A Robot Rehearses Internally and Learns an Affordance Relation

Erdem Erdemir*, Carl B. Frankel*, Sean Thornton, Baris Ulutas and Kazuhiko Kawamura

Abstract—**This paper introduces a novel approach to a crucial problem in robotics: Constructing robots that can learn general affordance relations from their experiences. Our approach has two components. (a) The robot models affordances as statistical relations between actual actions, object properties and the experienced effects of actions on objects. (b) To exploit the general-knowledge potential of its actual experiences, the robot, much like people, engages in internal rehearsal, playing-out "imagined" scenarios grounded in but different from actual experience. To the extent the robot veridically appreciates affordance relations, the robot can autonomously predict the outcomes of its behaviors before executing them. Accurate outcome prediction in turn facilitates planning of a sequence of behaviors, toward executing the robot's given task successfully. In this paper, we report very first steps in this approach to affordance learning, viz., the results of simulations and humanoid-robot-embodied experiments targeted toward having the robot learn one of the simplest of affordance relations, that a space affords traversability vs. impediment to a goal-object in the space.**

Index Terms — **Affordance, internal rehearsal, robotics, cognitive science**

I. Introduction

In the future, robots will need to accomplish more and more complex tasks in increasingly challenging environments, exhibiting robust performance in a wide range of situations.

It is expected that robot control systems will become more complex, to the point that adaptivity and robustness could be compromised. A promising approach qualitatively to advance robotic technology is to train robots' attention on that which is most important to accomplish their goals, across the broad range of changing circumstances the robot is expected to encounter: the *affordance relations* that connect situational features to behavioral repertoire so as to subserve goal accomplishment [1]. As the robot comes to appreciate what its situation and its repertoire, taken together, afford for its goal accomplishment, the robot is likely to perform more adeptly in the service of its goals. For robots to come to recognize affordance relations from their limited experiences, robots need capabilities to revisit and to reconsider their own experiences [2], the ability to learn and internally rehearse the possible outcomes of the behaviors, to increase the efficiency and effectiveness with which robots learn affordance relations on their own. Robots that can anticipate and account for the effects and expected performance of their behaviors will behave more like living things that are aware and knowledgeable of their capabilities and shortcomings. The capability to learn and to deploy goal-subserving knowledge of affordance relations is a logical extension to the architecture of the ISAC—Intelligent Soft Arm Control—humanoid robot in our laboratory [2]

A. *Affordance Relations*

The notion of affordance was originally introduced by a psychologist studying perception, J.J. Gibson, who gave special attention to the problem of explaining how the living organisms perceive the environment and link available action possibilities to environmental objects [3]. For Gibson, affordance is a directly perceivable attribute of objects. For example, to perceive a ball is perceive that it affords throwing. Recent thinking [4] sees affordance as an emergent property of the task-object relationship. For example, a ball affords throwing when the task is to play a game of catch, but the ball affords a reduction of friction when the task is to move a heavy object over a surface.

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 behavior selection so as to satisfy internal drives; thereby enabling a mobile robot to exist autonomously within its environment was investigated [5]. In an ambitious effort [6], Stoytchev 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], function-based object recognition [10], and grasping learning [11].

A central limitation of prior work is that, following Gibson, affordances are taken to be directly perceivable attributes intrinsic to objects themselves. As such, robots' learning of affordances to-date occurs with very limited generalization to different and/or unfamiliar objects. By complete contrast, by seven months of age, a human infant is already starting to shape and orient her or his hand while moving the hand toward an object, in anticipation of grasping the object, something the

The authors are with Center for Intelligent Systems, Vanderbilt University, Nashville, TN, USA, emails:{erdem.erdemir, kazuhiko.kawamura, sean.thornton, baris.ulutas, carl.frankel}@vanderbilt.edu

Carl B. Frankel is also affiliated with the Psychology Department, Vanderbilt University, Nashville, TN, USA.

* Principal Authors contributing equally

infant can do robustly with objects she or he has never previously encountered [12].

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 observable in brains. By contrast, robots' hardware and software are fully exposed, so an internal goal state is a simple fact, not a problematic Aristotelian final cause. Following [1], a central proposal in this paper is that, for complex goals in complex, changing environments, a robot's adaptive effectiveness will be qualitatively enhanced to the extent that the robot leverages the affordance relations that characterize how situational features can be coupled to the robot's behavioral repertoire, so as to take actions that advance the robot's goals. This notion of an affordance relation advances beyond neo-Gibsonian thinking, to offer an original perspective on how to bind together perceived situational features, behavioral repertoire and reasoning. Recognizing and reasoning about affordance relations thus has important potential to advance intelligent robotics research, toward the design of new, powerful and intuitive robot control architectures [13].

B. *Internal Rehearsal*

The ability to rehearse possible future steps of action in the mind is an important human cognitive skill. People are able mentally 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 that 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 experience and yet reflect potentially informing parametric variations of experience. A robot endowed with similar capability can usefully estimate the consequences of its actions so as to improve performance. In some circumstances, the robot could even use internal rehearsal to learn how to perform new tasks. Jirenhad et al., have proposed a basis for an ‘inner world’ that allows robots to behave and anticipate the future event in the absence of external sensory stimuli [14]. Shanahan has 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 chooses a poor course of action [15]. Kawamura extended Shanahan’s work to demonstrate how a robot could internally rehearse actions to avoid obstacles [16]. Meeden et al., have shown 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 [17]. 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 [18]. Internal simulation of functions of the sensory and motor cortices has been deployed in robots [19]. A growing body of research is showing how fairly complex robot behaviors can be learned or organized with rich enough high-level world representations as to comprise an inner world in which the robot internally rehearses scenarios of adaptive import.

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 affordance relations such that, given its current situation, the robot selects 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 and later in real-world experiments, we bring the robot to learn a general affordance relation about arbitrary objects placed arbitrarily in a space: That a region of the space is *traversable* without collision, or is *impeded.*

II. ISAC Cognitive Architecture and Controller

A. *Cognitive Architecture*

Work in our laboratory has yielded an operational humanoid robot that implements crucial features of human working memory under an NSF grant (ITR: A Biologically Inspired Adaptive Working Memory System for Efficient Robot Control and Learning, NSF grant # EIA0325641) [20]. In this implementation, ISAC—Intelligent Soft Arm Control—humanoid robot, shown in Figure 1, learns how to respond to a limited set of tasks using an untrained long term memory model, in conjunction with working memory system training that is grounded in a computational neuroscience model of working memory of the prefrontal cortex. This work demonstrated how to provide robotic systems with a means of maintaining task-related information during task execution in a manner similar to human task execution [21]. 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 offline reflective module called the Internal Rehearsal System (IRS) [16]. In its original implementation, ISAC reviews its experiences and uses the Internal Rehearsal System for internally exploring alternative motor associations in order to predict likely consequences of such behavioral alternatives, thereby to learn how to improve its performance when similar situations arise in the future [22][2].

This approach to and utilization of Working Memory and Internal Rehearsal should also be useful for forms of cognition more abstract than sensori-motor learning. A vitally important yet challenging example is learning about those affordance relations that materially affect the likelihood of success and failure at a task. 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 repertoire as well as the situational features of the world as the agent perceives them. As such, one logical next step in Internal Rehearsal research is for a robot explicitly to impute, to register and to explore potential affordance relations in its working memory.

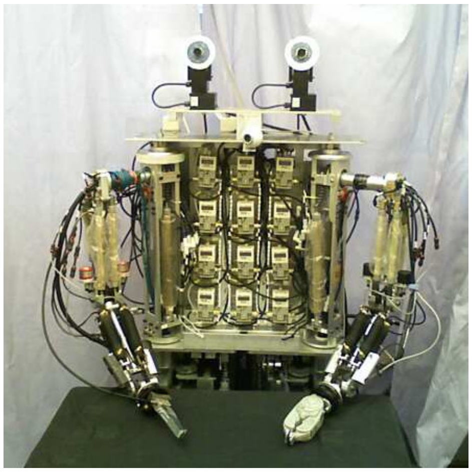

Figure 1: ISAC Humanoid Robot

B. ISAC Controller

ISAC is an upper-torso humanoid with two 6-dof arms that are actuated pneumatically by artificial muscle actuators, providing a relatively safe human-robot interaction for manipulation, automation and other tasks. We have developed a hybrid open-loop artificial neural network-based and vision-based impedance controller for ISAC [23][24]. This controller regulates the virtual impedance between the ISAC arm and the external objects using visual information and impedance surfaces.

III. LEARNING AFFORDANCES

In this paper 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 correctly either to traverse the environment with its arm and reach the designated goal object, or else refuse to traverse an environment in which collision with non-goal objects is unavoidable.

Others have already started to make progress on related problems, albeit, as we said earlier, with limited generality. Affordance learning has been recently studied within robot manipulators [25] [26] and mobile robots [27]. Stoytchev [26], worked on representing and learning tool affordances by a robot. 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. [25], 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. [27] studied the learning and generalization of the traversability affordance on a mobile robot and optimized the learning process. As mentioned in [27], the results reported in both [25] and [26] were far from a general knowledge of affordances, because [25] and [26] 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 [25], 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's Central Executive Agent (CEA) primes the Internal Rehearsal Subsystem (IRS), by having ISAC engage in random behavior, "motor babbling" [26], in order to accrue a baseline of experiences and consequences from which to generalize. 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. These rewards and punishments are tracked by the Affect Agent (AA) and the Intention Agent (IA), in order to structure ISAC's motivational processing to be congruent with the demand to reach only into traversable spaces.

In the learning stage, ISAC's IRS 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 Equation 1 [28].

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

The unknown parameters, $\theta=\{\mu_1,\ldots\mu_n,\ \sigma_1,\ldots\sigma_n,\ \alpha_1,\ \ldots,\alpha_n\}$, are the means, variances and priors of each Gaussian submodels The expectation maximization (EM) is an iterative optimization method to estimate some unknown parameters of the model, given the measurement data. The process is repeated iteratively until it converges to a local maximum likelihood estimate for the model, so this algorithm requires a good initial estimate, to prevent the model converging into poor local maxima. As discussed in [28], applying a rough k-means clustering technique partially solves this problem.

Using the estimation maximization toolbox, supplied in [29], ISAC iteratively optimizes the centers, the widths and the weights of the Gaussian submodels, as shown in Figure 2.

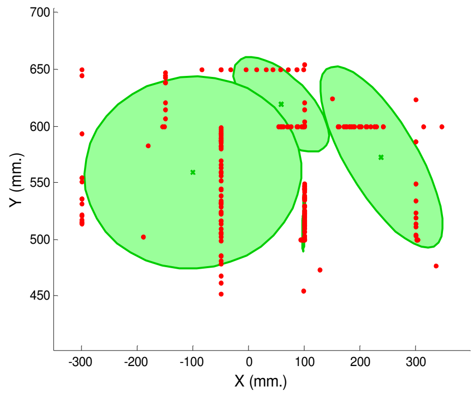

Figure 2. The ellipsoids are the Gaussian submodels. The points are the collision points (data set), gathered in the babbling stage.

As mentioned in section II-B, our arm controller has heretofore moved the manipulator using impedance spheres. Instead of using spheres, however, ISAC can as easily use the high impedance Gaussian surfaces, shown in Figure 3, where we predefined the damping and spring constants to be big enough that the arm controller prefers going around the surfaces rather than penetrating the surfaces. By this means, ISAC learns and generalizes a traversability affordance relation that it can directly instantiate 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 and then assigns the probability of collision to these edges and creates high impedance surfaces to build the reaching trajectories.

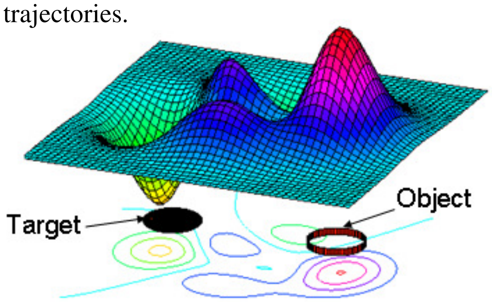

Fig. 3. High-Impedance Gaussian Surfaces

IV. INTERNAL REHEARSAL SUBSYSTEM AND GMM UPDATE

A robot endowed with internal rehearsal of scenarios that are grounded in experience can consider the consequences of its actions before they are 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, before the robot enacts them.

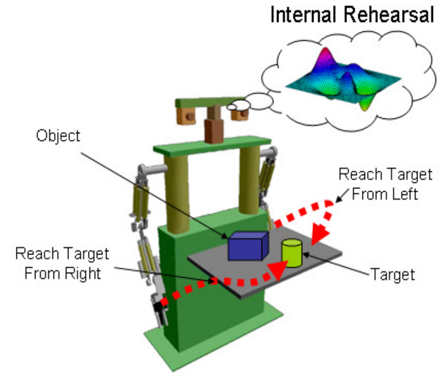

Fig. 4. ISAC Simulator and Internal Rehearsal

We implemented a simulation, the results from which are discussed in section V, and real-world experiments, discussed also in section V, to show how the system learns the affordances and use in the internal rehearsal. In these experiments, ISAC tries to reach to the target using one of its arms as shown in Figure 4. First, ISAC detects the edges of the objects and using these edge features, ISAC internally creates the virtual high-impedance Gaussian surfaces based on learned affordances. Then ISAC checks whether it can traverse the environment with its arm and reach the designated target or not. If ISAC finds a trajectory around the surfaces, it executes the action. However, if these actions don't traverse the environment, then ISAC will not execute the action.

During this stage, ISAC could experience some new collisions that did not exist in the babbling training set. In order to include the effects of these new experiences, ISAC will update GMM to represent the learned affordances better. In this process, the important point is to create a GMM that generalizes and covers the workspace better, i.e. a GMM which has well-distributed submodels with the larger variances.

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 Figure 5. Compared to the original GMM submodels in Figure 2, the new GMM has more submodels that include the both the babbling data set and randomly generated new collisions.

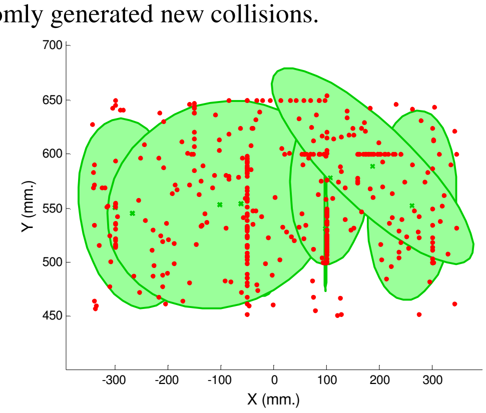

Fig. 5. The ellipsoids are the Gaussian submodels. The points are the collision points (data set), gathered in the babbling stage and randomly added collision points added later.

V. EXPERIMENTAL METHODS

In our experiment, each ISAC arm had a different gripper, as depicted in Figure 1. Objects of varying shapes were presented in the workspace, and the heights and edges were determined by simple stereo vision and edge detection techniques. In order to receive collision feedback, a human experimenter provided a reward or a punishment whenever an arm reached the target or collided with an obstacle, respectively.

The first step of the experiment was to generate collision data during the babbling stage. As shown in Figure 6, various shapes of obstacle were placed in various positions in the workspace. ISAC then attempted to reach to a number of goal objects placed by a human trainer throughout the workspace. Since ISAC had no prior knowledge of collision, it naively plotted paths (using internal rehearsal) and attempted the shortest path from the starting position to each goal position. If the arm collided with an obstacle, the point at which the collision occurred was recorded (shown as red points in Figure 2) and the attempt to reach to the goal was terminated. In this manner, ISAC babbled throughout its workspace and discovered the edges of obstacles by colliding with them.

The second step was to create the submodels to represent the babbling data as a GMM using the expectation maximization algorithm as described in [28]. The GMM submodels for the babbling data are shown as ellipsoids in Figure 5. These models summarize and start to generalize the likelihoods of collisions in different regions of space for each arm.

The third step involved visually discriminating the edges of the otherwise completely unfamiliar 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 the position [0 550], this component finds the edges of the cylinder and assigns a virtual-high impedance Gaussian surface to this object as shown in Figure 6.

The final step of the experiment involved the Internal Rehearsal System (IRS). This step creates a Gaussian surface for the current environment comprising unfamiliar objects in a novel configuration. Using these surfaces, IRS evaluates the limits of its kinematics to project whether or not it can traverse the environment with one of its arms and reach the designated goal object without collision. This internal rehearsal allows ISAC to make a decision as to which actions it can take. Such actions are: "collision with the left arm so will use right arm to reach", "collision with the right arm, so will use left arm to reach", "collision with the both arms, so won't do anything" and "no collision with either arm, so will use one of the arms to reach".

VI. RESULTS

These outcomes of the IRS were evaluated for adequacy and for optimality by a human experimenter. For all trials, ISAC exhibited an adequate performance: that is, ISAC chose a course of action that would not result in a collision. 8% of trials resulted in sub-optimal actions, i.e. there was a collision-free action ISAC could have taken but ISAC did not recognize such action.

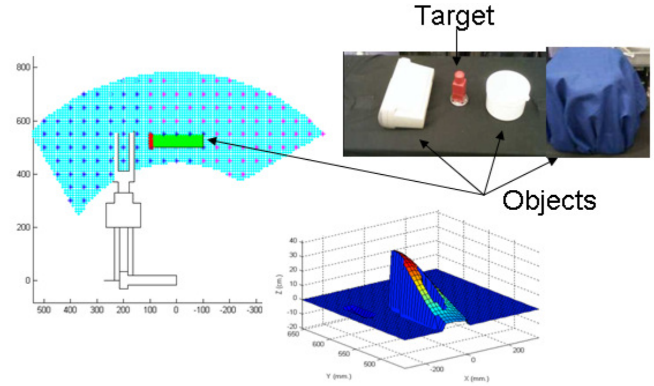

Fig. 6. The babbling stage simulation sample and virtual-high impedance Gaussian surfaces assigned to the object and the target

An interesting result we discovered from our experiment was the impact of the shape of the gripper on collision probability and the formation of impedance surfaces as shown in Figure 7. In simulation, the shape of the gripper was an intrinsic part of the simulation and it had no effect on experiment. In the real-world experiment, we found that since we did not predefine the exact gripper shape for each arm, additional collision data was generated near the edges of the obstacles. This data was found to follow a Gaussian distribution. We therefore added an additional term to the collision probability to represent different grippers used. This in turn yielded the result that ISAC was willing to move the arm with the smaller gripper closer to an obstacle than the other arm. This shows that ISAC is beginning to learn how to use each gripper distinctively.

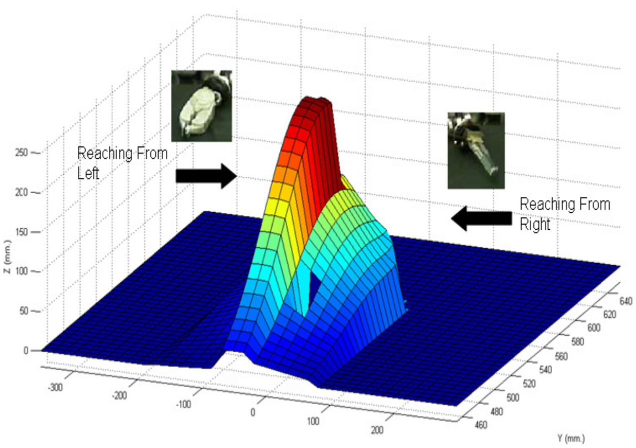

Fig. 7. The impedance surface created for an object located at (0 , 550). The impedance surface does not allow left hand to reach the object, but ISAC can reach the object using its right hand.

We analyzed ISAC's performance. During babbling, ISAC collided with objects in the workspace in 78 of 100 trials, which is significantly worse than random (50-50), $\chi 2 = 31.36$, $p < .000$. By contrast, as a result of what ISAC learned during babbling, ISAC's internal rehearsal yielded correct assessments of traversability in 72 of 100 trials, significantly better than random (50-50), $\chi 2 = 40.96$, $p < .000$. To place this level of performance in meaningful human context, we constrained a person (author Ulutas) to have ISAC's visual vantage point, and to move his arms with ISAC's degrees of freedom. Under these constraints, the person incurred 8 collisions in 100 trials, even after 100 trials of babbling during which the human exhibited 7 collisions. The human agent's performance was significantly better than ISAC's, $\chi 2 = 13.59$, $p < .000$. However, the performance of an adult human was significantly worse than near-perfect (99-1), $\chi 2 = 49.45$, $p < .000$, and was too rigidly over-learned to benefit from practice.

VII. CONCLUSION

The goal of our research is to enable a humanoid robot like ISAC to learn general affordance relations that ISAC can then deploy toward successful accomplishment of its goals. We reported herein a first success in augmenting ISAC's current architecture and capabilities [2], so as to bring ISAC, in simulation and in humanoid robotic embodiment, to experience, provisionally to learn, internally to rehearse and then, while not yet perfectly, significantly correctly to generalize affordance relations. Affordance relations are provisionally learned during a babbling stage, and then are represented as a Gaussian mixture model. ISAC can use this model to create 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: 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 so doing, ISAC has gained significant purchase on a general affordance relation that ISAC can instantiate whenever ISAC has to reach target objects, without colliding with any non-target objects.

In this paper, we have reported a first step of progress toward human-like capabilities to learn and generalize affordance relations from experience. In simulation and in humanoid robotic embodiment, starting from experiences, ISAC has internally rehearsed to estimate the general affordance relations of traversability of a space containing a target and impediment objects. ISAC has demonstrated significant ability to leverage a general appreciation of traversability in the context of an arbitrary reaching task within its workspace.

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