Towards a Cognitive Robot that Uses Internal Rehearsal to Learn Affordance Relations

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***Abstract*—This paper introduces a new approach to develop robots that can learn general affordance relations from their experiences. Our approach is a part of larger efforts to develop a cognitive robot and has two components: (a) the robot models affordances as statistical relations among actions, object properties and the effects of actions on objects, in the context of a goal that specifies preferred effects and outcomes, (b) to exploit the general-knowledge potential of actual experiences, the robot engages in internal rehearsal by playing out virtual scenarios grounded in yet different from actual experiences. To the extent the robot accurately appreciates affordance relations, the robot can autonomously predict the outcomes of its behaviors before executing them. Internal rehearsal-based outcome production in turn facilitates planning of a sequence of behaviors toward successful task execution. We also report simulation results of internal rehearsal-based traversability affordance learning of a humanoid robot.**

I. INTRODUCTION

IN the future, robots will need to accomplish increasingly complex tasks in dynamic and challenging environments, exhibiting robust performance in a wide range of situations. Expectably, robot control systems will become more complex to a point that robot adaptivity and robustness to select appropriate actions could be compromised. A promising approach to advance robotic action selection is to train robot attention so that it learns which situational features are most important to accomplish their tasks across the broad range of changing circumstances the robot is expected to encounter. In this paper, we use the *affordance relations* that connect situational features to behavioral repertoire. As the robot comes to appreciate what its situation and action repertoire, taken together, afford for its goal accomplishment, the robot is likely to perform more adeptly to achieve its goals. For a robot to come to recognize affordance relations from its limited experiences, the robot needs to revisit and to reconsider its own experiences. We use *internal rehearsal* to refer to an internal simulation, grounded in prior experiences, which estimates outcomes of possible actions, thereby increasing the efficiency and effectiveness with which the robot learns affordance relations on its own [1]. This paper reports on the use, in simulation, of internal rehearsal-based action selection to learn the affordance relation of space traversability.

A. Affordance Relations

The notion of affordance was originally introduced by a psychologist J.J. Gibson [2]. Gibson defined affordance to be a directly perceivable attribute of the environment. For example, to perceive a ball is to perceive all that it affords: throwing, catching, rolling, *etc*. Similarly, taking the environment as a whole system, to perceive different rates of optic flow is to perceive an environment with distinct objects at different distances. Stoffregen [3] made affordance dynamic, as an emergent property of the task-environment relationship. For example, *when* the task is to play catch, a ball affords throwing; and *when* the task is to move an object over a surface, the ball (bearing) affords reduced friction.

In the last decade, robotics and AI researchers have started to explore and exploit the concept of affordances for the design and implementation of intelligent systems accomplishing tasks in dynamic environments. Affordances have been learned and then used for a mobile robot to move about its environment [4]; and for behavior selection in a mobile robot so as to satisfy internal drives; thereby enabling it to exist autonomously within its environment [5]. Stoytchev [6] adds Piaget's developmental theories [7] to Gibson's notion of affordance, to take a developmental approach to learning affordances. Additional exploratory research has utilized backpropagation of reinforcement learning signals to enable affordance cueing [8], combined imitation learning with a world model developed through learned affordances [9], and function-based object recognition [10].

A central limitation of prior work is that, following Gibson, affordances are taken to be directly perceivable attributes intrinsic to the environment itself. As such, robot's learning of affordances to-date occurs with limited generalization to new objects and contexts. By complete contrast, by seven months of age, a human infant is already starting to shape his/her hand while moving the hand toward an object, in anticipation of grasping the object, something the infant does robustly with objects unlike any previously encountered [11].

To move toward this level of generality of affordance learning, the notion of affordance is taken one logical step further in this paper. Both Gibson and neo-Gibsonians like Stoffregen would adamantly eschew any invocation of an internal state like a goal, because these are not directly

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observable in brains. In the same vein, though taking no explicit position, Şahin et al. [12] do not invoke goals in their Effect (Entity, Behavior) formalization of affordance, so that there is an equivalence between observer (allocentric) and agent (autocentric) perspectives. For us, by contrast, a robot's hardware and software are fully exposed, so an internal goal state is a simple fact, not a problematic Aristotelian final cause.

We thus propose that, for complex goals in complex, changing situations, a robot's adaptive effectiveness will be qualitatively enhanced when a robot leverages its own autocentric, unique-experience-based view of affordance relations, so as to characterize how to couple features of the robot's own specific situation to the robot's own behavioral repertoire, so as to take actions likely to yield preferred effects that advance the robot's own goals. This notion of an affordance relation offers an original perspective on how to bind together percepts, behavioral repertoire and reasoning. An ability to recognize and reason about affordance relations has important potential to advance intelligent robotics research, toward the design of new, powerful and intuitive control architectures for autonomous cognitive robots [13].

B. Internal Rehearsal

The ability to simulate steps of action in the mind is an important human cognitive skill [14]. People are mentally able to consider the nature of a problem with its potential solutions and to evaluate many possible plans of action before they physically deploy one. In effect, thinking often involves mental rehearsal which allows people to practice and thereby to improve what they intend to do.

Sometimes people can learn performance-improving lessons directly from very few experiences. Typically, however, people do well to explore their actual experiences with mental rehearsal of scenarios that are grounded in experiences and yet reflect potentially informing parametric variations of experiences. A robot endowed with similar capability could likewise estimate the consequences of its actions to improve its performance. In some circumstances, the robot could also use internal rehearsal to learn how to perform new tasks. Jirenhad et al. proposed a basis for an 'inner world' that allows robots to anticipate the future event and behave in the absence of external sensory stimuli [15]. Shanahan constructed an internal simulation that plays a critical role in allowing the cognitive higher-order loop to suppress a reactive loop when the reactive loop is about to choose a poor course of action [16]. Kawamura extended Hesslow's and Shanahan's work to demonstrate how a robot could internally rehearse actions to avoid obstacles [1][17]. Meeden et al., showed how a simple recurrent network can exhibit behavior that is "plan-like" in the sense of associating abstract behavioral goals with sequences of primitive actions [18]. A connectionist robot controller has been shown to be able to acquire an internal 'model' of the world through training on sensor prediction while moving around in a room [19]. Internal simulation of functions of the sensory and motor cortices has been deployed in mobile robots [15].

C. Rehearsing Affordance Relations

In this paper, we describe first steps in a program of neurobiologically inspired robotics research toward human capabilities to learn and generalize affordances relations from experience. Specifically, we describe an implementation of internal rehearsal processes that work toward generalizing the robot's actual experiences, so that the robot learns to direct its attention toward affordance relations. The robot then leverages its knowledge of affordances to select behaviors that the robot correctly predicts to yield outcomes that advance its goals. After reviewing the bases for this approach, we report the results of first proof-of-concept experiments, in which, in a realistic simulation, we bring the robot to learn a general affordance relationship, the *traversability* of a space.

II. ISAC COGNITIVE ARCHITECTURE

A. Humanoid Robot ISAC

Work in our Cognitive Robotics Laboratory has yielded an operational humanoid robot ISAC that implements crucial features of human working memory under an NSF grant [20]. ISAC is an upper-torso humanoid with two 6-degree-of-freedom arms that are actuated pneumatically by artificial muscle actuators which provide a relatively safe human-robot interaction for manipulation, automation and other tasks. Features such as lightweight, high power-to-weight ratio, and natural compliancy make such actuators advantageous over commonly used rigid motor actuators in human-robot coexisting environments [21].In this implementation, ISAC (Intelligent Soft Arm Control) humanoid robot, shown in Fig. 1, learns how to respond to a limited set of commands using a short term memory, a long term memory, and the working memory system that is grounded in a computational neuroscience model of working memory of the prefrontal cortex [22]. The working memory system provides ISAC with a means of maintaining task-related information during task execution in a manner similar to human task execution [1].

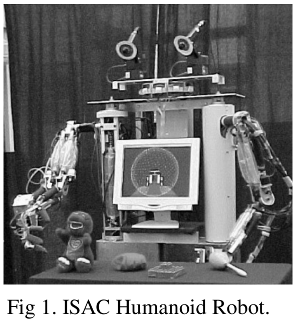


Fig 1. ISAC Humanoid Robot.

When a novel stimulus is present, this system explores different sensory-motor responses and, over time, learns which sensory-motor association is most appropriate for a given situation. One of the novel features implemented is an offline reflective module called the Internal Rehearsal System (IRS) [1]. In its original implementation, ISAC reflects on its experiences and uses the IRS for internally exploring alternative sensory-motor associations in order to predict likely consequences of alternative action selections, thereby to learn how to improve its performance when similar situations arise in the future [23][24].

This approach using working memory and internal rehearsal should also be useful for forms of cognition more abstract than sensory-motor learning. A vitally important yet challenging example is learning about those affordance relations that materially affect the likelihood of success and failure. Affordance relations do not exist objectively in the world. Rather, they are imputed by an agent, and thus are perforce constructed internally, in light of the agent's goals and action repertoire as well as situational features of the world. As such, one logical next step in the Internal Rehearsal System research is for a robot to explicitly impute, to register and to explore potential affordance relations in its working memory.

B. *ISAC Cognitive Architecture and Central Executive*

Fig. 2 illustrates the multiagent-based ISAC cognitive architecture composed of agents and associated memory structures. Various agents are designed to encapsulate all aspects of a single element (logical or physical) of a hardware component, computational task, or data.

The Self Agent is actually a virtual agent consisting of a number of atomic agents that maintain tight communications among them in order to share the working memory and act on executing high-level cognitive processes. Among them, the Central Executive Agent (CEA) is responsible for *cognitive control* [25] [26] during task execution. It makes decisions and invokes skills necessary to perform the given task using the Focus of Attention (FOA) and past experiences. CEA operates to affect an *intention* given the results of *internal rehearsal*. Decision making within CEA is mediated by *affect*, which is managed by another agent called the Affect Agent.

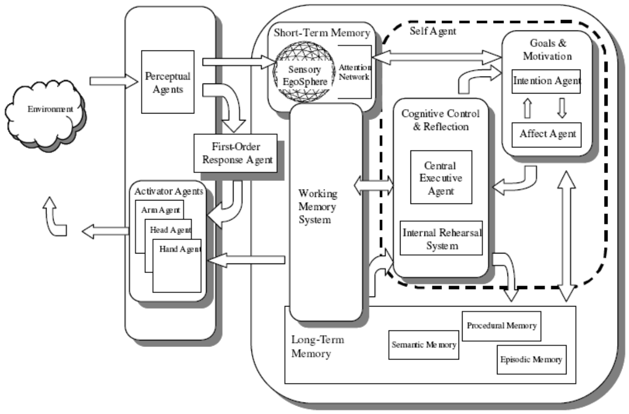


Fig. 2. Multiagent-based ISAC cognitive architecture [1].

III. LEARNING AFFORDANCES

In our current research, we consider the following reaching task for ISAC: Given an environment of unfamiliar objects, one of which is a goal object, ISAC should be able either correctly to traverse the environment with its arm and reach the goal object, or else refuse to traverse the environment in which a collision with non-goal objects is unavoidable.

Other researchers began making progress on related problems, albeit with limited generality. Affordance learning has been studied within robot manipulators [27] [28] and mobile robots[4][12]. Stoytchev [28] worked on representing and learning tool affordances by a robot. For example, the 'binding affordances' allows a robot to learn how to attach an object to its body in order to control the object's movements. The 'tool affordances' allows robot to discover the outcomes of tool-action pairs. Fitzpatrick et. al. [27] showed how the robot acquires affordances from the outcomes of its actions, and then deploys this knowledge of affordance to interpret human actions and mimic these actions. Ugur et. al. [4] studied the learning and generalization of the traversability affordance on a mobile robot and optimized the learning process. Sahin et al. [12] have proposed a new formalism for affordances and implemented these ideas for autonomous robot control. As mentioned in [4], the results reported in both [27] and [28] were far from a general knowledge of affordances, because they both used color to recognize objects, so the robot acquired no knowledge of the visual features of the objects that signal the manual operations afforded by the objects. In our work, we use the visible edge features of the objects as a basis for acquiring the affordance relation of traversable vs. impeded, and then use internal rehearsal to generalize to the point that the robot reliably finds the most appropriate behavior in every situation. Instead of recognizing objects and learning affordances to be attributes of specific objects, as is done in [27], we use the edge features as the basis of a traversability affordance relation. Then, instead of interpreting human behaviors and mimicking these, we allow ISAC to rehearse its behaviors internally to estimate general affordance relations, and how best to leverage these for any given task.

ISAC acquires knowledge of affordance relations in two stages, a babbling stage followed by a learning stage.

In the first stage, ISAC exhibits random behavior called "motor babbling" [28], to generate consequences from which it can start to learn. In the first part of this stage, ISAC reaches to the goal object in an obstacle-free environment. Every time it reaches the goal, it gets a reward. In the second part of this stage, an impediment object is put between ISAC and the goal object. Every time ISAC's end-effector hits the impediment object, ISAC gets a punishment and keeps the position where its end-effector hits the object.

In the learning stage, ISAC creates and optimizes a Gaussian Mixture Model (GMM) to represent its accrued experiences. GMMs comprise a weighted sum of gaussian probability density functions, or mixtures. GMMs are one of the more widely used methods for unsupervised clustering of data, where clusters are approximated by Gaussian distributions and fitted on the provided data.

Assume we have a set of experienced collisions with positions, $y_1,\ldots,y_m$. The probability that a particular y comes from the Gaussian distribution is shown in (1),

$$P(y\,|\,\theta)=\sum_{j=1}^{n}\alpha_j\frac{1}{\sqrt{(2\pi)^2\sigma_j}}\exp^{\left(-\frac{1}{2}(y-\mu_j)^T|\sigma_j|^{-1}(y-\mu_j)\right)} \qquad (1)$$

where n is the number of components, θ is the $n\ x\ 3$ vector containing the means, variances, and prior probabilities for the Gaussians, $\theta=\{\mu_1,\ldots\mu_i,\ \sigma_1,\ldots\sigma_n,\ \alpha_1\ldots,\alpha_n\}$.

To estimate θ, given the sample of positions at which the collisions occurred, the expectation maximization (EM) algorithm was used. As discussed in [29], applying a rough k-means clustering provides an initial estimate of the number of Gaussians. Using the estimation maximization toolbox [30], ISAC iteratively optimizes the centers (means), the widths (variances) and the weights (priors) of the Gaussian submodels in θ, as shown in Fig. 3.

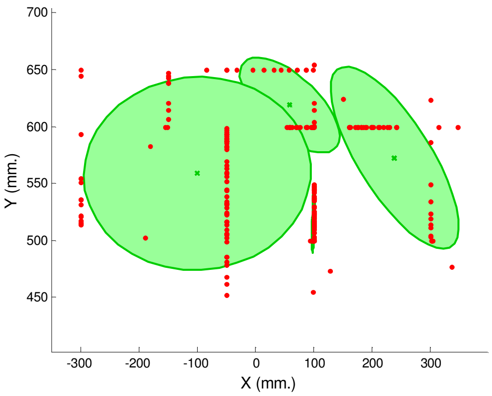


Fig. 3. The ellipsoids are the Gaussian submodels. The points are the collision points (data set), gathered in the babbling stage.

Our arm controller currently moves the manipulator using impedance spheres [31]. Instead of using spheres, however, ISAC can as easily use the high impedance Gaussian surfaces (Fig. 4). We accomplished this by predefining the damping and spring constants to be big enough that the arm controller prefers going around the surfaces rather than penetrating the surfaces. Thus, ISAC learns and generalizes a traversability affordance relation. ISAC directly instantiates this relation by estimating the high-impedance Gaussian surfaces that characterize the relationship between the behavioral repertoire of its arms, and objects in the environment, goal and impediment. Whenever a target and an obstacle are presented to ISAC, ISAC first finds the edges of these objects, assigns the probability of collision to these edges, and then creates high impedance surfaces to build the reaching trajectories.

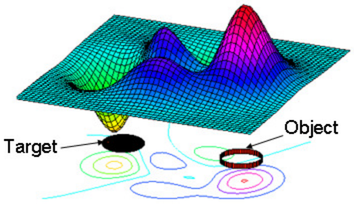


Fig. 4. High-Impedance Gaussian Surfaces.

IV. INTERNAL REHEARSAL AND GMM UPDATE

Endowed with the capability internally to rehearse scenarios that are grounded in prior experiences, a robot can reflect on the consequences of its actions before they are physically performed by the actuation system. The robot can thereby predict its future state and the future state of the surrounding environment by emulating actions internally.

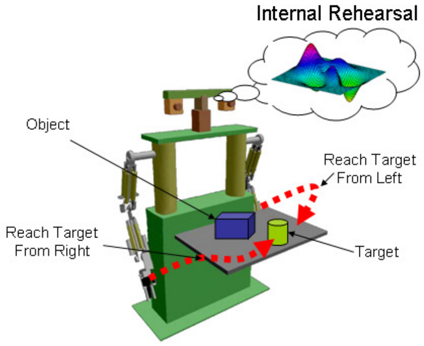


Fig. 5. ISAC Simulator and Internal Rehearsal.

In this section, we present a simulation to demonstrate how the system learns the affordances using internal rehearsal. In the simulation, ISAC attempts to reach to the target using one of its arms as shown in Fig. 5. First, ISAC detects the edges of the objects and using these edge features, ISAC internally creates the virtual high-impedance Gaussian surfaces based on the affordance relation ISAC learned. Then ISAC checks whether or not it can traverse the environment with its arm and reach the designated target. If ISAC finds a trajectory around the surfaces, it executes the action. However, if these actions do not traverse the environment, then ISAC will not execute the action.

During this stage, ISAC could experience new collisions not encountered in the motor babbling stage. To include the effects of these new experiences, ISAC updates the GMM to better represent the learned affordance relation. In so doing, ISAC creates a GMM that generalizes and covers the workspace better, i.e. a GMM which has well-distributed submodels with the larger variances.

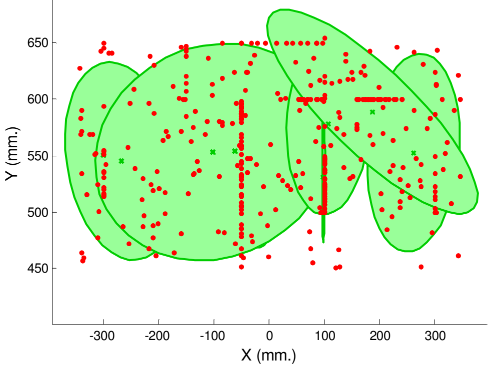


Fig. 6. The ellipsoids are the Gaussian submodels. The points are the collision points (data set), gathered in the babbling stage and randomly added collision points added later.

To show how the GMM update process works, we have added some random collision points to the training set and let ISAC select the best GMM for the new data set. The result of the new GMM selection is shown in Fig. 6. Compared to the original GMM submodels in Fig. 3, the new GMM contains more submodels that include both the motor babbling data set and randomly generated new collision set.

V. RESULTS

The first step in the simulation was to generate data from "actual" collisions during the motor babbling stage. As shown in Fig. 7, various shapes of obstacles were placed in random positions within the workspace. The ISAC arm then attempted to reach to a number of goal positions throughout the workspace. Since ISAC had no prior knowledge about the obstacles or possible collisions, it naively attempted the shortest path through the workspace from the starting position to each goal position. If the simulated arm collided with an obstacle, the point at which the collision occurred was recorded (shown as points in Fig. 3) and the reach attempt was terminated. In this manner, ISAC babbled throughout its workspace and discovered the edges of obstacles through colliding with them.

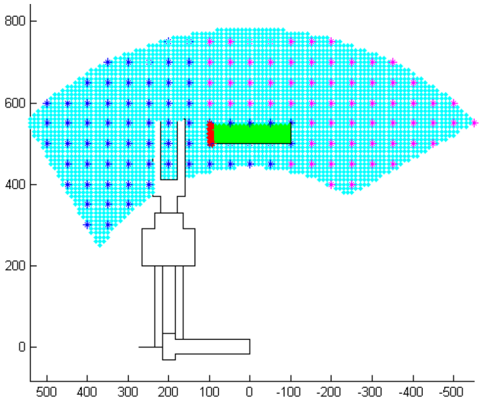


Fig. 7. The babbling stage simulation sample.

The second step of the simulation was to create the submodels to represent the babbling data as a GMM, using the expectation maximization algorithm as described in [29]. The submodels of the GMM for the babbling data are shown in Fig. 3 as ellipsoids. These models generalize the likelihoods of collisions in different regions of space for each of ISAC arms for any given configuration of the babbling environment.

The third step of the simulation involved "visually" discriminating the edges of the otherwise completely unfamiliar given objects and fusing these edge data with the collision data to create the virtual-high impedance gaussian surfaces. For example, given a cylinder located at [0 550] this step finds the edges of this cylinder and assigns a virtual-high impedance Gaussian surface to this object as shown in Fig. 8.

The final step of the simulation is internal rehearsal. This step creates a Gaussian surface for the current environment comprising unfamiliar objects in a novel configuration. Using these surfaces, the Internal Rehearsal System (IRS) evaluates the limits of manipulator kinematics and projects whether or not the arm can traverse the workspace and reach the designated goal object without colliding with all other non-goal objects. The possible projected outcomes and actions IRS can take are; “collision with the left arm, use the right arm to reach”, “collision with the right arm, use the left arm to reach”, “collision with both arms, do not do anything” and “no collision with either arm, use one of the arms to reach”.

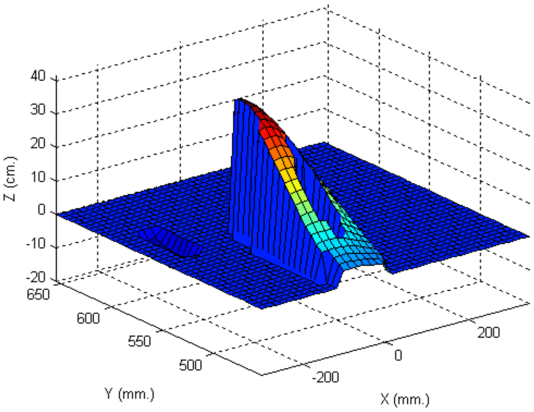
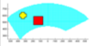
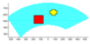
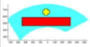
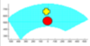
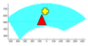
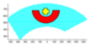
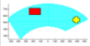
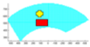


Fig. 8. The virtual-high impedance Gaussian surfaces assigned to the object and the target.

These outcomes of the IRS were evaluated for adequacy and for optimality by a human experimenter. Table 1 depicts a random sample of the 100 test trial runs. For all trials, ISAC exhibited an adequate performance, i.e. ISAC chose a course of action that would not result in a collision. In 8% of trials ISAC did not take an action when a successful action was possible. This was due to insufficient training experience, and thus larger standard errors occurred in the models.

TABLE I
THE SIMULATION RESULTS OF IRS

Trial #	The Environment	IRS Output	The human experimenter
1		It can only reach from left, use left arm	Correct
2		It can only reach to object from right, use right arm	Correct
3		It can not reach to object, Stop	Correct
4		It can reach to target using both arm, select one	Correct
5		It can only reach to object from right, use right arm	Correct, but it can reach from left also
6		It can not reach to object, Stop	Correct
7		It can reach to target using both arm, select one	Correct, but it doesn't find the optimal solution
8		It can only reach from left, use left arm	Correct but it can reach from right also

The sign represents the target and the other objects, rectangle, cylinder, triangle and the block arc represent the impediment objects.

VI. CONCLUSION

The goal of our research is to enable a humanoid robot like ISAC to experience, provisionally learn, internally rehearse and then correctly generalize affordance relations. In the case of traversability of a space, the affordance relation is provisionally learned during a babbling stage, and then is represented as a Gaussian mixture model. ISAC can use this model to create the high impedance Gaussian surfaces, by detecting the edges of the objects and using the GMM derived from its experience to assign a probability of collision or collision-free traversal. This will allow the arm controller to create collision free trajectories for traversing around the objects in its environment. By this means, ISAC learns and generalizes a traversability affordance relation that it can directly instantiate with arbitrary objects in arbitrary configurations: Estimating the high-impedance Gaussian surfaces that characterize the relationship between the behavioral repertoire of its arms, the obstacles in the environment, and its goal to get to a target without colliding with any other (impediment) objects.

In this paper, we have reported the first step of progress toward human-like capabilities for a robot to learn and generalize affordance relations from its own experiences. Our next step is to validate our approach on ISAC. As stated in Section 2, learning affordance relations is a part of a much larger project to develop an operational cognitive robot. Following [12], we are working to formalize our notion of an affordance relation as a goal-situation-repertoire relationship, to characterize agents and their environment as a system [32]. In so doing, we hope our overall cognitive approach will lead ISAC to learn more complex and more useful affordance relations, like graspability, manipulability of an object in a space, and acquirability-from / transferability-to another agent, which are all essential for ISAC to learn.

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