Commonsense Knowledge in Cognitive Robotics: A Systematic Literature Review - Reviewprotocol

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Abstract

One of the big challenges in robotics is the generalisation necessary for performing unknown tasks in unknown environments on unknown objects. For us humans, this challenge is simplified by the commonsense knowledge we can access. For cognitive robotics, representing and acquiring commonsense knowledge is a relevant problem, so we perform a systematic literature review to investigate the current state of commonsense knowledge application in cognitive robotics. For this review, we combine a keyword search on six search engines with a snowballing search on six related reviews, resulting in 2,048 distinct publications. After applying pre-defined inclusion and exclusion criteria, we analyse the remaining 52 publications. Our focus lies on the use cases and domains for which commonsense knowledge is employed, the commonsense aspects that are considered, the datasets / resources used as sources for commonsense knowledge and the methods for evaluating these approaches. Additionally, we discovered a divide in terminology between research from the knowledge representation and reasoning and the robotics community. This divide is investigated by looking at the extensive review performed by Zech et al. [98], with whom we have no overlapping publications despite the similar goals. This document is the reviewprotocol, providing additional information about our search procedure and analysis.

Keywords: Commonsense knowledge, cognitive robotics, systematic literature review, reviewprotocol

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1. Introduction

Robots have the potential to support us in a number of activities: On the one hand, there has been a massive adoption of cost-efficient robots that support us in house cleaning (e.g. vacuum cleaning) and gardening (e.g. lawn mowing) activities. On the other hand, research in household robotics has led to robots being able to clean the breakfast

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table [41] or prepare drinks [81] and pizzas [23]. Yet, the ability of robots to support us in more complex everyday tasks is still very limited. In particular, they break down in situations where they are challenged by new tasks, new environments or new objects for which they lack knowledge [10].

In order to increase the robustness of cognitive robots in everyday tasks, robots need to be equipped with *commonsense knowledge (CSK)*. As the name suggests, CSK in humans is understood as "information that people usually take for granted and, hence, normally leave unstated" [13], which increases the difficulty for the automatic acquisition and deployment. Regarding the robotics domain, we follow the definition provided by Gupta and Kochenderfer [29], which focuses on knowledge about human desires, physics & causality as well as objects with their locations, properties & relationships.

To provide an overview over the coverage of CSK for cognitive robotics, we perform a systematic literature review following the principles and guidelines provided by Kitchenham and Charters [43] and Okoli [62]. To increase repeatability and traceability of our review, we tracked our progress in this reviewprotocol.

This document is structured as follows: We provide our research questions in Section 2. In Section 3, we provide an overview over related work and describe, how we found similar surveys and reviews. The search procedure we employ to find suitable publications for the data analysis is presented in Section 4. The in- and exclusion criteria we rely on during our search are provided in Section 5. In Section 6 we summarise all of the 52 publications we found during our search before before mapping them to the CSK questions they are equipped to answer in Section 7.

2. Research Questions

RQ1 For which use cases has the use of CSK been considered in robotics research?

RQ2 Which aspects of CSK have been considered? Which aspects of CSK have received less consideration?

RQ3 Which datasets or resources are mainly considered in robotics as a source for CSK?

RQ4 What methods are employed to assess the approaches? Which CSK datasets or resources are utilised in these evaluations?

3. Related Work

3.1. Overview and Summary

A summary over all related literature reviews we found and examined can be viewed in Table 1. All in all, only six of the 30 related literature reviews can be classified as *systematic* ([12, 55, 60, 63, 87, 98]) and only six are close enough to the focus of our literature search that we include them in our snowballing search ([12, 55, 63, 65, 80, 87]). More information about that can be read in Section 4.2.

3.2. Search Process

- Guan et al. [28], Huang et al. [32], Olivares-Alarcos et al. [63], Sarkheyli-Hägele and Söffker [76], Tellex et al. [82] were found on Google Scholar by one of the following *keyword searches*:
  - *"knowledge-enabled robot" (taxonomy OR survey OR review OR overview)*
  - *"knowledge-based robot" (taxonomy OR survey OR review OR overview)*
  - *"robot cognition" (taxonomy OR survey OR review OR overview)*
  - *"common sense knowledge" AND robot AND (taxonomy OR survey OR review OR overview) -human*
- Zech et al. [98] was provided by Michael Beetz as an example for a survey about (knowledge) representation from the perspective of the robotics domain
- Kahraman et al. [38], Li et al. [49], Manzoor et al. [55], Min et al. [57], Prasad and Ertel [67], Redfield [71], Wu et al. [94] were found by looking at the in- and outgoing references (on Google Scholar) of other reviews (*snowballing*):
  - publications citing Olivares-Alarcos et al. [63]: [55, 67, 94]
  - publications citing Zech et al. [98]: [71]
  - publications cited by Paulius and Sun [65]: [57]
- Brunner et al. [11], Buchgeher et al. [12], Coradeschi et al. [18], Ersen et al. [26], Gouidis et al. [27], Kahraman et al. [38], Khamassi et al. [42], Kroemer et al. [44], Li et al. [49], Liu and Zhang [52], Malhotra and Nair [54], Nocentini et al. [60], Paulius and Sun [65], Prasad and Ertel [67], Qin et al. [70], Saghiri [74], Sun and Zhang [80], Tepjit et al. [84], Thosar et al. [87] were found during our review (see Section 4)

4. Search Procedure

To gather suitable publications to answer our research questions, we combine a keyword search using four keywords on six different search engines with a snowballing procedure looking at the in- and outgoing references of six different literature reviews introduced in Section 3. A summary of the procedure and its result can be examined in Figure 1 and a comprehensive overview over the found duplicates is provided in Figure 2.

4.1. Keyword Search

We employ the following search engines: Google Scholar (GS), Scopus, IEEE Xplore (IEEE X), ACM Digital Library (ACM DL), Web of Science (WoS) and Science Direct (SD). We use the following four keyword strings on each search engine while restricting the search results to only include publications from the last 10 years:

K1 *"knowledge-enabled robot" OR "knowledge-based robot" OR "knowledge-driven robot"*

K2 *"knowledge processing" AND robot AND question AND NOT interaction AND NOT hardware*

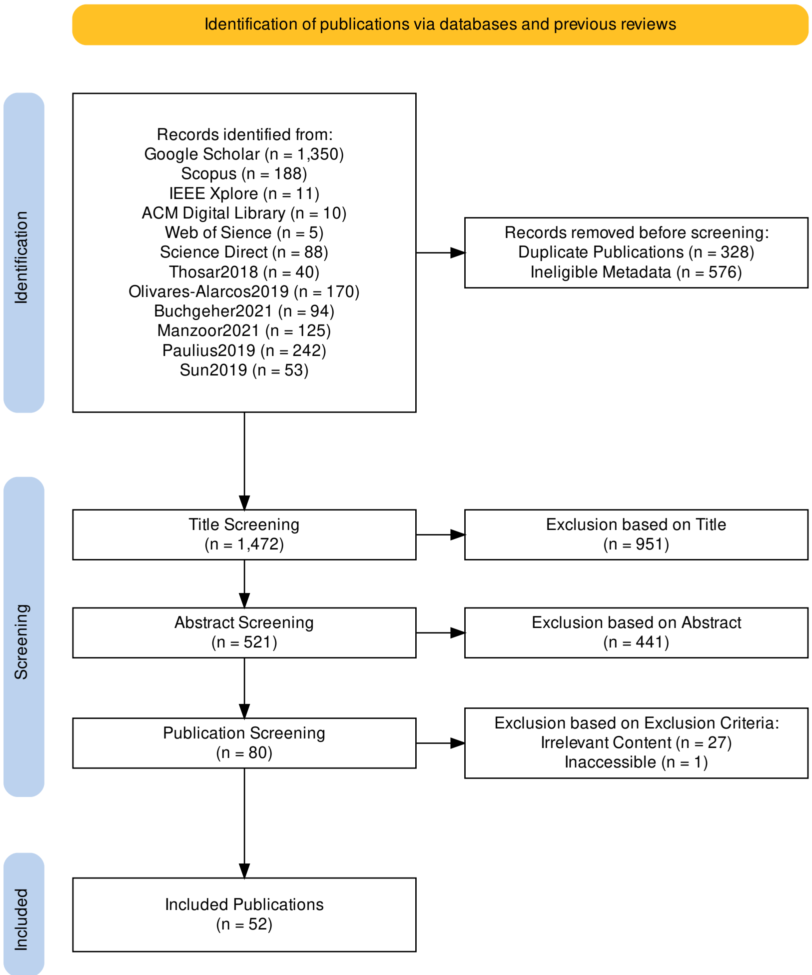

Figure 1: Visualization of the search procedure with its intermediate steps and the amount of publications found and analyzed in each step. This image was created with [30].

K3 *"common sense knowledge" AND robot AND NOT interaction AND NOT hardware*

K4 *"common sense" AND ("robot cognition" OR "cognitive robot")*

The results, separated based on keywords and search engines, can be examined in Table 2.

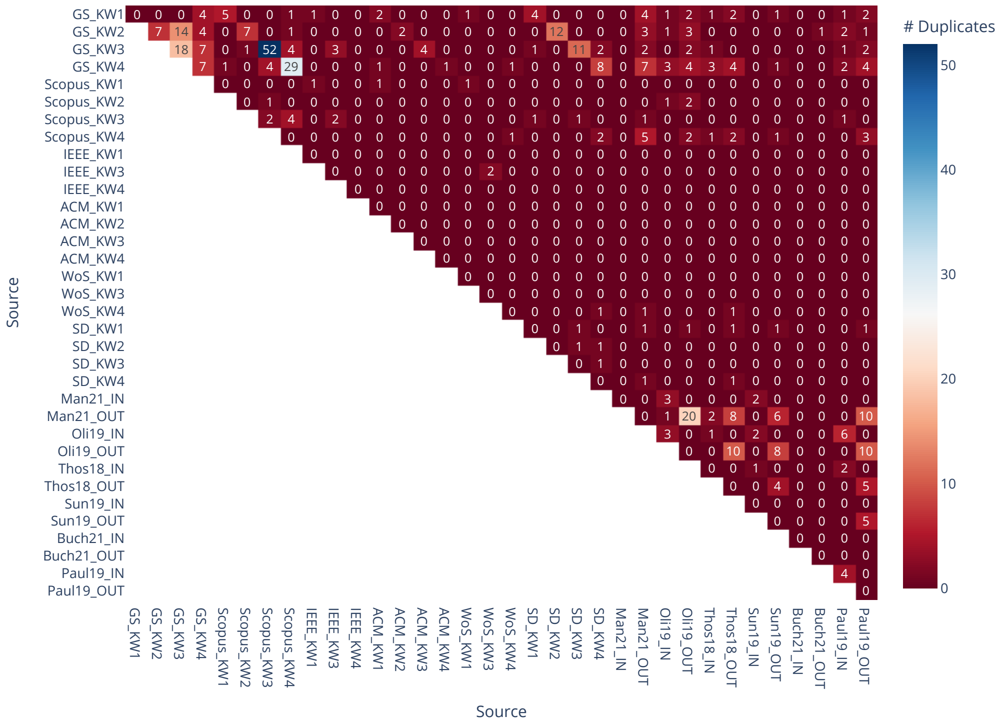

Figure 2: Duplicate entries between the different data sources from the keyword and the snowballing procedure.

Table 2: Keyword search.

Source	K1	K2	K3	K4	Σ
GS	67	380	703	200	1350
Scopus	6	28	107	47	188
IEEE X	1	0	9	1	11
ACM DL	2	2	4	2	10
WoS	1	0	3	1	5
SD	14	23	14	37	88
Σ	91	433	840	288	**1652**

Table 3: Snowballing search

SLR	# Ingoing	# Outgoing	Σ
[87]	14	26	40
[63]	61	109	170
[65]	82	160	242
[80]	4	49	53
[12]	22	72	94
[55]	14	111	125
Σ	197	527	**724**

4.2. Snowballing

In addition to the keyword search, we also included the in- and outgoing references[1] for the following six literature reviews presented in Section 3.1: [12, 55, 63, 65, 80, 87].

[1]information about the ingoing references is taken from Google Scholar

We choose these, because the focus of their review is close enough to our SLR that the inclusion of their publications can result in valuable additions. During this search, we followed the guidelines by Wohlin [93]. The results can be examined in Table 3.

5. Inclusion and Exclusion Criteria

5.1. Inclusion Criteria for the Metadata

A publication is included when ...

- ... it is peer-reviewed (**No** thesis, technical report, patent, presentation or book).
- ... it is written in English.
- ... it was published in the last ten years ($\in [2012 - 2022]$).
- ... its metadata contains enough information to evaluate if it is peer-reviewed (at least the title, authors, year and venue).

5.2. Inclusion Criteria for the Title, Abstract and Content

A publication is included when ...

- ... it applies CSK through a robot on a specific scenario or use case (**RQ1**).
- ... it describes a technique that equips cognitive robots with the possibility to answer certain questions about CSK (**RQ2**).
- ... it introduces or employs a (novel) source for collecting the necessary CSK (**RQ3**).

5.3. Exclusion Criteria

A publication is excluded when ...

- ... no complete version of the paper is accessible.
- ... it does not employ CSK, it is not applied in the robotics domain or it does not provide new content but instead gives an overview over work done in other publications.

6. Summarizing All 52 Included Publications

The contributions of the 52 final publications (see Figure 1) that are analyzed as part of our SLR are briefly summarized in the following:

1. Agostini et al. [1]: Planning architecture employing logic-based data to automatically find replacements for missing objects in the context of manipulation tasks. The object replacement uses the affordances of the missing as well as the available objects.

2. Aker et al. [2]: Using Answer Set Programming on housekeeping robotics to automatically embed CSK extracted from ConceptNet [79] as well as embedding geometric and temporal reasoning. This reasoning takes the current action duration and actor location into account to ask for support from other agents if needed.
3. Al-Moadhen et al. [4]: Framework for modelling high-level actions called Semantic Action Model (SAM) which is integrated with CSK to support a more efficient and reasonable planning by modelling actions through their in- and outputs, preconditions and effects.
4. Al-Moadhen et al. [3]: Framework for modelling high-level actions called Semantic Action Model (SAM) which is integrated with CSK to support a more efficient and reasonable planning. Evaluation by employing robots for fetching objects in a household and looking for object replacements. Updated version of [4].
5. Ayari et al. [5]: Distributed cognitive architecture for seamless integration of actors in an ambient assisted living environment, including an expressive model for CSK representation and reasoning on events.
6. Beetz et al. [6]: Extension and redesign of the *KnowRob* [83] framework that includes highly detailed (sub-)symbolic models of environments & robot experiences, visual reasoning and simulation-based reasoning.
7. Beßler et al. [8]: Introducing the foundations of the Socio-Physical Model of Activities (SOMA), an ontology covering the physical and social context for everyday activities. For each aspect of a task (e.g. events, objects) the physical and social aspects as well as their relationship are described.
8. Chernova et al. [15]: Domain-independent and probabilistic framework for generating a context-specific knowledge network from seed words obtained from the task description. This networks covers the following relations: `IsA, AtLocation, HasProperty` and `UsedFor`.
9. Chiatti et al. [16]: Augmenting Deep Learning methods for object recognition with knowledge-based reasoning about the typical size and spatial relations of objects to optimize object recognition. This knowledge is taken from CSKBs like ShapeNet [14].
10. Daoutis et al. [19]: Model for grounding symbolic and perceptual data about concepts originating on the web in the physical perception. Employing the Cyc upper ontology [48] to learn semantic concepts about perceived objects.
11. Daruna et al. [20]: Computational framework for semantic reasoning called *RoboCSE* that encodes CSK knowledge mined from a highly realistic simulation environment in multi-relational embeddings. Based on the mined CSK, the robot can automatically infer missing parts of RDF triples.
12. De Silva et al. [22]: Identify keywords in incomplete natural language commands and use them and CSK to understand the incomplete instructions. Based on already identified commands, a model is built for the robot to employ for future instructions.
13. Dhanabalachandran et al. [25]: Proposes a plan adaptation method based on event segmentation of the image-schematic states of subtasks within action descriptors. This approach is applied on the task of "Cutting bread".
14. Haidu and Beetz [31]: Special-purpose knowledge acquisition, interpretation and processing system called AMEvA that mines CSK and physics knowledge from

observed humans by simulating virtual living and working environments where humans interact through VR.

15. Jäger et al. [33]: Framework to use robots to collect information about six physical and four functional object properties to fill a robot-centric knowledge base. In this approach, instead of mapping abstract symbols to sensory data, the symbols are grounded by deriving them from the sensory data.
16. Jakob et al. [34]: Approach for handling semantic inconsistencies in a robot household scenarios by relying on CSK, sensor inputs and the situational knowledge of the robot. The approach employs ConceptNet [79] to find inconsistencies by comparing the antonyms and synonyms of currently relevant object properties.
17. Javed et al. [35]: Creation of an dynamic ontology-based agent architecture that can learn from past experiences for better action planning and adaptation by dynamically constructing rules to provide multiple solutions for the current situation.
18. Javia and Cimiano [36]: Knowledge-based robot architecture to describe robot behaviour through declarative action representation using ontologies and logical programming (*Prolog*), where executable plans are inferred through Prolog resolution.
19. Jebbara et al. [37]: Three approaches (2x unsupervised, 1x supervised) for extracting manipulation-relevant relations regarding object locations and use, ranked by their 'prototypicality'.
20. Kaiser et al. [39]: Automatic acquisition of CSK from natural language text corpora for the inference of relevant objects and their possible locations in the kitchen domain. The objects are organized in an automatically learned domain ontology consisting of concrete nouns and verbs.
21. Kanjaruek et al. [40]: Systematic architecture and an algorithm to automatically create and manipulate an ontology for robots in domestic environments. The ontology is focused on identifying objects and creating their hierarchy, querying WordNet [56] to automatically add unknown objects.
22. Kümpel et al. [45]: Connecting robot sensors to linked data to provide agents with semantic product information about the detected objects in a retail environment using a knowledge graph called *NonFoodKG*.
23. Lam et al. [46]: Evaluation method for weighing object-activity connections in the *Basic-Level Knowledge Network* [47], which is used as a foundation to automatically build a robot ontology for *bring something* tasks.
24. Li et al. [50]: Knowledge-based method for remote object navigation (RON) using a hierarchical scene knowledge graph and a probability-based navigation strategy to minimize navigation costs. Focus on the correlation of objects and rooms as well as objects and other objects inside a room.
25. Liu and Zhang [51]: Fuzzy context-specific intention inference (FCII) method based on a CSK database for objects, their affordances and the current context.
26. Liu et al. [53]: *WebIA* approach to establish a knowledge database for robots performing context-specific intention awareness by querying and evaluating WikiHow instructions. Uses object affordances extracted from WikiHow as foundations for possible human intentions.
27. Mitrevski et al. [58]: Strategy for generalising parameterised execution models for action manipulations over different objects based on an object ontology.

28. Mühlbacher and Steinbauer [59]: Approach for reusing existing CSK from OpenCyc [48] in a belief management system to find inconsistencies between the current sensor data and information in the knowledge base. It checks whether a detected object occurs at the expected location.
29. Nyga and Beetz [61]: Introduces the concept of *probabilistic action cores (PRACs)*, which represents action-specific knowledge for everyday activities to generalize concepts of an action that have been attached to a set of relations assigning semantics to all entities that are required to effectively perform the action
30. Pangercic et al. [64]: Extension of the first generation Semantic Object Map (SOM) called SOM^+, which also includes knowledge about the appearance and articulation of furniture objects and is created through more inexpensive means.
31. Pradeepani et al. [66]: Providing an improved training model to give robots the ability to act more human-like when performing tasks by answering questions about incomplete commands / inquiries related to a given context using BERT [24] to re-train the ontology.
32. Pratama et al. [68]: Conceptual design for a context-influenced Long-Term Memory (LTM) architecture and an analysis how the context-sensitivity influences the robots behaviour.
33. Riazuelo et al. [73]: Link the RoboEarth KB [90] with visual perception and object recognition for robot planning and action selection. Inside the RoboEarth KB, location information from the OMICS project [29] is included and employed here to calculate the probable location of an object.
34. Riazuelo et al. [72]: System for semantic mapping as part of the RoboEarth framework [90] that consists of an ontology describing concepts and relations as well as a SLAM map providing scene geometry and object locations.
35. Salinas Pinacho et al. [75]: Extension of an existing robot architecture to be able to reason about, understand & obtain information from human demonstration in VR. The robots are equipped with CSK that allows them to ask questions about object placements in a table setting environment.
36. Shylaja et al. [77]: Architecture called *Consciousness and Common Sense Architecture (COCOCA)* for designing cognitive models focusing on consciousness and common sense actions. In this architecture, the learned knowledge is converted into CSK over time.
37. Skulkittiyut et al. [78]: Method to automatically sort objects into three classes using machine learning methods (SVM, ANN) based on the object attributes from ConceptNet [79] and the normalized Google distance [17]. This method is applied on objects placed on a table that a robot should *tidy up*.
38. Tenorth and Beetz [83]: Knowledge processing systems for automated robots called *KnowRob* that employs virtual knowledge bases (VKBs) and is part of the CRAM framework [7]. Decisions are formulated as inference tasks that can be answered using the robot's internal data structures.
39. Thosar et al. [85]: Tool substitute recommendation based on robot-centric knowledge by generating conceptual knowledge about objects and identifying functional properties required to achieve the goal of the current task.
40. Thosar et al. [86]: Framework for generating robot-centric conceptual knowledge about physical and functional object properties based on quantitative sensory data. This approach combines [85] and [33].

41. Varadarajan and Vincze [88]: Introduction of *AfRob*, an extension of *AfNet* focused on robotic applications. This extension defines semantic affordance features that are independent of model representations, it introduces a mechanism for affordance filtering and a mechanism for task-based grasp adaptation and it describes a platform to implement and test affordance-based object recognition.
42. Vassiliades et al. [89]: Knowledge retrieval framework to extract information about household objects and activities from the VirtualHome dataset [69]. Additionally, this information is semantically matched with entities taken from semantic web sources like WordNet [56], ConceptNet [79] and DBpedia [9].
43. Wang et al. [91]: Unified framework to extend iCORPP's [99] probabilistic action language to better express utility, belief states and observations while also better reflecting on CSK.
44. Welke et al. [92]: Learning a representation of space applicable on task planning and on the sensori-motor level from experience. This experience comes from two places: the robot exploring its memories and CSK from text corpora.
45. Wu et al. [95]: Social robot companion that evokes people's memories by asking relatable and engaging questions about a presented photograph depicting a social event from the persons life.
46. Xin et al. [96]: Fine-grained tool recommendation based on the task and the manipulated object relying on a hierarchy of tools that describes the semantics of tasks, tools and manipulated objects on two different levels of granularity.
47. Yang et al. [97]: Method for desire-driven reasoning about everyday objects and their properties and functions for robots employed in personal care scenarios.
48. Zhang and Stone [99]: Algorithm called *CORPP* that combines probabilistic Answer Set Programming (*P-Log*) with non-deterministic state transitions and unreliable observations (*POMDP*s) to combine reasoning with logical and probabilistic CSK with planning under probabilistic uncertainty.
49. Zhang et al. [100]: Procedural knowledge understanding through the brain-inspired active learning architecture (BALA) that combines deep learning techniques with knowledge graphs to replicate the human brain as much as possible.
50. Zhang et al. [101]: General probabilistic model for spatial locations of dynamic and environment objects in a household environment as a foundation for a search strategy. Employing CSK about spatial locations for rooms, static and dynamic objects to increase efficiency during planning.
51. Zhou et al. [102]: Online knowledge acquisition mechanism for discovering Common Sense about Object Locality (CSOL) knowledge for mobile robot search and planning tasks.
52. Zhu et al. [103]: Framework for task-oriented object recognition as a foundation for imagining and choosing arbitrary objects as possible tools for household tasks. The approach represents / calculates 4 aspects of each object: the grasping location, the target interaction location, the imagined action and the physical concepts of the produced end results.

7. CSK Questions and Their Corresponding Approaches

- *What is the expected location for an object?* - [2, 6, 15, 20, 31, 37, 39, 40, 45, 50, 59, 64, 66, 72, 73, 78, 83, 89, 92, 97, 101, 102]

- *What affordances does an object have?* - [1, 6, 8, 15, 20, 25, 33, 35–37, 46, 51, 51, 88, 89, 96, 103]
- *Which tools can be used for a certain task?* - [1, 8, 15, 25, 35, 39, 61, 85, 86, 96, 103]
- *Which objects are similar to the given object?* - [1, 3, 33, 40, 85, 86, 89, 91, 96]
- *How can I interact with an object / container / etc.?* - [6, 8, 61, 64, 73, 83, 100, 103]
- *Can I accomplish the given task or do I need help?* - [2, 5, 6, 73, 83, 91, 99]
- *What are the physical properties of an object (e.g. size, shape, color)?* - [16, 19, 25, 33, 40, 64, 86]
- *Where to place objects (on a table)?* - [3, 4, 6, 31, 58, 75, 83]
- *How can an object be transported / grasped?* - [6, 31, 58, 83, 88, 103]
- *How can I react to an incomplete command by a human?* - [22, 61, 66, 91]
- *What are the spatial relations of this object?* - [16, 19, 68, 100]
- *What materials make up the object?* - [20, 40, 88, 103]
- *Which objects in the environment need to be avoided?* - [3, 4, 36, 77]
- *What are the intentions a human could have with a certain object?* - [51, 53, 97]
- *What is the outcome of my current action?* - [6, 25, 103]
- *Where are specific humans located?* - [5, 68, 99]
- *Does my new knowledge contradict my knowledge base?* - [34, 59]
- *What activity / event do I perceive?* - [95, 100]
- *What is the location where certain objects are currently located?* - [72, 92]
- *What parts does the object consist of?* - [40, 64]
- *Which brand produced the object?* - [40, 45]
- *What aspects of my environment are changing?* - [77]
- *What is the (current) functional state of the object?* - [97]
- *What is the (shortest) distance to my current goal?* - [50]
- *What is the sentiment of a concept (positive / negative)?* - [95]

Table 1: Brief summary of all literature reviews found through the search procedure described in Section 3.2. For each publication we provide a brief summary as well as checking whether the literature review follows the principles regarding systematic literature reviews described in [43, 62]. All reviews that we included in our snowballing search are marked in **bold**.

Ref	Focus of the Review	SLR
[18]	Different kinds of symbol grounding in AI	✗
[54]	Knowledge representation & acquisition (*no robots*)	✗
[42]	Integration of different action levels & associated learning mechanisms	✗
[57]	Recognition & Prediction of affordances for robot manipulation	✗
[11]	Ontology-based approaches for autonomous driving	✗
[26]	Recent advances & open problems for cognitive robot manipulation in human environments	✗
[32]	Developmental patterns and modeling methods for autonomous cognitive robot models	✗
[21]	Commonsense Reasoning in AI systems	✗
[70]	Usage of emotions by robots for affective computing & interaction	✗
[87]	**Knowledge Bases for service robots manipulating household objects**	✓
[49]	Neural mechanisms for perception, cognition, learning & robot control based on neuroscience	✗
[52]	Human–Robot cooperation methodologies supported through NLP	✗
[60]	Cognitive architectures, behavioral adaptation and empathy	✓
[63]	**Ontology-based approaches for robot autonomy & their applications**	✓
[65]	**Knowledge representation techniques for service robots**	✗
[80]	**Knowledge representation techniques for robot task planning**	✗
[84]	Front-End Frameworks for reasoning in smart cyber-physical systems	✗
[98]	**Robot actions, their representation and a possible taxonomy**	✓
[27]	Knowledge-based methods for object perception	✗
[38]	Basic principles and concepts of fuzzy sets for humanoid robots	✗
[67]	Knowledge Acquisition, Decision Management, Reasoning, Situation Awareness, Human-Robot Interaction & Planning	✗
[74]	Challenges in designing cognitive engines	✗
[76]	Application of fuzzy approaches to case-based reasoning for real-time applications	✗
[82]	Use of natural language for request understanding, learning & human-robot interaction	✗
[12]	**Knowledge Graphs and their application in the production / manufacturing domain**	✓
[44]	Machine Learning for manipulation tasks	✗
[28]	Techniques to transfer skills, applications, advancements & limitations	✗
[55]	**Ontology-based approaches for robot autonomy & their applications**	✓
[71]	Different robot taxonomies and their similarities (*tertiary study*)	✗
[94]	Learning from demonstration & semantic methods for robot learning	✗

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