Ubiquitous Semantics: Representing and Exploiting Knowledge, Geometry, and Language for Cognitive Robot Systems

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Abstract— **In this paper, we present an integrated approach to knowledge representation for cognitive robots. We combine knowledge about robot tasks, interaction objects including their geometric shapes, the environment, and natural language in a common ontological description. This description is based on the Web Ontology Language (OWL) and allows to automatically link and interpret these different kinds of information. Semantic descriptions are shared between object detection and pose estimation, task-level manipulation skills, and human-friendly interfaces.**

Through lifting the level of communication between the human operator and the robot system to an abstract level, we achieve more human-suitable interaction and thus a higher level of acceptance by the user. Furthermore, it increases the efficiency of communication.

The benefits of our approach are highlighted by examples from the domains of industrial assembly and service robotics.

I. Introduction

Knowledge representation for robotics is about connecting abstract representation with the "real world". Moreover, if a robot is deployed in an environment in which it will encounter humans or even other autonomous robots it will have to have flexible representations which allow an alignment of its own representations with those of the agents around it.

One can call this approach *ubiquitous semantics* which takes inspiration from the semantic web initiative. Using ontologies, one can tackle the problems which knowledge representation poses for modern robotics.

Ubiquitous semantics means that all relevant aspects of robot systems and their tasks are described in a way that preserves their inherent meaning. These semantic descriptions must be flexible and at a sufficiently generic level. This allows robots to share knowledge about how tasks are to be *performed and completed*. The descriptions are also flexible enough to describe the world in which the robot is moving but generic enough for a variety of environments and most importantly to allow for the *non-deterministic nature of the environments* in which robots are deployed, thus tackling the so-called "open world" problem. Also, such generic and flexible representations will be more amenable to the *plasticity of human communication*.

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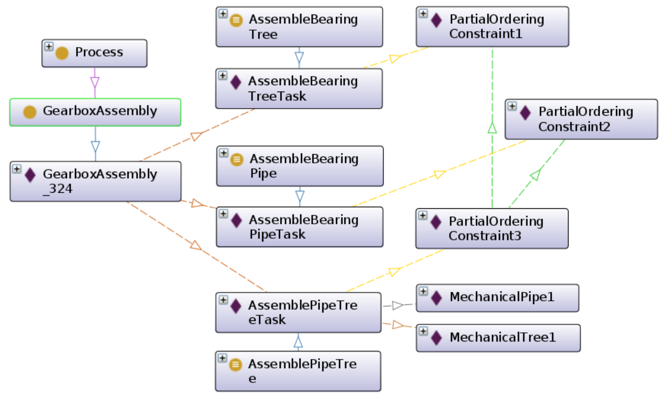
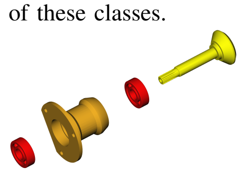
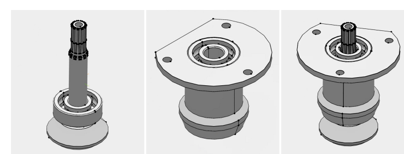


(a) Excerpt of semantic process description. Boxes containing a yellow circle represent classes, purple rhombi represent instances of these classes.



(b) Exploded view



(c) Assembly steps

Fig. 1: Industrial assembly of four objects in three steps building the core part of a gearbox. Example from [1].

The remainder of the paper is structured in the following way. We will address the related work in the next section. This will be followed by a more general discussion of knowledge representation – specifically for robots. Against this background, we will discuss object detection, pose estimation, task execution, and human-friendly interfaces. We conclude with a few remarks on the general use of our ontology based knowledge framework.

II. Related Work

Related work applies concepts from knowledge representation [2], symbolic task planning [3], and planning for natural language dialogs [4].

Many modern approaches of knowledge representation in robotics have taken the semantic web initiative as a source of inspiration. Those approaches make use of ontologies to organize knowledge in autonomous and intelligent systems.

The RoboEarth initiative [5] makes use of this approach with the goal of achieving effective sharing of knowledge [2], data [6], and processing resources [7] among robots. This is often referred to as cloud robotics, and has established advantages regarding memory and processing limits.

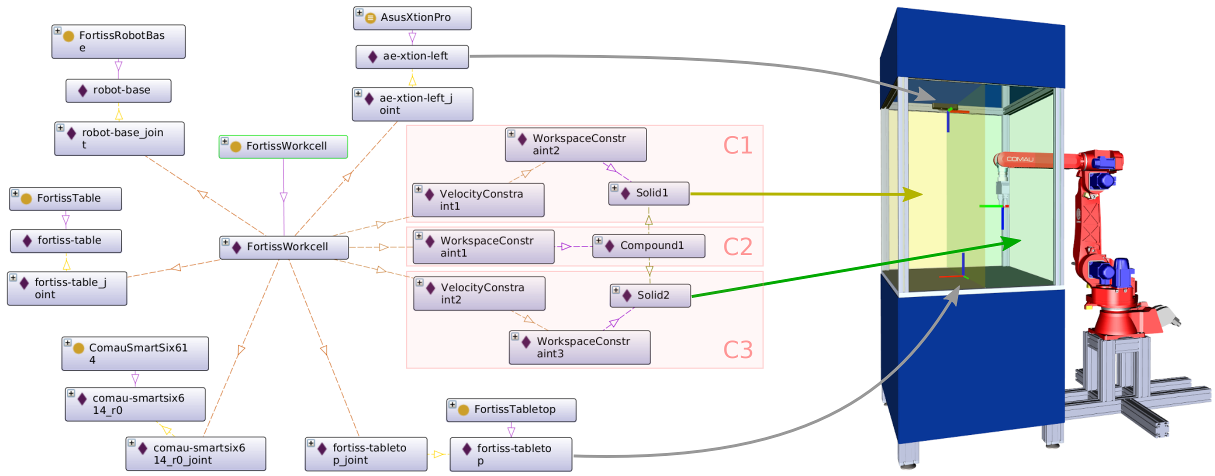


Fig. 2: A visualization of a robot workcell and an excerpt of the corresponding semantic description. Two velocity constraints (C1 and C3) and a workspace constraint (C2) have been specified.

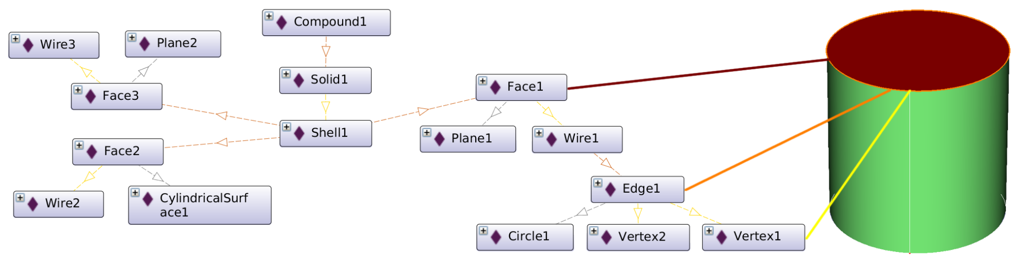


Fig. 3: Semantic description of a finite cylinder based on a boundary representation.

Additionally, models acquired by one robot can be re-used by another one.

There are other means by which robots can gain and apply knowledge. These can be categorized as "physical symbol grounding", "grounding words in action" and "social symbol grounding" [8].

III. Knowledge Representation

In order to endow robots with advanced cognitive capabilities, it is necessary to make all relevant aspects of their properties, tasks, and environment known to them. Encoding and interpreting knowledge about these different fields allows them to assess the applicability of their skills and to link their actions to a wider context.

In this section, we briefly summarize our methodology for semantically describing processes, related interaction objects, and their environment. We design a common description language based on the Web Ontology Language (OWL), which uses class taxonomies, instances of these classes, and properties for classes and instances.

A. Semantic process descriptions

Semantic process models are partially ordered sequences of tasks. Each type of task specifies its pre- and postconditions, and a set of parameters, of which some must be defined and others might be optional. An underspecified task can be fully parameterized through automatic reasoning, when a process model is assigned to a robot system, by combining the requirements of tasks with the capabilities of the selected system [1].

Fig. 1a depicts an excerpt of the semantic description of an industrial assembly process, which is visualized in Fig. 1b and Fig. 1c. It contains three tasks, i.e., *AssembleBearingTreeTask*, *AssembleBearingPipeTask*, and *AssemblePipeTreeTask*. Exemplarily, the associated object models for the *AssemblePipeTreeTask* are shown. The order of the tasks is given through *PartialOrderingConstraints*, which specify that the *AssemblePipeTreeTask* has to be executed after the other two tasks have been carried out.

B. Semantic environment description

Semantic environment descriptions encode the composition of physical entities of the real world, e.g., robots, tools, sensors, or tables, and abstract meta-information, e.g., available skills or environmental constraints [1].

The semantic description of the workcell in Fig. 2 specifies a robot, its base, a table, and an RGBD sensor. These entities are linked with the workcell instance *FortissWorkcell* through instances of type FixedJoint, e.g., *robot-base_joint*. The robot workspace is set to be constrained to the given cuboid (constraint C2), for which two subregions with different velocity limits have been defined (constraints C1 and C3).

C. Semantic object models

Next to basic object properties, e.g., type, name, weight, material, or bounding box, we are able to semantically describe the geometric shape of objects using a boundary representation (BREP) [1], [9]. BREP preserves the exact mathematical models of contained curves and surfaces. This enables the system to define and interpret various geometric interrelational constraints, e.g., coincidence, concentricity, parallelity, etc., between two objects' vertices, edges, or faces [9], [10].

Fig. 3 shows the BREP-based semantic description of a finite cylinder's geometry. Selected correspondances between the visualization on the right and the ontological instances on the left are highlighted.

IV. Object Detection and Pose Estimation

In this section, we present an approach for shape-based object detection and pose estimation based on semantic descriptions of object models. This involves deep object models that include exact information about the geometric properties of the object. This approach allows for the detection of symmetrical objects whose pose are inherently underspecified. Knowledge about sensor noise and manufacturing tolerances can also be explicitly included in the pose estimation step [11].

A. Geometric constraints from primitive shape matching

The object is modeled as a set of primitive shapes P (e.g. planes, cylinders) based on its boundary representation (BREP). Each primitive shape $P_i \in P$ enforces a set of constraints $(\boldsymbol{C_{p_i}}, \boldsymbol{C_{n_i}})$ on the position and orientation of the object respectively, where each row of $\boldsymbol{C_{p_i}}$ and $\boldsymbol{C_{n_i}}$ contains a direction along which the constraint has been set.

A *complete set* of primitive shapes is defined as a set where the constraints fully specify the 3D position and orientation of the object. A *minimal set* of primitive shapes is defined as a set which is *complete* but removing any primitive shape from the set would render it incomplete.

Table II presents the list of supported geometric constraints between primitive shapes, where

$$\acute{\boldsymbol{p}}_2 = \boldsymbol{R}\boldsymbol{p}_2 + \boldsymbol{t}, \acute{\boldsymbol{p}}_{21} = \acute{\boldsymbol{p}}_2 - \boldsymbol{p}_1, \acute{\boldsymbol{n}}_2 = \boldsymbol{R}\boldsymbol{n}_2$$

1) Feature Vectors for Sets of Primitive Shapes: Correspondences between the scene and model shape primitives are obtained by matching feature vectors constructed from geometric properties of the primitive shapes. These feature vectors not only encode the geometric properties of the shapes, but also of the relations between the shapes (see Table I). Minimal sets of primitives from the scene point cloud are calculated during the pose estimation stage (see Section IV-B.2), and the distance between the feature vectors provides a metric for obtaining hypotheses of shape associations.

B. Constraint Processing for incomplete pose estimation

1) Detection of minimal and complete sets of primitives: The constraints (C_{p_i}, C_{n_i}) enforced by each primitive shape P_i are stacked into two matrices C_p and C_n (each having 3 columns). The constraints are *complete* if the matrices C_p and C_n both have rank 3. Fig. 4b shows an example of a complete set of primitive shapes.

TABLE I: Feature vectors for primitive shape sets

Primitive shape	**Feature Vector (*fv*)**
Inf. Plane	ϕ
Sphere	*radius*
Inf. Cylinder	*radius*
Plane+Plane	*fv(plane1), fv(plane2), angle(plane1_normal, plane2_normal), min_distance(plane1, plane2)*
Plane+Cylinder	*fv(cylinder), fv(plane), angle(plane_normal, cylinder_axis)*
Cylinder+Cylinder	*fv(cylinder1), fv(cylinder2), angle(cylinder1_axis, cylinder2_axis), min_distance(cylinder1, cylinder2)*
Plane+Plane+Cylinder	*fv(plane1, cylinder), fv(plane2, cylinder)*

Algorithm 1 Detecting object poses using RANSAC

Input : $[P_s, [[P_m]_{\min}]]$ (set of scene primitive shapes and minimal sets of model primitive shapes)
Output : $[\boldsymbol{T}, s_{\max}]$ (best pose estimate with score for detected object instance)
forall $P_i \in [P_m]_{\min}$
$s_{\max} \leftarrow 0$
compute shape matching hypothesis (H_i) using fv's, see Section IV-A.1
calculate transformation estimate $\boldsymbol{T_i}$ for H_i , see Section IV-B.2
compute score s_i for hypothesis H_i
If $s_i \geq$ thresh & $s_i > s_{\max}$
    $\boldsymbol{T} \leftarrow \boldsymbol{T_i}$
    $s_{\max} \leftarrow s_i$
EndFor

2) Constraint solving for pose estimation: The optimization is performed over transformations $\boldsymbol{T}$ that align the object model to the objects in the scene. The transformations are represented as $\triangle\boldsymbol{x} = (\boldsymbol{t}, \boldsymbol{r})$ where $\boldsymbol{t}$ is the translation and $\boldsymbol{r}$ is the rotation in axis angle representation.

The optimization function is the absolute value of the transformation, i.e., minimization of $\|\triangle\boldsymbol{x}\|_2$. The constraint functions g_i along with their lower and upper bounds ($\mathrm{lb}(g_i)$, $\mathrm{ub}(g_i)$) are obtained from the primitive shape matching constraints shown in Table II. The bounds $(d_{\min}, d_{\max})$ of the constraints can be used to incorporate the noise in sensor data or primitive shape fitting errors, as well as manufacturing uncertainties.

The resulting optimization problem is:

$$\begin{aligned} \arg\min_{\triangle\boldsymbol{x}} \quad & \|\triangle\boldsymbol{x}\|_2 \\ \text{subject to} \quad & \mathrm{lb}(g_i) \leq g_i \leq \mathrm{ub}(g_i),\ i = 1, \ldots, m. \end{aligned}$$

This set of equations is then solved using a non-linear least squares min-max solver (MA27) from [12] using the deterministic non-linear optimization utility from library Coin-OR (named IPOPT) [13]. If the constraints are complete, the pose is uniquely defined. Otherwise, the constraint solver returns one possible solution.

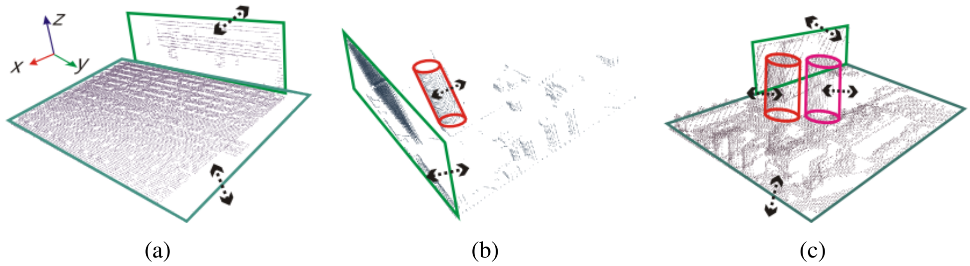


Fig. 4: Primitive shape groups for different views of an object. Using primitive shape sets, it can be calculated whether an object's pose can be fully estimated from a viewpoint. The arrows indicate the expected noise (qualitative only) in estimation of the primitive shape parameters. (a) the position of the object along y axis is not determined. In (b) and (c) the complete pose of the object can be estimated. (Note: The detected primitive shapes are highlighted for clarity.)

TABLE II: Summary of supported constraints between primitive shapes

Constraint (i)	**Cost Function** ($\mathrm{g_i}$)	**Bounds** (lb, ub)	**Constrained Spaces**
Plane-Plane	$[\boldsymbol{n}_1^{\mathrm{T}} \acute{\boldsymbol{p}}_{21}; \acute{\boldsymbol{n}}_2^{\mathrm{T}} \boldsymbol{n}_1]$	lb : $[d_{\min}; a_{\min}]$ ub : $[d_{\max}; a_{\max}]$	$\boldsymbol{C_n}$: $[\boldsymbol{n}_{1_{\perp 1}}; \boldsymbol{n}_{1_{\perp 2}}]$ $\boldsymbol{C_p}$: $[\boldsymbol{n}_1]$
Cylinder-Cylinder	$[\lVert \acute{\boldsymbol{p}}_{21} - (\boldsymbol{n}_1^{\mathrm{T}} \acute{\boldsymbol{p}}_{21}) \boldsymbol{n}_1 \rVert_2^2; \acute{\boldsymbol{n}}_2^{\mathrm{T}} \boldsymbol{n}_1]$	lb : $[d_{\min}^2; a_{\min}]$ ub : $[d_{\max}^2; a_{\max}]$	$\boldsymbol{C_n}$: $[\boldsymbol{n}_{1_{\perp 1}}; \boldsymbol{n}_{1_{\perp 2}}]$ $\boldsymbol{C_p}$: $[\boldsymbol{n}_1]$
Sphere-Sphere	$[\acute{\boldsymbol{p}}_{21}]$	lb : $d_{\min}$ ub : $d_{\max}$	$\boldsymbol{C_n}$: $[\boldsymbol{n}_{1_{\perp 1}}; \boldsymbol{n}_{1_{\perp 2}}]$ $\boldsymbol{C_p}$: $[\boldsymbol{n}_1]$

3) RANSAC based constraint solving for pose estimation: A shape matching hypothesis H_i consists of a set of associations between primitive shape sets that can be computed by matching feature vectors (Section IV-A.1). An algorithm for pose estimation using RANSAC-like iterations on minimal sets of primitive shapes is described in Algorithm 1. For efficient hypothesis verification, we use the approach from [14] that utilizes geometric information from CAD models and primitive shape decomposition of scene point clouds.

V. Execution of Constraint-Based Robot Tasks

In order to execute a manipulation task in the workcell, the robot system's knowledge base is queried to obtain a set of task-specific geometric constraints. These constraints are then solved to obtain poses and residual null-spaces and to generate optimized robot trajectories [10].

In our task-level approach to robot execution, robot tasks are defined by geometric constraints that relate objects $\mathcal{O}$ and robot manipulators (including their tools) $\mathcal{R}$. A kinematic structure $\mathbf{R} \in \mathcal{R}$ is a tuple $(\mathrm{FK}, \mathbf{P})$, composed of a forward kinematic function FK that maps to the pose of its tool $\mathbb{R}^n \mapsto \mathrm{SE}(3)$ and a set of primitive shapes $\mathbf{P}$. A primitive shape $P \in \mathbf{P}$ may be one of the shapes defined in Sec. IV-A and serves as a useful reference for geometric relations, e.g. the grasp point of a parallel gripper. Analogous to kinematic structures, a manipulation object $\mathbf{O} \in \mathcal{O}$ is composed of a configuration and a set of primitive shapes, given by a tuple $(\mathbf{x} \in \mathrm{SE}(3), \mathbf{P})$.

A manipulation task is then defined by a set of constraints $\mathbf{C}$ that refer to primitive shapes of both kinematic structures and objects. Compared to the constraint resolution scheme in the object recognition component (Sec. IV-A), we perform a generic, iterative minimization of a cost function. For that, each constraint $C \in \mathbf{C}$ is represented by a cost function $\mathrm{Cost} : \mathrm{SE}(3) \times \mathrm{SE}(3) \mapsto \mathbb{R}^c$ that depends on the poses of two referenced shapes and returns a zero vector iff the constraint is fulfilled. To solve a given manipulation task, we minimize the stack of cost functions $\boldsymbol{q} \in \mathbb{R}^n \mapsto \mathbb{R}^c$ and obtain a valid robot pose $\boldsymbol{q}$. To ensure reliable convergence, cost functions are defined such that they are differentiable and reflect the correct number of c constrained degrees-of-freedom [10].

Many robot tasks in manufacturing and service domains pose constraints on only a few degrees-of-freedom, while the remaining degrees-of-freedom can be used to fulfill qualitative, lower-priority goals. Such goals may include the avoidance of singularities or joint limits, waypoints close to a previous one for shorter trajectories, or distance maximization from obstacles. When cost functions Cost allow computation of a full-rank Jacobian $\boldsymbol{J}$, we can compute the *null-space projection* matrix $\boldsymbol{N}$ of a task, $\boldsymbol{N}(\boldsymbol{q}) = \mathbf{1} - \boldsymbol{J}^{\dagger}(\boldsymbol{q})\boldsymbol{J}(\boldsymbol{q})$, where $\dagger$ denotes the pseudo-inverse. Projecting a lower-priority control signal onto $\boldsymbol{N}$ then allows null-space optimization of qualitative goals. As an example, the task of grasping a cylindrical object can semantically be defined by several coincidence constraints between a parallel gripper and the object. Based on these constraints, the robot will find a posture-optimized grasp along the rotational axes of the object.

VI. Human-Friendly Interfaces

We aim at reducing the complexity of interacting with robot systems. But, relying solely on semantic descriptions would only shift the required expertise for using such systems from the field of robotics to the field of knowledge

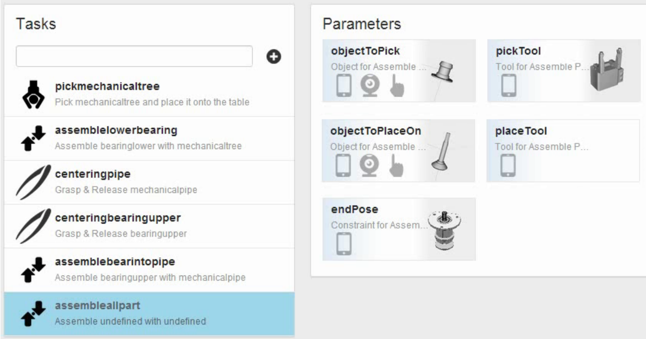


Fig. 5: Partial view of the intuitive interface which is used to program the robot and create or modify process descriptions.

engineering. Hence, we develop human-friendly interfaces, which act as a frontend to the semantic backbone.

A. Task-Level Programming Interface

The intuitive programming interface shown in Fig. 5 supports multiple input modalities: touchscreen, tracked 3D-pen, gestures, and speech [15]. By using these modalities during task-level programming, the user can define task parameters. We semantically describe modality and task parameter types, so that suitable modalities for certain parameter types can be automatically inferred and offered by the system [16].

For instance, the parameters *objectToPick* and *objectToPlaceOn* can be bound by selecting the desired object from a list, pointing at the object, or telling its name. This interface also supports the definition of assembly poses, grasp poses, and approach poses using geometric interrelational constraints [9], [10].

B. Natural Language Interface

This interface is not meant to support an open world dialog, but to instruct a robot system to perform a specific task. Interaction with our robot systems through natural language requires to map utterances to concepts in our ontologies, e.g., tasks and objects. We rely on a two-phases approach.

In the *configuration* phase, a human expert annotates the class taxonomies of tasks and objects with links to concepts in the Wordnet[1] ontology. As a second step in this phase, an OpenCCG[2] grammar is automatically generated [17], which serves as an input to our dialog component. The annotation has to be done only once for each type of task or object. The resulting grammar can be shared between all robots using our software framework. In the *runtime* phase, our dialog component uses the generated grammar to parse natural language input into a logical form, and to interpret it by mapping it back to concepts in the system's ontologies.

1) Configuration Phase: Natural language utterances can be ambiguous. As a result, a naïve one-to-one mapping of an instruction verb to a type of task would likely fail. Preferably, all synonyms for a given verb or noun should be considered,

[1]https://wordnet.princeton.edu
[2]https://github.com/OpenCCG/openccg

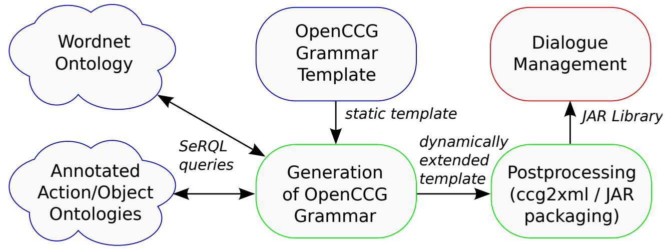


Fig. 6: Overview of configuration phase

when trying to interpret a command. For this reason, we annotate the classes in the task and object ontologies with Wordnet synonym sets (synset). Task classes are annotated with verb synsets, object classes with noun synsets, and classes that serve as discriminating features with adjective synsets.

Fig. 7 exemplarily shows the annotation of a service robot's task description called *ServeBeverage*. It contains the *AnnotationProperty linkedSynset*, which links to a particular synset in the Wordnet ontology, i.e., *synset-serve-verb-6*.

```
Declaration(Class(re:ServeBeverage))
Declaration(AnnotationProperty(re:linkedSynset))
AnnotationAssertion(re:linkedSynset re:
    ServeBeverage <http://www.w3.org/2006/03/wn/
    wn20/instances#synset-serve-verb-6>)
```

Fig. 7: Excerpt of an annotated semantic task description in OWL functional syntax linking the task type with a synonym set of associated verbs.

The grammar generation process takes an OpenCCG grammar template[3] as an input. It contains the static parts of the grammar, i.e., functions, macros, and category definitions. The functions and macros are then used during the generation of the dynamic part of the grammar, e.g., to create the singular, singular third person, and plural forms of a verb. Furthermore, the template describes commonly used words which are not linked with concepts in our ontologies. For instance, definite and indefinite articles, prepositions, and pronouns. As a next step, the knowledge base is queried for all annotated task and object concepts, which results in a set of ontology concepts and their Wordnet synset annotations. The verbs, nouns, and adjectives from these synsets are then added to the grammar. An overview of the configuration phase in given in Fig. 6.

2) Runtime Phase: The OpenCCG grammar generated during the configuration phase is used by a dialog component to parse natural language utterances into a logical form. This representation is used to analyze a sentence's structure, and how the different parts are semantically related to each other, e.g., which noun is the subject of which verb. Starting from the logical form, the robot system has to determine, which task the human operator intends to be executed.

This is achieved by grounding the sentence's referents in

[3]http://www6.in.tum.de/~perzylo/template.ccg

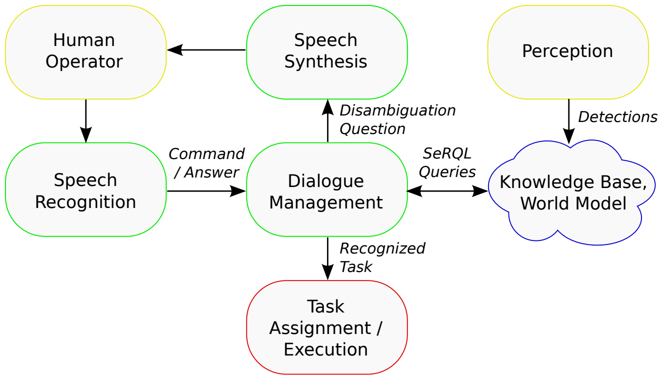


Fig. 8: Overview of runtime phase

the robot's knowledge base. Verb phrases are considered to correspond to a task that shall be executed. They have different numbers of associated noun or prepositional phrases, which form their arguments. They refer to objects the tasks have to be performed upon. Hence, each argument has to be grounded in the robot's knowlege base. The identification process first searches for all possible task candidates by matching the used verb with the synsets linked from the task concepts. This list is narrowed down by filtering out candidates, which require a different amount of arguments, or different types of arguments. If a single task could be identifed, it is selected for execution, otherwise a disambiguation dialog is initiated [17]. The runtime phase is summarized in Fig. 8.

VII. Conclusion

In this paper, we show how to specify and execute abstract process descriptions and their tasks, e.g., using geometric interrelational constraints between involved objects to define an assembly or grasp pose. The representation of deep object models, which are required to formulate such constraints on individual edges or faces, is based on the BREP formalism. It encodes the exact geometric properties of the objects' shapes. Using the knowledge on contained primitive shapes further improved the performance of our object detection and pose estimation.

In order to command the robot system through natural language, we automatically generate grammars to parse and map utterances to concepts in our ontological taxonomy of tasks and objects.

Having described all relevant aspects of a robot system and its tasks in a semantic way (ubiquitous semantics), the system can benefit from synergy effects created through linking the available information and reasoning about its implications.

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References

[1] A. Perzylo, N. Somani, S. Profanter, M. Rickert, and A. Knoll, "Toward efficient robot teach-in and semantic process descriptions for small lot sizes," in *Proceedings of Robotics: Science and Systems (RSS), Workshop on Combining AI Reasoning and Cognitive Science with Robotics*, Rome, Italy, July 2015, http://youtu.be/B1Qu8Mt3WtQ.

[2] M. Tenorth, A. C. Perzylo, R. Lafrenz, and M. Beetz, "Representation and Exchange of Knowledge About Actions, Objects, and Environments in the RoboEarth Framework," *IEEE Transactions on Automation Science and Engineering*, vol. 10, no. 3, pp. 643–651, July 2013.

[3] A. Gaschler, R. P. A. Petrick, M. Giuliani, M. Rickert, and A. Knoll, "KVP: A Knowledge of Volumes Approach to Robot Task Planning," in *IEEE/RSJ Intl Conf on Intelligent Robots and Systems (IROS)*, November 2013, pp. 202–208.

[4] M. E. Foster, A. Gaschler, M. Giuliani, A. Isard, M. Pateraki, and R. P. A. Petrick, "Two people walk into a bar: Dynamic multi-party social interaction with a robot agent," in *Proceedings of the 14th ACM International Conference on Multimodal Interaction (ICMI 2012)*, 2012.

[5] M. Waibel, M. Beetz, J. Civera, R. D'Andrea, J. Elfring, D. Gálvez-López, K. Häussermann, R. Janssen, J. Montiel, A. Perzylo, B. Schießle, M. Tenorth, O. Zweigle, and R. van de Molengraft, "RoboEarth," *IEEE Robotics & Automation Magazine*, vol. 18, no. 2, pp. 69–82, June 2011.

[6] J. Elfring, S. van den Dries, M. J. G. van de Molengraft, and M. Steinbuch, "Semantic world modeling using probabilistic multiple hypothesis anchoring," *Robotics and Autonomous Systems*, vol. 61, no. 2, pp. 95–105, Dec. 2012.

[7] D. Hunziker, M. Gajamohan, M. Waibel, and R. D'Andrea, "Rapyuta: The RoboEarth Cloud Engine," in *2013 IEEE International Conference on Robotics and Automation*. IEEE, May 2013, pp. 438–444.

[8] S. Coradeschi, A. Loutfi, and B. Wrede, "A short review of symbol grounding in robotic and intelligent systems," *KI-Künstliche Intelligenz*, vol. 27, no. 2, pp. 129–136, 2013.

[9] A. Perzylo, N. Somani, M. Rickert, and A. Knoll, "An ontology for CAD data and geometric constraints as a link between product models and semantic robot task descriptions," in *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2015.

[10] N. Somani, A. Gaschler, M. Rickert, A. Perzylo, and A. Knoll, "Constraint-based task programming with cad semantics: from intuitive specification to real-time control," in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2015.

[11] N. Somani, A. Perzylo, C. Cai, M. Rickert, and A. Knoll, "Object detection using boundary representations of primitive shapes," in *Proceedings of the IEEE International Conference on Robotics and Biomimetics (ROBIO)*, Zhuhai, China, December 2015.

[12] "HSL. A collection of Fortran codes for large scale scientific computation," 2013. [Online]. Available: http://www.hsl.rl.ac.uk

[13] A. Wächter and L. T. Biegler, "On the implementation of an interior-point filter line-search algorithm for large-scale nonlinear programming," *Mathematical Programming*, vol. 106, no. 1, pp. 25–57, 2006.

[14] N. Somani, E. Dean-Leon, C. Cai, and A. Knoll, "Scene perception and recognition in industrial environments for human-robot interaction," in *9th International Symposium on Visual Computing*, July 2013.

[15] S. Profanter, A. Perzylo, N. Somani, M. Rickert, and A. Knoll, "Analysis and semantic modeling of modality preferences in industrial human-robot interaction," in *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2015.

[16] A. Perzylo, N. Somani, S. Profanter, M. Rickert, and A. Knoll, "Multimodal binding of parameters for task-based robot programming based on semantic descriptions of modalities and parameter types," in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Workshop on Multimodal Semantics for Robotic Systems*, Hamburg, Germany, September 2015.

[17] A. Perzylo, S. Griffiths, R. Lafrenz, and A. Knoll, "Generating grammars for natural language understanding from knowledge about actions and objects," in *Proceedings of the IEEE International Conference on Robotics and Biomimetics (ROBIO)*, Zhuhai, China, December 2015.