Ontological Knowledge Management Framework for Grasping and Manipulation

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Abstract—**A holistic task based grasping system requires the use of perception modules that are tied with knowledge representation systems in order to provide optimal solutions. Task based grasping has been a well-researched field. One of the most comprehensive systems for task based grasping is the K-CoPMan system that uses semantic information in mapping and planning for grasping. However, this system as well as other lacks conceptual knowledge that can aid the perception module in indentifying the best objects in the field of view for task based manipulation. Furthermore, the system depends on full 3D models of objects in order to perform grasping. This restricts the scalability, extensibility, usability and versatility of the system. In this paper, we propose an alternate knowledge representation and inference framework based on the concept of functional and geometric part affordances in order to aid task based grasping. The performance of the system is evaluated based on complex scenes and indirect queries.**

Keywords- Ontologies, Knowledge Representation, Grasp Affordances, ConceptNet

I. INTRODUCTION

In the area of robotics, as well as other systems requiring the use of ontologies, Semantic Web based knowledge acquisition systems have been typically defined using Web Ontology Languages (OWL), that are characterized by formal semantics and RDF/XML-based serializations. Extensions to OWL have been used in semantic editors such as Protégé and semantic reasoners and ontology bases such as Pellet, RacerPro, FaCT++, HermiT, etc. In the area of semantic text parsing and knowledge management, a number of frameworks such as Framenet, Lexical Markup Framework (LMF), UNL, WordNet and WebKB are available. Alternatively, a number of tools for conceptual knowledge management have also been developed recently. These include reasoners and concept ontologies such as Mindpixel, Cyc, Learner, Freebase, YAGO, DBpedia, and MIT ConceptNet. These semantic reasoners and ontology databases can be directly exploited for applications in robotic manipulation.

The most significant of semantic knowledge acquisition systems for robotic vision systems is KnowRob (Knowledge Processing for Robots) [13], which uses reasoners and machine learning tools such as Prolog, Mallet and Weka, operating on ontology databases such as researchCyc and OMICS (indoor common-sense knowledge database). In the case of KnowRob, the data for the knowledge processing stems from three main sources: semantic environment maps, robot self-observation routines and a full-body human pose tracking system. Extensions to KnowRob, such as the K-CoPMan (Knowledge-enabled Cognitive Perception for Manipulation) system [14], enable autonomous robots to grasp and manipulate objects.

All the above frameworks for knowledge acquisition based object grasping and manipulation suffer from the fact that they require the use of explicit model databases containing object instances of the query to be processed, in order to obtain successful object recognition. K-CoPMan, for instance, uses CAD for matching 3D point clouds in order to identify the queried object in the given environment. Furthermore, while using semantic knowledge of the scene in order to improve object recognition and manipulation, these systems are largely devoid of performing implicit goal-directed cognitive tasks such as substituting a cup for a mug, bottle, jug, pitcher, pilsner, beaker, chalice, goblet or any other unlabeled object, but with a physical part affording the ability to hold liquid and a part affording grasping, given the goal of 'bringing an *empty cup*' and no cups are available in the work environment.

In order to alleviate these issues, we have utilized the concept of part affordances for building a scalable grasping system [29]. Gibson proposed the original idea of affordances grounded in the paradigm of direct perception. Physical affordances define the agent's interaction possibilities in terms of its physical form [16]. For example, stable and horizontal surfaces are needed to support objects, objects need to have a brim or orifice of an appropriate size, in order to be functional as a container to drink from. Additional examples of affordances studied with respect to robotic manipulation in [16] include 'sittability' affordance of a chair that depends on body-scaled ratios, doorways affording going through if the agent fits through the opening, and monitors afford viewing depending on lighting conditions, surface properties, and the agent's viewpoint. The spectrum of affordances have been extended to include social-institutional affordances, defining affordances based on conventions and legally allowed possibilities leading to mental affordances. Affordances based on History, Intentional perspective, Physical environment, and Event sequences (HIPE) leading to functional knowledge from mental simulations have been studied in [15]. Affordances serve as key to building a generic, scalable and cognitive architecture for visual perception. 'Affordance based object recognition' or recognition based on affordance features is an important step in this regard.

II. OVERVIEW

The primary contribution of this paper is in providing a scalable knowledge assimilation and deployment framework for robotic grasping that is free of 3D model instance representations.

The fundamental basis of our framework revolves around the theme of 'Conceptual Equivalence Classes'. These classes are defined as sets of objects that are interchangeable from the view-point of usage for the primary functionality of the object. Hence, objects such as mugs, cups and beakers form an equivalence class. Bags and baskets also form an equivalence class, so do cans and bottles, bikes and motorbikes and so forth. Equivalence classes can be uniquely defined and recognized in terms of their (a) Part Functional Affordance Schema and (b) Part Grasp Affordance Schema. It should be noted here that the definition of conceptual equivalency class used here is distinct and unrelated to the equivalency class definitions provided by the OWL framework, which uses only textual or named entity equivalency.

A. *Unit Definitions based on Textual Semantics*

In our framework, we employ WordNet [5] for generating textual unit definitions for concepts or objects queried for. While WebKB provides improvements over WordNet, while returning results that are restricted to nouns (of specific interest to our framework), the standalone nature of WordNet recommends its usage. WordNet provides a lexical database in English with grouped sets of cognitive synonyms (synsets), each expressing a distinct concept. It also records the various semantic relations between these synonym sets, such as hypernyms (higher level classes), hyponyms (sub-classes), coordinate terms (terms with shared hypernyms), holonyms (encompassing structure) and meronyms (constituent parts). The system interacts with the WordNet interface based on the queried term to obtain a possible match. The system also assimilates concept 3D geometric shape information such as Sphere, Cylinder, Cube, Cone, Ellipsoid, Prism, etc., 2D geometric shape information such as Square, Triangle, Hexagon, Pentagon, Ellipse etc. and abstract structural concepts such as Thin, Thick, Flat, Sharp, Convex, Concave etc. by parsing the concept definition. Additionally, information on material properties of the concept such as Metal, Wood, Stone, Ceramic etc. and part functional affordance properties (based on terms such as Cut, Contain, Store, Hold, Support, Wrap, Roll, Move, Ride, Enter, Exit, Gap, Hole) are also obtained and stored by the system.

B. *Unit Definitions based on Conceptual Properties*

For the case of conceptual unit definitions, we employ the Open Mind Common Sense (OMCS) [11] based ConceptNet framework. ConceptNet has been used in the context of robotic task management [12]. The particular choice of this ontology database is due to its exhaustiveness, ease of use and suitability of attributes with respect to our affordance framework. The ontology provides English language based conceptual groupings. The database links each concept with properties such as 'InstanceOf' and 'SymbolOf' – possibile semantic replacements, 'ConceptuallyRelatedTo' – possible functional/conceptual replacements, 'PartOf' – encompassing structures, 'ReceivesAction', 'CapableOf', 'UsedFor' – possible functional affordances as well as 'MadeOf', 'HasProperty' etc. that provide further information about the concept. The use of these properties enables the part affordance based equivalence class selection.

C. *Unit Definitions based on Visual Features*

While visual unit definitions can be used to improve the performance of the system or to obtain instance level recognition, our novel framework for conceptual equivalence class recognition and grasping system does not require the use of these databases and hence is 3D/2D model free. Furthermore, it should be noted that from the viewpoint of grasping using range images, monocular image information is largely superfluous. Instance level recognition, if necessary in future revisions to the system, can be carried out using a bag of features approach working with SIFT/SURF or other state-of-art feature descriptors on labeled image or 3D shape databases (such as LabelMe, LabelMe 3D and ImageNet).

D. *Unit Definitions based on Grasp Affordances*

For the case of part grasp affordance definitions, a number of systems are available. These can be used for limiting the large number of possible hand configurations using grasp preshapes. Humans typically simplify the task of grasping by selecting one of only a few different prehensile postures based on object geometry. One of the earliest grasp taxonomy is due to Cutkosky [4]. In our system we employ the 'Human Grasping Database' [3] from KTH-Otto Bock. This taxonomy lists 33 different grasp types hierarchically assimilated in 17 grasp super-types. It is possible to most of these grasp types to geometric shapes they are capable of handling. A representative set of grasp affordances from the database are presented in Fig 1. Each query concept is defined (as a whole or in parts) to provide grasp affordances of the types listed in the taxonomy database.

E. *Unit Definitions based on Part Functional Affordances*

The most important component of the presented system is the Part Functional Affordance Schema. This component essentially performs the symbol binding – mapping concepts: in our case – the *Conceptual Equivalence Classes* to visual data in the form of 3D geometries. While various schemes for affordance definitions have been studied in the past, we utilize a set of part functional affordance schema, largely with respect to objects found in households and work environments. These affordances are based on functional form fit of the Conceptual Equivalence Classes. A representative section of the part functional affordance schema is presented in Table 1. Note that the functional affordance here is defined with respect to objects of the class being able to perform the defined function.

Table 1. Representative Part Functional Affordance Schema.

Part Functional Affordance	Geometric Mapping	Examples
Contain - ability	High convexity	Empty bowl, Cup
Support - ability	Flat - Convex	Plate, Table
Intrinsic contain - ability	Cylinder/Cube/Cuboid/ Prism	Canister, Box

Incision - ability	Sharp edge (flat linear surface)	Knife, Screwdriver
Engrave - ability	Sharp Tip	Cone, Pen
2D Roll - ability	Circular/ Cylindrical	Tire, Paper Roll
3D Roll - ability	Spherical	Ball
Weed - ability[a]	Linear textural structures	Comb, Brush
Filter - ability[a]	Bi-linear textural structures	Grid, Filters
Wrap(p) -ability	w.r.t. given shape	Shoe, Glove
Connect - ability[a]	Solid with support (m)	Plug, USB Stick

The scale of each part is also defined with respect to a discrete terminology set based on comparative sizes – (finger (f), hand (h), bi-hand (b), arm/knee (a), torso (t), sitting posture (i), standing posture (d), non-graspable (n) etc.). The conceptual equivalence classes are defined based on joint affordances of parts of the objects, along with their topological relationships. Some of the various topological relationships (for 2-part objects) used are Table 2.

Table 2. Part Joint Topological Relationships

Relationship Code	Details
1v2	1 vertical 2
1h2	1 horizontal 2
1v2n	1 opposition vertical 2
1h2n	1 opposition horizontal 2
1s2	1 staggered 2
1os2	1 orthogonally staggered 2

In Table 2, 1 indicates the larger object and 2 the smaller one, vertical dimension refers to the smallest of the 3 dimensions and horizontal to the largest. All relationships are with respect to the non-symmetrical axis of the object (for e.g. the opening in a roughly cuboidal bag). Opposition refers to the relationship with respect to the face opposite to the non-symmetrical face.

Based on these attribute definitions, the equivalence classes can be uniquely represented. Examples of equivalence classes are provided in Table 3. Note that (ga) denotes grasp affordance and (pa) denotes part affordance.

Table 3. Example Equivalence Class defintions.

Equivalence Class	Definition
Basket	1v2, b-a, handle (ga), opening (pa: containability)
Plate	h-b, (ga), (pa: supportability)
Cup	1h2, f-h, handle (ga), opening (pa: containability)
Chair	1os2, a-i, 2x(pa: supportability)
Canister	h-b, (pa: intrinsic containability)
Box	h-i, (pa: intrinsic containability)
Plug	1v2n, f-h, support, contact (pa: connectability (m))
Knife	1h2, f-h, grip, blade (pa: incisionability)
Bike	b,a,a, 1v2(3hv4), seat (pa: supportability), 2xwheels (pa: 2drollability)
Laptop	b-a, (pa: supportability)
Pen	f-h, grip, tip (pa: engravability)
Ball	h-a, (pa: 3drollability)
Spoon	1h2, f-h, grip, opening (pa: containability)
Spatula	1h2, f-h, grip, opening (pa: supportability)
Faucet	1h2, f-h, pipe, orifice (pa: filterability)
Suitcase	1v2, b-a, handle, box (pa: intrinsic containability)
Desk	a-d (pa: supportability)
Cabinet	a-d (pa: intrinsic containability)
Stair	nx(pa: supportability)
Shoe	opening (pa: containability), (pa: wrappability/ ellipsoid)
Key	1v2n, f-h, support, contact (pa: connectability (m))
Brush	grip, bristles (pa: weedability)
Shelf	nx(pa: supportability)
Scissors	2xblade (pa: incisionability)
Cars	4xwheels (pa: 2drollability) (intrinsic containability)

F. *Query Evaluation*

For any given query term, the system checks for availability of concept definition in the following list of attributes in a sequential order. The first database to be queried for is (a) the Part Affordance Schema. If unavailable, the system checks for the availability of a concept in the Part Affordance Schema that is matched using (b) the synsets of the queried term, followed by the 'InstanceOf' and 'SymbolOf' properties from ConceptNet, if necessary. If a match is not found, the system tries to use (c) the ConceptuallyRelatedTo property returned by ConceptNet (in response to the query term) to define possible alternatives for the object to be found. Alternatively, (d) the coordinate terms of queried object are searched for in order to obtain a conceptual replacement object. If a match is still not found, the system searches in (e) the holonym list and (f) the 'PartOf' list from ConceptNet. This is followed by matching for (g) 'ReceivesAction', 'CapableOf', 'UsedFor', which denote possible functional equivalency of the objects.

The frequency scores on each of these properties are also returned as a measure of confidence in the object found. If no matches are found in the Part Affordance Schema for the queried object or any of the alternatives to be searched for, as suggested by the above list of related objects, the system parses the definitions of the queried object returned by both WordNet and ConceptNet to search for structural properties associated with the object. These include shape geometry information such as cylindrical, spherical or cuboidal or its alternate surface forms as well as abstract geometrical property terminologies such as flat, thick, thin, concave or convex.

Material properties of the object from the parsed definitions such as wood, stone or metal, (as well as those returned by the 'MadeOf' property from ConceptNet) as well as functional affordances from WordNet are stored as properties of the concept being queried for. While it is possible that the given range scene can be searched for the required object entirely based on the geometry information or the defined geometries (from the Part Functional Affordance Schema) based on a matched affordance property returned from parsing the concept definitions, the confidence level (based on frequency scores and weighted by property confidence measures) returned by such an unit recognition scheme is very low. Furthermore, based on a learned appearance database of different material types (such as wood, stone or metal), the classification can be improved if monocular scene imagery is also available. Such a material classification approach can also be used to select salient regions in the scene in order to reduce computation requirements of the range image processing.

G. Detection of Part Affordances

As discussed earlier, the Part Functional Affordance Schema defines unique symbol binding from affordance concepts to observables in terms of functional geometry mapping. While certain affordances are defined based on geometrical shape structures such as cylinders, cubes, cuboids and spheres or continuous space parametric variations of these shapes (as defined by superquadrics), other affordances are defined in terms of abstract geometrical attributes such as flat, concave, convex, sharp tip, sharp edge, linear textural structures, bi-linear textural structures. Joint affordances are defined in terms of more than one part. While detection results of the first set (geometrical shape structures) is directly available from the superquadrics, results for the second set (abstract geometries) can be inferred from the superquadrics. Since superquadrics model objects or parts as convex structures, presence of a concavity (such as the open cylindrical portion of a cup) can also be verified using visibility tests for cloud points and normals (for e.g. belonging to the inner surface of the cup, in comparison with a solid cylinder). Other attributes such as flatness and sharpness, linear and bi-linear textures can also be roughly estimated based on measures of size, shape and thickness of the quadric

H. Detection of Grasp Affordances

Most of the grasp affordances based on the Otto Bock Grasping Database, can be uniquely represented in terms of geometrical shapes. For e.g., the small diameter affordance can be structurally defined as a superquadric with a high linear dimension value along one axis and small diameters along the others. This also holds true of prismatic affordance, though the diameter is much smaller. Power disk is suited for disk type structures of the size of the palm, parallel extension for cuboidal structures and distal for objects with disjoint ring shaped parts.

I. Query Matching

In the given scene of interest, the queried object for the given task is found using attributed graph matching of the concept node built for the query with all geometrical objects found in the scene. Among the several attributed graph matching approaches [17, 18] available, we use a low complexity approach based on Heterogeneous Euclidean Overlap Metric (HEOM) using the Hungarian Algorithm [18] for the matching process. Each object in the scene is represented as a graph with its parts defining nodes along with vector attributes that may be symbolic (such as affordances) or metric (scales). Given the limited number of objects in a given scene, the matching process is fast and accurate. In the case that more than one object is found in the scene, the nearest object is selected for manipulation.

III. RESULTS AND EVALUATION

The performance of the concept evaluation algorithms for a given scene is demonstrated using a set of queries.

For the first scene (Fig. 1), a search query for 'jug' is presented. It should be noted that the query 'jug' is not available in our equivalence class database, hence causing the search to be non-trivial. Using WordNet based parsing, renders the part affordance of 'containability' with a weight measure of 2 (out of 10), based on frequency scores for primary (from definition text) and secondary characteristics (from other attributes). ConceptNet also renders the 'containability' affordance along with a 'HasA' attribute of 'handle' which provides the grasp affordance for the given case. The attributed graph for the given query is simple and is composed of nodes for 'containability' part affordance and a 'handle' – small diameter grasp affordance with an overall weighted confidence score of 1.66/4 (using concept and textual unit definitions of 1 and 3 respectively). The range image processing algorithms yield both the mugs in scene as results (prioritized by the closest object), since these objects contain concavities (affordance: containability) and handles (grasp affordance) that match the query graph attributes exactly (normalized HEOM score of 1).

For the second scene (Fig. 2), a search query - 'bag' is presented. Again, since no equivalence class has been defined for the term 'bag', the computation of the search is non-trivial. For the given case, WordNet and ConceptNet render the 'containability' affordances along with the 'handle' grasp affordance. In addition, ConceptNet renders the scale parameter to be 'large' and equivalent to that of a 'box'. The confidence score on the resulting affordance description is 3.64/4 (since WordNet returns a high frequency score of 8). Since the queried scene contains 2 true 'bags', the range processing algorithms return both the bags as query results. Again the normalized HEOM score is 1, indicating a perfect match for known attributes. It can also be seen that the confidence in the result is high for the second scene, as compared to the first, since the rate of occurrence of the object in typical scenes (reflected in the frequency score from WordNet) is higher. The algorithms used for symbol binding (from affordances to visual data) include range data segmentation, detection of object geometry and evaluation of grasp points/ approach vectors. Details of these algorithms and their evaluation are presented in [30]. Besides other attributes, differences in topological relationships (such as 1v2 for bag/basket and 1h2 for cup/mug/jug) enable robust separation between the object classes in the demonstrated examples.

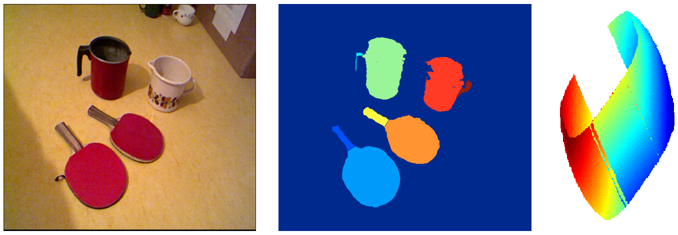

Fig. 1. Left to Right: (a) Input Scene, (b) Detected objects and their corresponding parts in the point cloud (c) Fitting of a cylinder corresponding to the 'jug' in the scene

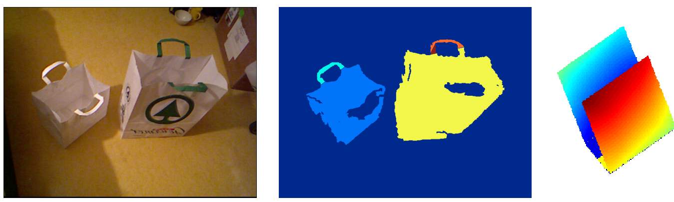

Fig. 2. Left to Right: (a) Input Scene, (b) Detected objects and their corresponding parts in the point cloud (c) Fitting of a cuboid corresponding to the 'bag' in the scene

IV. Conclusion and Future Work

In this paper, we have presented a scalable knowledge assimilation and deployment framework for robotic grasping that is free of 3D model instance representations. We have used the paradigm of '*Conceptual Equivalence Classes*' and uniquely defined them in terms of the minimalistic features of Part Functional Affordances and Part Grasp Affordances, leading to implicit cognitive processing for successful goal attainment. We have also provided a practical pathway for symbol binding – from concepts to observables by defining functional geometry mappings. The system is also capable of knowledge of affordance and interaction modes for unknown/ un-modeled objects based on partial information obtained from the constituent parts.

Currently, the number of part functional affordances supported by the system is quite limited. We plan to extend the number and range of the supported functional affordances in the future. This would also necessitate more advanced algorithms for the attributed graph matching. Furthermore, the current system is geared towards robotic grasping and manipulation while being capable of functional class level object recognition. As such, it uses only range information for the processing, without the need for 2D/3D databases. Extension of the scheme to perform instance level object recognition will necessitate the use of these databases. Moreover, while current system has been evaluated on a stand-alone system, actual deployment of the system on a robot with an arm and gripper for grasping is ongoing research. Finally, while the current system is intended to serve as a core component for goal-directed object recognition and manipulation, it can be used in a more holistic system for semantic visual perception such as the K- CoPMan.

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