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The learning and use of traversability affordance using range images on a mobile robot

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Abstract— **We are interested in how the concept of affordances can affect our view to autonomous robot control, and how the results obtained from autonomous robotics can be reflected back upon the discussion and studies on the concept of affordances. In this paper, we studied how a mobile robot, equipped with a 3D laser scanner, can learn to perceive the traversability affordance and use it to wander in a room filled with spheres, cylinders and boxes. The results showed that after learning, the robot can wander around avoiding contact with non-traversable objects (i.e. boxes, upright cylinders, or lying cylinders in certain orientation), but moving over traversable objects (such as spheres, and lying cylinders in a rollable orientation with respect to the robot) rolling them out of its way. We have shown that for each action approximately 1% of the perceptual features were relevant to determine whether it is afforded or not and that these relevant features are positioned in certain regions of the range image. The experiments are conducted both using a physics-based simulator and on a real robot.**

I. INTRODUCTION

Do we perceive all the qualities of the environment to accomplish a simple task like wandering around? Do we detect the objects on our path, distinguish all their properties, and only then infer whether the path is traversable or not? Do we think "this circular gray object towards my right is a small yellow cobblestone, and I know that the stones that are smaller than my leg length can be walked over, therefore I can safely walk over it"?

J.J. Gibson, one of the most influential figures in the field of psychology, objected such a view to perceptual processing, and its link to action. Instead, he set out to develop a "theory of information pick-up" in which he conceived the concept of affordance as: *"The affordances of the environment are what it offers the animal, what it provides or furnishes, either for good or ill. The verb to afford is found in the dictionary, but the noun affordance is not. I have made it up. I mean by it something that refers to both the environment and the animal in a way that no existing term does. It implies the complementarity of the animal and the environment." (J.J. Gibson, [1], 1979/1986, p. 127)*

J.J. Gibson claimed that:

- The 'meaning of objects' in the environment, for tasks such as wandering around, are directly apparent to the agent acting in it. This was different from the contemporary view of J.J. Gibson's time, that the meaning of objects were created internally with further "mental calculation" of the otherwise meaningless perceptual data. Hence affordances support *direct perception*.
- Each action needs only the relevant perceptual information for its execution, and this can be supplied by using specialized and concurrent perceptual modules or filters dedicated to extract certain, but not all, cues from the environment. Hence the use of affordances provides *perceptual economy* for the organism.
- "an affordance points both ways, to the environment and to the observer". Therefore, a human's judgment of whether he can climb a stair step is not determined by the height of the step, but rather by its ratio to his/her leg-length [2]. Hence, affordances are *relative* to the organism.

In his writings, J.J. Gibson did not explicitly state how affordance perception is attained in animals. Later E. Gibson claimed that affordances are learned through exploratory activities, like mouthing in infants, and she asserted that humans learn to "discover *distinctive* features and *invariant* properties of things and events"[3], instead of constructing representations from smaller pieces.

Although J.J. Gibson introduced the term to clarify his ideas in psychology, it turned out to be one of the most elusive concepts that influenced studies ranging from human-computer interaction to robotics. In the MACS project, we are interested in how the concept of affordances can affect our view to autonomous robot control, and how the results obtained from autonomous robotics can be reflected back upon the discussion and studies on the concept of affordances.

Physical characteristics of the environment, such as size and shape of objects it contains, are good indicators of the affordances that the environment offers to a robot, and we are interested in how these characteristics can be perceived, learned, and used on a mobile robot. In this paper, we studied how a mobile robot, equipped with 3D range sensing ability, can perceive, learn and use the traversability affordance to wander in an environment filled with different types of objects that change the traversability of the environment depending upon their shape, size, and relative position and orientation with respect to the robot.

II. AFFORDANCE-RELATED RESEARCH IN ROBOTICS

The concept of affordances is highly related to autonomous robot control and influenced many studies in this field. The parallelism between the theory of affordances and reactive/behavior-based robotics has already been pointed out(pp 244,[4];[5]). A similar parallelism also exists with studies carried under the heading of action-oriented perception(pp. 267, [4]). These studies suggested a "qualitative" representation of the environment based on the task/intention at hand, and criticized the classical approach to perception (particularly computer vision) which aimed to recover a metric model of the environment [6].

Recently, the relation between the concept of affordances and robotics has started to be explicitly discussed. *Developmental robotics* (or the closely related *epigenetic robotics*) [7] treats affordances as a higher level concept, which a developing cognitive agent learns about by interacting with the objects in its environment [8]. There are also other studies that look at how affordances reflect to high-level processes such as learning [9], [10], tool-use [11], or decision-making [12]. The studies that focus on learning mainly tackles two major aspects. In one aspect, affordance learning is referred to as the learning of consequences of a certain action in a given situation [8], [10], [11]. In the other, studies focus on the learning of invariant properties of environments that afford a certain action [9] . Studies in this latter group also relate these properties to the consequences of applying an action, but these consequences are in terms of internal values of the agent, rather than changes in the physical environment.

Stoytchev [10], [11] studied learning, for the so-called 'binding affordances' and 'tool affordances', where learning binding affordances corresponds to discovering the behavior sequences that result in the robot arm binding to different kinds of objects, whereas learning tool affordances corresponds to discovering tool-behavior pairs that give the desired effects. In [8], Fitzpatrick et al. also studied learning of object affordances in a developmental framework, where a robot can learn what it can do with an object (e.g. rolling) only by acting (e.g. tapping or pushing away) on it, and observing the effects in the environment. In both Stoytchev's and Fitzpatrick et. al.'s studies, the objects are differentiated using their colors only, and no association between the visual features (that affect the affordances) of the objects and the corresponding affordances are established, giving no room for the generalization of the affordance knowledge for novel objects.

In [13], it was proposed that an affordance can be represented as a *(entity, action, outcome)* triple, where *entity* stands for the perceptual representation of the environment. It was proposed that, the learning of affordances corresponds to the learning of bilateral relations between three components of this representation. Fritz et al. [14] demonstrated a system that learns to predict the lift-ability affordance for different objects, where predictions are made based upon features of object regions extracted from camera images.

Traversability problem in outdoor navigation has recently been studied in [15], where low level features, which are extracted from stereo-vision and texture based methods, are used in learning and predicting of affordances of outdoor objects. The proposed architecture supports on-line learning

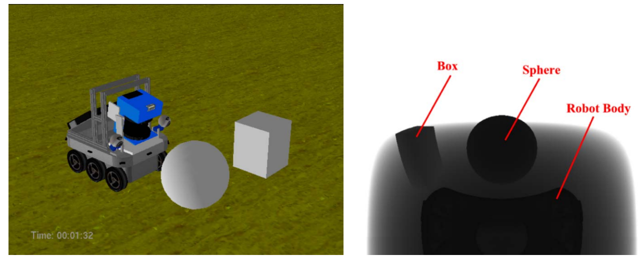


Fig. 1. Left: A snapshot from MACSim showing the KURT3D robot facing two objects. Right: The resulting range image resembles a fish-eye image, where the range value of each laser beam is coded as gray-scale values.

of the traversability affordances in unknown environments, and enables successful execution of path plans while adapting to a completely unknown environment. Although our point of view is similar, we gave special emphasis on the learning of relevant features for different actions, and we used range images and a different perceptual representation that is suitable for acquiring the physical affordances of the environment.

III. TRAVERSABILITY FOR MOBILE ROBOTS

The verb "traverse" is defined as "to pass or move over, along, or through". Since most actions depend on mobility, traversability is a fundamental affordance for autonomous robots. Traversability also becomes a very interesting problem when one does not limit himself/herself with classic obstacle avoidance where the robot tries to avoid making any physical contact with the environment, and only heading open-spaces to traverse. When such approaches are used, the robot's response would be the same whether it encounters an unpenetrable wall or a balloon that can be just pushed aside without any damage. Thus, a method that can automatically learn the traversability affordance from the robot's interactions with the world would be a solution to this problem.

In this work, we studied how physical affordances of the environment, such as traversability for a mobile robot, can be learned. In particular, we studied how the physical properties of the environment, as acquired from range images obtained from a 3D laser scanner mounted on a mobile robot platform, can specify the traversability affordance.

A. The Kurt3D robot platform

Kurt3D is a medium-sized ($45cm \times 33cm \times 47cm$), differential drive mobile robot, equipped with a 3D laser range finder[1]. The 3D laser scanner is based on a SICK LMS 200 2D laser scanner, rotated vertically with an RC-servo motor. The 3D laser scanner has a horizontal range of $180°$, with a maximum resolution of $0.25°$, and is able to sweep a vertical range of $\pm 82.8°$ with a resolution of $0.23°$. The scanner is capable of taking full resolution (720×720) range image in approximately 45 seconds.

- rectangular boxes ( ) that are non-traversable,

[1]URL: `http://www.ais.fraunhofer.de/ARC/kurt3D/`

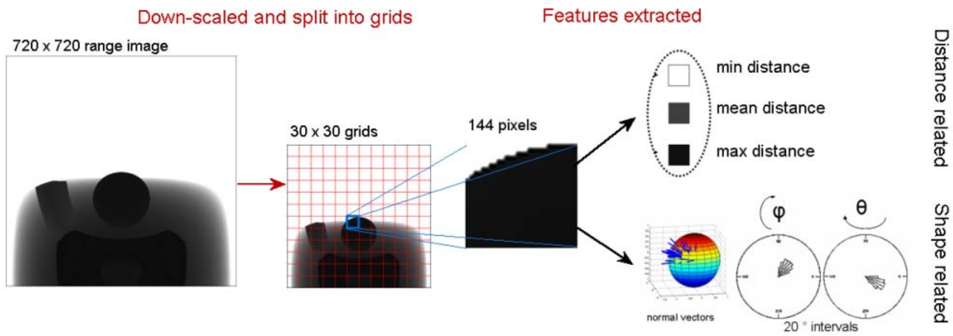


Fig. 2. Phases of perception.

- spherical objects ( ) that are traversable since they roll in all directions,
- cylindrical objects, either in upright position ( ) (non-traversable), or lying on the ground ( ) (traversability depends on their orientation with respect to the robot).

Kurt3D is simulated in MACSim[16], a physics-based simulator, built using ODE (Open Dynamics Engine)[2], an open-source physics engine. The sensor and actuator models are calibrated against their real counterparts. Fig. 1 shows a scene from the simulator and the range image generated by the simulated 3D laser scanner.

B. *Traversability for Kurt3D*

The environment is said to be traversable in a certain direction, if the robot (moving in that direction) is not enforced to stop as a result of contact with an obstacle. Thus, if the robot can push an object by rolling it away, that environment is said to be traversable even if the object is on robot's path, and a collision occurs. Since in this new view of traversability, the physical properties of the objects are important, a set of simple objects, with different shapes and arbitrary sizes are included into the environment:

IV. AFFORDANCE-BASED PERCEPTION, LEARNING AND CONTROL

The traversability affordance for a robot highly depends on the location, orientation, and shape of the objects in the environment. The robot should be able to perceive the features related to the traversability affordance, in order to learn these affordances and use them in control. Sensing capabilities of the robot have a determining role in perceiving certain affordances and the laser range scanner suits well to the traversability problem.

In this study, learning the affordances and using the learned affordances in the control of the robot are separated into two phases. In the *learning* phase, the robot moves in an environment containing one or more objects, and tries to learn the traversability of the environment. The robot is provided with seven simple hand-coded actions, which drives the robot in seven different directions. For each action the wheel speeds are set to certain values for a certain duration. One of the actions makes the robot go forward, while the others makes it turn to either side with different angles. Along with each action, the expected displacement of the robot is provided as its success criteria. In the *execution* phase, the robot uses the learned affordances to navigate in different environments.

A. *Perception*

The robot makes a 3D scan of the environment to obtain a range image. As shown in Fig. 2, first, the image is down-scaled to a resolution of 360×360 pixels, reducing the noise. Then, it is split into uniform size rectangular grids. Finally, for each grid, a number of distance and shape related features are extracted.

The distance related features are chosen as the distances of the closest, furthest, and mean distances of the grid. The shape related features are computed from the normal vectors of the surfaces that are computed from the range image. The direction of each normal vector is represented using two angles φ and θ, in latitude and longitude respectively and two angular histograms are computed. The frequency values of these histograms are used as the shape related features.

In this study, the 360×360 pixel range image is divided into $30 \times 30 = 900$ grids of 12×12 pixels, and the angular histogram is divided into 18 intervals, so that total number of features computed over a downscaled range image is $900 \times (3 + 2 \times 18) = 35100$ where 3 corresponds to the three distance values (minimum, maximum, and mean) and the multiplication by 2 corresponds to the two angle channels.

B. *Learning*

In the learning phase the robot learns a mapping between environmental situations and the results of its actions, by physically interacting with the environment. It perceives the environment, executes an action, and records the result of applying the action (success or failure) and the feature vector that was perceived before the execution of the action. This interaction occurs in episodes, in which all seven actions are performed in the same configuration of the environment. After a number of episodes, learning is conducted as a batch process.

Learning is performed for each different action separately and consists of two steps. In the first step, relevant features

[2]URL: `http://ode.org/`

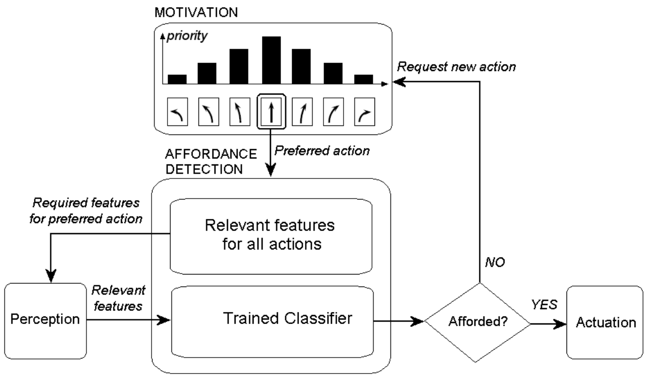


Fig. 3. The robot control system in the *execution* phase.

of the feature vector for each action are selected. Next, a classifier is trained to learn a relation that maps the (initially perceived) relevant features to predict the success/fail result of applying that action.

Selection of relevant features is done using the ReliefF algorithm, originally proposed by Kira and Rendell [17]. This method aims to estimate the weight of each feature in a feature set, based on its impact on the target category of the samples. In ReliefF, the weight of any feature is increased, if it has similar values for the samples in the same category, and if it has different values for the samples in different categories. After finding the weights of all features, most relevant features are selected based on a threshold. In our case, the threshold is also optimized to select the features that give the best performance on the classifier that is described below.

Support Vector Machines (SVMs)[3] are used to classify (relevant) features into affordance categories (traversable/non-traversable). Introduced by Vladimir and Vapnik as supervised learning tools for classification problems, they are very robust in the face of noisy input, and able to deal with large datasets and input spaces. We used a linear kernel (with tolerance parameter set as 1) since more complex kernels did not increase the performance in our case.

C. Control

The robot is driven using a simple control system (Fig. 3), which utilizes learned relevant feature perception and affordance classification schemes explained in the previous sections. Whenever a new action is requested, the motivation based control system sets a new *preferred* action with highest priority, among a set of actions with fixed priorities. The features which are relevant to the *preferred action* are then requested from perception, and these features are supplied to the trained classifier (SVM) to predict whether this action is afforded or not. If the immediate environment does not afford this action, a lower priority action is requested from the motivation module. Otherwise, it is executed (robot moves in a certain direction for a certain duration), and a new action is requested upon the completion of the action.

[3]The LibSVM software that is used in this study, is available at `http://www.csie.ntu.edu.tw/~cjlin/libsvm`

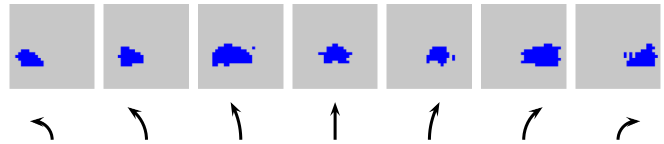
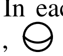


Fig. 4. The relevant grids in the range image for each action.

V. Experimental Results

A. Learning to predict traversability

The motivation behind these experiments is to analyze the discovered relevant features for different actions in detail, and evaluate the performance of the trained classifier. A total of 3000 episodes are executed on the simulator for each action. In each episode, 10 randomly selected objects (among , , , ) are scattered in $[-90°, +90°]$ of robot's frontal area. They are placed within a certain distance in various orientations and sizes (20-40 cm.). In each episode the features that are perceived and the result of the executed action (success or failure) are recorded. 2000 of these training data are then used to learn the traversability affordance for each action, and the prediction accuracy of the trained model is tested using the other 1000 independent test data. After training, the prediction accuracy of the trained SVM for all different actions is found to be within the range of $[93.0\%, 95.1\%]$.

Among the 2000 training data, 1000 are used for finding the relevancy weights of the features using ReliefF. A subset of the features are then selected by thresholding according to these relevancy weights. This threshold is optimized by selecting the value that results in the best performance of the SVM on the remaining 1000 data (see Section IV-B). With the optimized threshold, $100 - 400$ features among 35100 are automatically selected to be relevant to perceive the traversability affordance for each different action. In other words, at most, 1.1% of the whole feature set is found to be relevant to determine if an action is afforded or not.

The discovered relevant features are analyzed as to understand to which grids and to which features in these grids they correspond to. The grids, which include relevant features are marked as *relevant*. In Fig. 4, the relevant grids for all actions are shown, where dark areas correspond to relevant, and gray areas correspond to irrelevant grids. Note that, only certain regions of the whole image are found to be relevant, and they shift from left to right with the direction of movement. Since the number of features is very large compared to the number of training samples, resulting distributions of the relevant grids are not compact, and they are not symmetrical for (different) symmetrical actions. Additionally, when the individual features in grids are examined, it is found out that the features that are related to the shape in vertical axis are more important than the features related to the shape in horizontal axis.

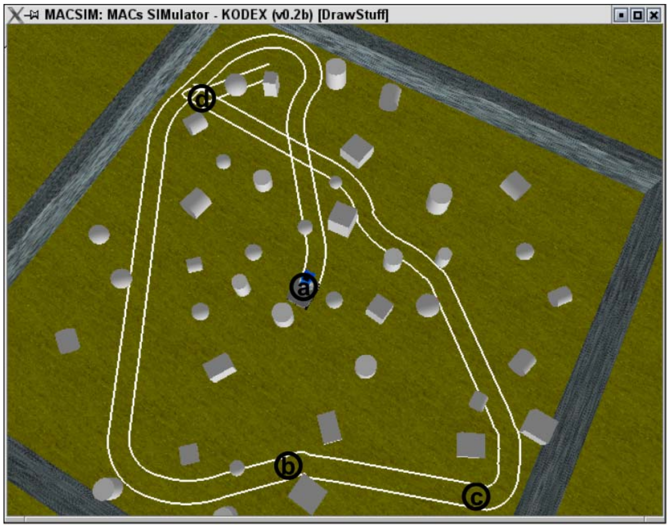


Fig. 5. The course of the robot resulting from the execution of the controller described in Fig. 3 in a virtual room cluttered with 40 objects. The motivation module tries to make the robot to go forward as much as possible. In (a), a turn to the left is afforded, and the robot drove towards the spherical object. In (b), although the robot made a contact with the box on its right, it selected forward move. Small contacts were expected to occur because they were tagged as successful actions in the training phase (if the robot continued to move on its present course). In (c), the only action that is afforded was turning left sharply. In (d), none of the actions were afforded, so the robot made a random turn.

B. Wandering using traversability

The relevant feature knowledge and the trained classifier from the previous section are used to test the control system presented in Fig. 3. The simulated robot is placed in a virtual room cluttered with objects of different sizes and types. The trajectory of the robot in such a room, with 40 objects included, is shown in Fig. 5. In this experiment the motivation module tries to drive the robot forward as much as possible, because the highest priority is given to the action which moves the robot forward (Fig. 3). So, the robot makes a 3D scan of the environment and predicts if the forward action is afforded or not. If the action is afforded according to the learned model, the robot executes the action, if not, it asks from the motivation module for a lower priority action and repeats the process until it finds an afforded action. If none of the actions are afforded according to the learned model it makes a random turn. After the execution of the afforded action the whole cycle starts again. Note that the robot does not only drive towards the open-spaces, but if a higher priority action requires it, the robot chooses to drive towards spherical and cylindrical objects (which are in appropriate orientations).

C. Generalization of traversability for novel objects

In this section, the generalization capability of the system when encountered with novel objects is analyzed. Since such a training should be done in the lack of some object types, the training setup is constrained to include only a subset of object types. Testing, on the other hand, is performed with all types of objects, so that the affordance prediction for novel

TABLE I

GENERALIZATION PERFORMANCE OF THE LEARNED MODEL.

The left-most two columns show case number and the set of objects in the environment where the corresponding model is trained. The second row shows which object types are included into the test sample set, where each set contains only one object type. For each of the given training set, and test object, the accuracy of the learned model's predictions are given in the rest of the table.

Case	Training object types	Accuracy in prediction (%)			
		□	⊖	▯	⊂⊃
1	□	100	0	100	53.4
2	⊖	0	100	0	46.6
3	▯	100	0	100	53.3
4	⊂⊃	100	83.8	100	94.7
5	□ ⊖	100	100	100	86.4
6	□ ▯	100	0	100	53.4
7	□ ⊂⊃	100	83.8	100	95.6
8	⊖ ▯	99.2	100	100	85.9
9	⊖ ⊂⊃	100	100	100	93.8
10	▯ ⊂⊃	100	83.8	100	94.7
11	□ ⊖ ▯	100	100	100	86.4
12	□ ⊖ ⊂⊃	100	100	100	95.6
13	□ ▯ ⊂⊃	100	83.8	100	95.6
14	⊖ ▯ ⊂⊃	100	100	100	94.7
15	□ ⊖ ▯ ⊂⊃	100	100	100	94.7

situations can be evaluated. In both training and testing, only one object is placed in front of the robot, and the forward action is executed.

After being trained in the constrained learning space, each model is tested with all object types one by one, and the prediction accuracy regarding the traversability affordances for that object type is computed (Table I).

As shown in cases 1, 2, 3, and 6, when the training set includes only traversable or non-traversable objects, but not both, the model predicts same affordance on all objects. In case 4, the robot is trained with only ⊂⊃, yet it is able to predict the affordances of all other object types that are not included in training set with high accuracy. We obtained such a good generalization performance, since the robot made interactions with different sides of ⊂⊃, and the affordances of various surfaces are learned and later generalized for novel objects. In case 5, since the training set contains samples for both success and fail, the affordances of novel objects (⊂⊃ and ▯) are also correctly predicted. As a result, we can say that our method successfully predicts the affordances of the novel objects that were never before.

D. Traversability on the real robot

The controller that was trained in the first set of experiments was also transferred to Kurt3D. Various objects, including simple geometrical ones and office environment objects like trash bins and PC cases, are then placed in front of Kurt3D to test the performance of the controller. Two sets of experiments are then conducted, using boxes in the first set and cylinders in the second one. As shown in Fig. 6, the robot was able to correctly perceive the affordances of these objects, which are placed in different distances and angles.

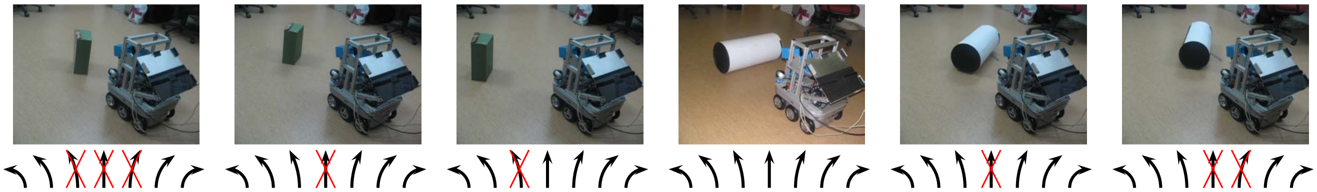


Fig. 6. Based on the bearing and proximity of the box and cylinder, Kurt3D was able to eliminate the non-afforded actions.

VI. CONCLUSIONS

In this study, the traversability affordances of the environment for a mobile robot is learned through physical interactions in a physics based simulation environment. Since the traversability depends on the location of the objects and their geometrical properties, range images are used to perceive the physical affordances of the immediate environment. A simple perceptual representation is proposed, where intermediate high-level processes like object detection or world modeling are not utilized, thus favoring Gibsonian direct perception view. Based on the low-level features that are perceived and the results of the interactions with the world, the robot is able to learn $i)$ relevant features for different actions, and $ii)$ the affordances provided. The prediction accuracy in perceiving the traversability affordances of the environment, which includes several boxes, cylinders, and spheres is found to be around 95%. Furthermore, it is presented that the robot uses only 1.1% of the extracted features while perceiving the affordances. This in turn saves the time 76.6% in scanning and 81% in feature processing, and J.J. Gibson's *perceptual economy* is obtained through learning to use relevant features.

After learning the affordances of the environment, the robot, which is controlled by a simple motivation system, was able to successfully traverse a virtual room cluttered with objects. Additionally, the experiments showed that the robot was able to perceive the traversability affordances of the novel objects that it has never seen before. Finally, the affordance-based action selection scheme that is learned in simulator is successfully transfered to the real robot without any further modification. Although only objects with basic geometries are used in our experiments, we expect that the performance of our affordance prediction scheme will not degrade in environments that include everyday office objects or outdoor environments. Thus, we plan to train and test the robot in more realistic environments in the future.

The work presented in this paper is novel from prior studies on multiple fronts. First, in our work range images, which are more informative about the physical affordances of the environment, are used for sensing. Second, we proposed a perceptual representation which represents the shape and orientation information in a proper way for learning. Third, we performed a more complete and comprehensive testing of the learned affordances, and that showed that the proposed system can successfully predict the affordances of completely novel object types.

VII. ACKNOWLEDGMENTS

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