and "release card" behaviors, and then combine these two new behaviors to teach the shared plan "repair electronic card," and finally execute the shared plan with the robot. Prior to the experiment, subjects were given a scenario description as illustrated in Figure 1A, and a printed page that summarized the possible types of vocal commands as identified in Tables 1-3.

Five users, who had never interacted with the system, participated in the experiment. They enacted this scenario twice, to allow us to measure how they adapted to the system. In the following dialog excerpt we provide the literal transcription of the human-robot dialog during the interaction (illustrated in Figures 3 and 4), annotated with explanation about the corresponding human and robot behavior and key system functions in < > brackets. Robot language will be indicated *in italics*, and human language in **bold** text. This was the second use of the system by a subject, whom the robot still considered a beginner (based on the number of recorded interactions), and thus the system provided more instructions of what user can do.

1) Phase 1. Learning "hold card" and "release card" behaviors

Dialog: *Who am I working with?* **Maxime**. *Did you say Maxime?* < Asking confirmation > **Yes**. *Okay, what can I do for you?* **Learn demo hold** . *Did you say learn demo hold?* **Yes**. *Okay, I am ready to learn hold. Move my joints to show me. You can use special move like open both hands while teaching. Say learn stop when you have finished.* < Human moving Nao's arms > **Open both hands.** < Inserting the electronic cards between Nao's hands > **Close both hands.** < Nao closes its hands > **Learn stop.** *Did you say learn stop? Yes. Okay. I have successfully stored hold. Was it successful according to you?* **Yes.** < Nao stays in the final position of hold > **Learn demo release** . *Did you say learn demo release?* **Yes**. *Okay, I am ready to learn release. Move my joints to show me. You can use special move like open both hands while teaching. Say learn stop when you have finished.* **Open both hands** < Taking the electronic card and moving Nao's arms > **Learn stop**. *Did you say learn stop?* **Yes.** *Okay. I have successfully stored hold. Was it successful according to you?* **Yes**. *Okay.*

2) Phase 2. Learning the shared plan "repair electronic card"

Dialog: **Learn shared plan repair electronic card**. *Did you say learn shared plan repair electronic card?* **Yes**. *Okay, I am ready to learn the shared plan repair electronic card. Tell me step by step what we have to do and say learn stop when you have finished.* **You do hold**. *Did you say you do hold?* **Yes**. *Okay, then?* **I do connect**. *Did you say I do connect?* **Yes**. *Okay, then?* **You do release**. *Did you say you do release?* **Yes**. *Okay, then?* **Learn stop**. *Did you say learn stop?* **Yes**. *Okay, I have to hold, then you have to connect,*

then I have to do release. Okay, I got it. I have successfully stored repair electronic card, was it successful according to you? **Yes**. *Okay.*
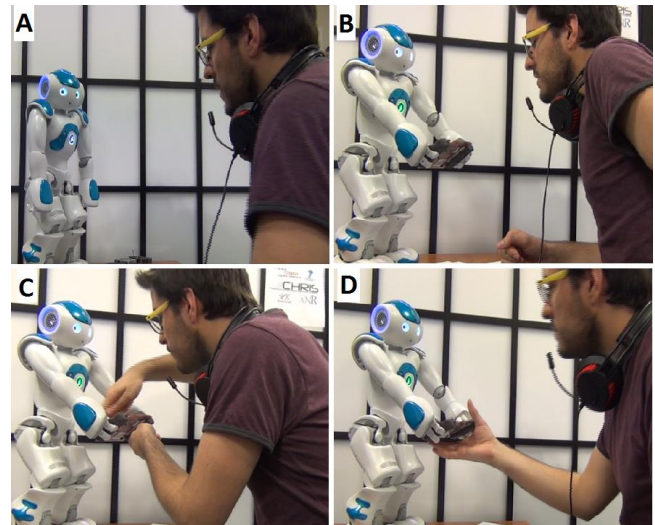

Figure 4 – Naïve subject executing shared plan. A. Nao in initial posture. B. Nao holding electronic card. C. User connecting wires. D. Nao releasing electronic card

3) Phase 3. Executing the shared plan with the robot

Dialog: **Replay repair electronic card**. *Did you say replay repair electronic card?* **Yes**. *I have to do hold, tell me when I have finished by saying replay next.* < Nao holds electronic card > **Replay next**. *You have to do connect, tell me when you have finished.* < User connects wires > **Replay next**. *I have to do release, tell me when I have finished.* < Nao releases electronic card > **Replay next**. *Shared plan is finished.* **Replay stop**. *Did you say replay stop?* **Yes**. *Okay, was it successful according to you?* Yes. *Okay*. **Go to sleep**. *Did you say go to sleep?* **Yes**. *Okay, bye bye, see you soon.* <System shuts down>

Figure 5 - Average time spent on learning individual behaviors, learning shared plan, and execution of shared plan, for 5 naïve users.

Figure 5 illustrates the action performance times for the different sub-tasks in the shared plan - repair electronic card. The considerable time difference to accomplish the scenario in the first vs. second repetition indicates the user's relatively rapid adaptation to the system. The first time, users accomplish the complete interaction scenario in about 9 minutes 36 seconds and the second time, they realize the scenario on average in 5 minutes 27 seconds. We compared times for the first vs. second repetitions using a Wilcoxon signed-rank test for the global scenario, and on each sub-task. The repetition effect was significant for overall scenario realization and "hold" learning (p= 0.029, p= 0.014 respectively). The significant repetition effect for "hold" is likely due to the fact that this corresponds to the user's first contact with the robot and the system. We do not consider this as a statistically significant result, but simply a description of the performance of 5 subjects in a proof of concept demonstration.

These results demonstrate that naïve subjects can use the system to teach the robot new simple behaviors, and build these into a cooperative shared plan, and that they adapt readily to the system.
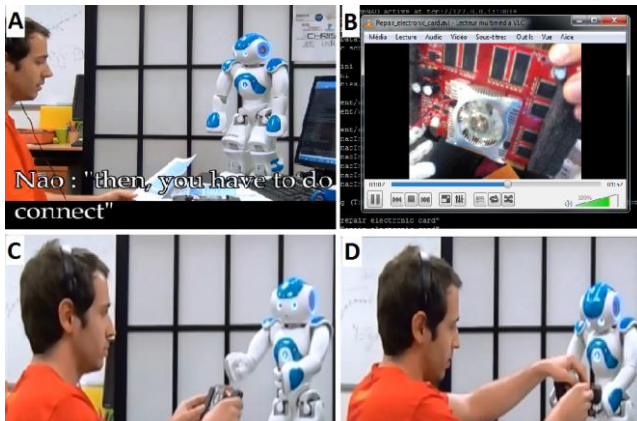

Figure 6 – Demonstration of the system in tier 4 mode. A. Nao explains shared plan to user. B. Video of shared plan shown on a screen. C. and D. User executes shared plan with Nao.

4) Phase 4. Robot Transmission to New User

Until this point we remain in the standard situation of shared plan learning. Now we go beyond this so that the robot can be used to teach the shared plan to a new user. Figure 1B illustrates the scenario for this reversed situation, where the robot becomes the teacher and the human learns from the robot, who shares what it experienced. After learning from Agent1, the robot then teaches the learned plan to a new user, Agent2. The robot explains the learned shared plan, and physically shows a video of what it perceived during the shared plan execution (illustrated in Figure 7). Execution of this scenario with a naïve subject is illustrated in Figure 6, and the corresponding dialog excerpt provided here:

Dialog: **Explain me how to repair electronic card**. *Did you say explain me how to repair electronic card?* **Yes**. *Okay. I have to do hold, then you have to connect, then I have to release.* **Video replay repair electronic card**. *Did you say video replay repair electronic card?* **Yes**. *Okay. Look at the screen, I show you.* < Video of what was seen by the robot while executing the shared plan repair electronic card is displayed on a computer screen – see Figure 7 >.

At this point the subject in Figure 6 has seen the video illustrating the unfolding of the shared plan. Based on this knowledge, he can then proceed with execution of the shared plan. The subject illustrated in Figure 6 successfully used the system functionalities and repaired the electronic card, thus demonstrating proof of concept that the system can be used in this tier 5 mode.
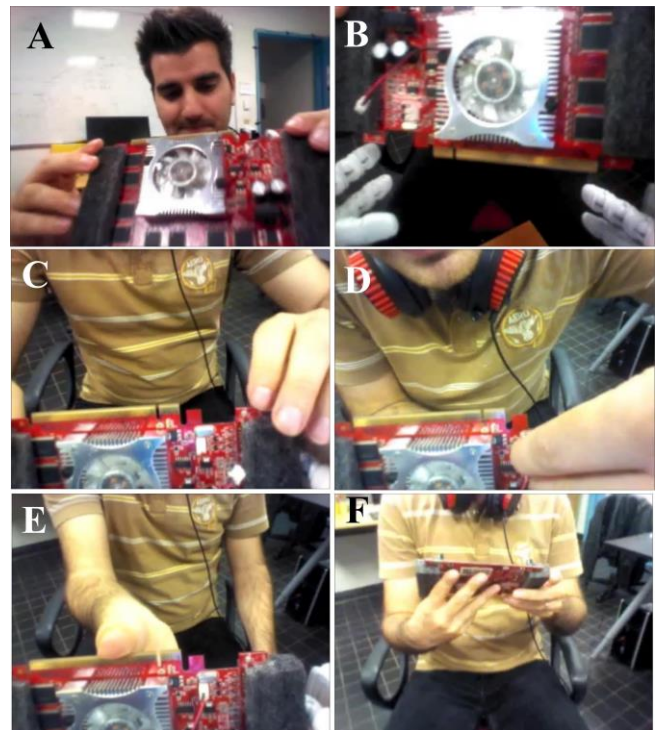

Figure 7. Excerpts from the video recorded by Nao during teaching by Agent1, visualized by Agent2 in the Tier 4 – Knowledge transmission Context. A. Agent1 inserting card in Nao's grasp during teaching of "hold". B. Just prior to insertion. C. Card being held by Nao. D. Agent1 performing "connect cable" on card while Nao holds the card. E. Agent1 taking card as Nao performs "release". F. Agent1 inspecting his work after the shared plan has been executed.

5) Phase 5. Explaining Origin of Shared Plan Using Autobiographical memory

All of the events experienced by the Nao have are stored in its Autobiographical memory. This memory provides an important source for the accumulation of knowledge that can be used by future agents. Here we provide a dialog excerpt that illustrates how an agent can interrogate the ABM in

order better understand how certain behaviors have been taught to the robot.

Dialog: **When was the first time you learned repair electronic card?** *It was the 13 of March of 2014. You want to know more about it?* **No. When was the last time you learned repair electronic card?** *It was the 14 of June of 2014.* **Who was there?** *Marwin was there. You want to know more about it?* **No. When was the first time you did hold?** *It was the 13 of March of 2014. You want to know more about it ?* **No. When was the last time you did hold?** *It was the 29, of April, of 2014. You want to know more about it ?* **How many times did this happen?** *It happened 282 times You want to know more about it ?***Who was present ?** *Colas was present. You want to know more about it ?***What have you done?** *He taught me hold, and it worked. He taught me release, and it worked. He taught me Repair electronic card, and it worked. We did release, and it worked.*

This ability to interrogate the autobiographical memory in the tier 5 interaction represents and

C. Real-time control

While we concentrate on the scenarios in Figure 1, the system allows open ended construction of actions that can contribute to shared plans. In this context, the advantage of the modular software architecture is that we can duplicate the interaction-related modules (SpeechRecognizer and Supervisor) so that the robot can interact with two different people at the same time. This allows two agents to interact together, via the robot, in real time.

Let us again imagine the robot aboard the ISS, with two astronauts separated by several meters and performing tasks that prevent them from changing location. One agent needs a tool that the second agent is using. Agent1 will send the robot to get the tool but he has no time to teach anything, he will use direct commands in collaboration with the other human. Here is a dialog segment from a demonstration of this interaction.

Dialog: < First agent > **Turn left.** *Did you say turn left?* **Yes.** *Okay.* < Nao turns left > **Turn Stop. <** Repetition not needed, because it's a real-time command **> Follow red t-shirt on.** *Did you say follow red t-shirt on?* **Yes.** *Okay.<* Nao walks to the red t-shirt it sees > < Second agent > **Follow red t-shirt off.** *Did you say follow red t-shirt off?* **Yes.** *Okay.* < Nao stops tracking the red t-shirt > **Replay left arm up**. *Did you say replay left arm up?* **Yes.** *Okay* < Nao raises it left arm, this behavior was previously learned in kinect mode> **Open left hand.** *Did you say open left hand?* **Yes.** *Okay.* < Nao opens left hand and second agent puts the tool in its hand > **Close left hand.** *Did you say close left hand?* **Yes.** *Okay.* < Nao closes left hand > **Turn right.** *Did you say turn right?* **Yes.** *Okay.* < Nao turns right > **Turn stop. Walk forward.** *Did you say walk forward?* **Yes.** *Okay.* **<** Nao walks back to first agent > < First agent > **Walk stop. Open left hand.** *Did you say open left hand?* **Yes.** *Okay.* **<** First agent gets the tool> **Go to sleep.** *Did you say go to*

sleep? **Yes.** *Okay, bye bye, see you soon*. <System shuts down>

This scenario could then be saved as a shared plan, for example, called "Get it". Part of the objective of this final experiment is to demonstrate that the system allows the open-ended execution of the robot's capabilities, as suited for a novel given task, rather than being hard wired just for the task. That is, while we concentrated on the repair electronic card task, the system is open ended and can learn arbitrary shared plans within the 5 tier framework.

VI. DISCUSSION AND FUTURE WORK

A. Novelty

We demonstrated a 5-tiered learning system that allows users (1) to teach low level behaviors, then (2) to teach composite shared plans that employ these learned primitives. (3) At the third level, once this learning has occurred, the shared plan can then be used in an efficient manner, allowing for reduced execution time. Then, inspired by the notion of "role reversal" [15] we introduced a novel extension of the human-robot cooperation paradigm in the fourth level of interaction: (4) The notion is to use the robot as a vector for transmission of knowledge between humans. We thus demonstrated that the robot could explain the shared plan, step by step to a new user, showing the user a video recorded from its on-board camera. This allows the robot to become an effective vector of knowledge transfer between two humans who are not physically present together. (5) The fifth level of interaction allows the new user to question the robot, in order to better understand the origin of the shared plan, who created it, when it was used etc. The proof of concept of this 5 level interaction provides a stepping stone for the development and deployment of such interaction algorithms to allow the accumulation and transmission of knowledge in the space flight operations environment.

B. Related Work and Limitations

This research is situated in the developing context of cooperative human-robot interaction [16], language based interaction [17-19], imitation and demonstration based learning [20-25]. While Crangle and Suppes [26] state that "the user should not have to learn specialized technical vocabularies to request action from a robot", this is not the case for our system. That is, users must learn to use unconventional utterances such as "learn stop", to end the learning. Rather than directly accessing internal commands, an intermediate layer for communication can make the link between human language (and the variety of sentences possible referring to the same thing) and understandable action for robot. We have begun to address how such mappings can be learned [27], and future research will address such mapping in the current context.

C. Applications

Because the system is quite modular, and all internal kinematic configurations are in a platform independent representation (the human kinematic model native to Kinect) we can replace Nao by another robot, only by replacing the module teleopNao (which contains the algorithm that converts Nao joints to Kinect human joints and all low level functions: motion controller, LED controller, etc.).

A potential application for such a system will be in space flight operations aboard the ISS. The robot assistant will be able to allow astronauts to accomplish cooperative tasks (such as repair electronic card) by learning these tasks directly from the astronaut. The resulting stored knowledge can then be of particular value in the context of crew renewal, where new crew members will replace the old crew, and the question of transfer of acquired experience will arise. The robot autobiographical memory provides a useful store of this knowledge. The learned shared plans can be reused, and the robot can teach these new plans to new crew members. By interrogating the ABM, the crew members can better understand the origin of these shared plans. This proof of concept of a 5 tiered knowledge accumulation and transfer system should have useful application in human robot cooperative interaction.

References:

[1] T. D. Ahlstrom, M. A. Diftler, R. B. Berka, J. M. Badger, S. Yayathi, A. W. Curtis, and C. A. Joyce, "Robonaut 2 on the International Space Station: Status Update and Preparations for IVA Mobility," 2013.

[2] M. Tomasello, M. Carpenter, J. Call, T. Behne, and H. Moll, "Understanding and sharing intentions: The origins of cultural cognition," *Behavioral and Brain Sciences,* vol. 28, pp. 675-691, 2005.

[3] S. Lallée, K. Hamann, J. Steinwender, F. Warneken, U. Martienz, H. Barron-Gonzales, U. Pattacini, I. Gori, M. Petit, G. Metta, P. M. J. Verschure, and P. F. Dominey, "Cooperative Human Robot Interaction Systems: IV. Communication of Shared Plans with Naïve Humans using Gaze and Speech," presented at the IEEE/RSJ International Conference on Intelligent Robots and Systems, Tokyo, 2013.

[4] S. Lallée, S. Lemaignan, A. Lenz, C. Melhuish, L. Natale, S. Skachek, T. van Der Tanz, F. Warneken, and P. Dominey, "Towards a Platform-Independent Cooperative Human-Robot Interaction System: I. Perception," presented at the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Taipei, 2010.

[5] S. Lallée, U. Pattacini, J. Boucher, S. Lemaignan, A. Lenz, C. Melhuish, L. Natale, S. Skachek, K. Hamann, J. Steinwender, E. A. Sisbot, G. Metta, R. Alami, M. Warnier, J. Guitton, F. Warneken, and P. F. Dominey, "Towards a Platform-Independent Cooperative Human-Robot Interaction System: II. Perception, Execution and Imitation of Goal Directed Actions," in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS),* San Francisco, 2011, pp. 2895 - 2902.

[6] S. Lallée, U. Pattacini, S. Lemaignan, A. Lenz, C. Melhuish, L. Natale, S. Skachek, K. Hamann, J. Steinwender, E. A. Sisbot, G. Metta, J. Guitton, R. Alami, M. Warnier, T. Pipe, F. Warneken, and P. Dominey, "Towards a Platform-Independent Cooperative Human-Robot Interaction System: III. An Architecture for Learning and Executing Actions and Shared Plans," *IEEE Transactions on Autonomous Mental Development,* vol. 4, pp. 239-253, 2012.

[7] M. Petit, S. Lallee, J.-D. Boucher, G. Pointeau, P. Cheminade, D. Ognibene, E. Chinellato, U. Pattacini, Y. Demiris, G. Metta, and P. F. Dominey, "The Coordinating Role of Language in Real-Time Multi-Modal Learning of Cooperative Tasks," *IEEE Transactions on Autonomous Mental Development,* vol. 5, pp. 3-17, 2013.

[8] S. Calinon, F. Guenter, and A. Billard, "On learning, representing, and generalizing a task in a humanoid robot," *IEEE Trans Syst Man Cybern B Cybern,* vol. 37, pp. 286-98, Apr 2007.

[9] M. Pardowitz, S. Knoop, R. Dillmann, and R. D. Zollner, "Incremental learning of tasks from user demonstrations, past experiences, and vocal comments," *IEEE Trans Syst Man Cybern B Cybern,* vol. 37, pp. 322-32, Apr 2007.

[10] B. Caldwell, "Multi-team dynamics and distributed expertise in mission operations," *Aviation, space, and environmental medicine,* vol. 76, pp. B145-B153, 2005.

[11] P. Fitzpatrick, G. Metta, and L. Natale, "Towards Long-Lived Robot Genes," *Robotics and Autonomous Systems,* vol. 56, pp. 29-45, 2007.

[12] G. Metta, P. Fitzpatrick, and L. Natale, "YARP: yet another robot platform," *International Journal on Advanced Robotics Systems,* vol. 3, pp. 43-48, 2006.

[13] G. Gibert, F. Lance, M. Petit, G. Pointeau, and P. F. Dominey, "Damping robot's head movements affects human-robot interaction," presented at the ACM/IEEE International Conference on Human-Robot Interaction, Bielefeld, Germany., 2014.

[14] G. Pointeau, M. Petit, and P. F. Dominey, "Successive Developmental Levels of Autobiographical Memory for Learning Through Social Interaction," *Autonomous Mental Development, IEEE Transactions on* 2014.

[15] M. Carpenter, M. Tomasello, and T. Striano, "Role reversal imitation and language in typically developing infants and children with autism," *Infancy,* vol. 8, pp. 253-278, 2005.

[16] T. Kruse, A. Kirsch, E. A. Sisbot, and R. Alami, "Exploiting human cooperation in human-centered robot navigation," in *RO-MAN, 2010 IEEE*, 2010, pp. 192-197.

[17] F. Doshi and N. Roy, "Spoken language interaction with model uncertainty: an adaptive human–robot interaction system," *Connection Science,* vol. 20, pp. 299-318, 2008.

[18] T. Kollar, S. Tellex, D. Roy, and N. Roy, "Toward Understanding Natural Language Directions.," in *Proceeding of the 5th ACM/IEEE International Conference on Human-robot Interaction - HRI '10. Osaka, Japan, .* , 2010.

[19] S. Lauria, G. Bugmann, T. Kyriacou, and E. Klein, "Mobile robot programming using natural language," *Robotics and Autonomous Systems,* vol. 38, pp. 171-181, 2002.

[20] B. Argall, S. Chernova, M. Veloso, and B. Browning, "A survey of robot learning from demonstration," *Robotics and Autonomous Systems,* vol. 57, pp. 469-483, 2009.

[21] C. Breazeal and B. Scassellati, "Robots that imitate humans," *Trends in Cognitive Sciences,* vol. 6, pp. 481-487, 2002.

[22] S. Calinon, F. D'Halluin, E. Sauser, D. Caldwell, and A. Billard, "Learning and reproduction of gestures by imitation: An approach based on Hidden Markov Model and Gaussian Mixture Regression," *IEEE Robotics & Automation Magazine,* p. 11, 2010.

[23] Y. Demiris and M. Johnson, "Distributed, predictive perception of actions: a biologically inspired robotics architecture for imitation and learning," *Connection Science,* vol. 15, pp. 231-243, 2003.

[24] M. Kaiser and R. Dillmann, "Building elementary robot skills from human demonstration," in *Proceedings of the International Conference on Robotics and Automation*, 1996, pp. 2700-2705.

[25] J. Saunders and C. L. K. D. A. A. Nehaniv, "Self-imitation and Environmental Scaffolding for Robot Teaching," *International Journal of Advanced Robotic Systems,* vol. 4, 2008.

[26] C. Crangle and P. Suppes, *Language and learning for robots* vol. 41: Center for the Study of Language and Inf, 1994.

[27] X. Hinaut, M. Petit, G. Pointeau, and P. F. Dominey, "Exploring the acquisition and production of grammatical constructions through human-robot interaction with echo state networks," *Front Neurorobot,* vol. 8, 2014.