Application of MSDL in Modeling Capabilities of Robots

Muhammad Raza Naqvi[1,2,*], Arkopaul Sarkar[1], Farhad Ameri[2], Sina Namaki Araghi[1] and Mohamed Hedi Karray[1]

[1] *(LGP-INP-ENIT), Universit ´e de Toulouse, 47 Av. d'Azereix, Tarbes, 65016, France.*
[2] *Engineering Informatics Lab, Texas State University, San Marcos, TX 78666, USA.*

Abstract

Robotic systems' flexibility, precision, and effectiveness are changing various industries. As these systems grow more versatile, a complete model of their capabilities becomes increasingly important. The Robotic Capability Ontology (RCO), an application ontology created explicitly for capturing robotic capabilities, is presented in this paper. Modeling robot capabilities according to user manuals or design/technical specifications from manufacturers is the main objective of RCO. The RCO utilizes the Manufacturing Service Description Language (MSDL), a domain reference ontology designed for manufacturing services and aligned with the Basic Formal Ontology (BFO) and Information Artifact Ontology (IAO). MSDL's modular structure and manufacturing domain-neutral classes allow RCO to describe robotic capabilities and expand upon them precisely. For those seeking to install and use robots, RCO has significance because it promotes collaborative behavior, design help, appropriate use of resources, enhancements in efficiency, and optimized planning. Additionally, it encourages research initiatives to develop. The development and applicability of the RCO are covered in greater length in this article.

Keywords

Autonomous Robotics, Ontological Modeling, Robot Capability, Flexible Manufacturing

1. Introduction

We are on the leading edge of a robotics revolution that promises to transform the world in multiple dimensions as the new era of modern technology takes shape. Robotics has wholly transformed our society and economies [1], redefining industries [2] such as healthcare [3], manufacturing [4], education [5], and other emerging industries [6], introducing competence, dependability, and even innovation on a scale that wasn't possible before. Nowadays, robots can not only do predefined tasks but also evolve and grow, providing a range of capabilities that extend past their initial design.

We must represent the idea of capability in robotics, collecting pre-designed capabilities via the robot's manufacturer design specification or robot manual to determine the robots' factual capability. An ontological model can offer the framework for recognizing and distinguishing these capabilities. We demonstrate the design of an ontological model that precisely captures

---

RobOntics 2023: Workshop on Ontologies in Autonomous Robotics, August 28, 2023, Seoul, South Korea

[*] Corresponding author.

✉ snaqvi@enit.fr (M. Naqvi); asarkar@enit.fr (A. Sarkar); ameri@txstate.edu (F. Ameri); snamakia@enit.fr (S. Araghi); mkarray@enit.fr (M. Karray)

CEUR Workshop Proceedings (CEUR-WS.org)

these notions of the robot from its design specifications. We utilize Manufacturing Service Description Language ontology[7]. MSDL was chosen as the foundation for our application RCO ontology because of its intended design for manufacturing services and alignment with Basic Formal Ontology (BFO)[1] a top-level ontology that is widely used, serves as the foundation for a concept's hierarchy. BFO is intended to be a multipurpose ontology that may be used as a model for ontologies that are specialized to particular domains. It offers a collection of fundamental categories and relations that may be applied to describing items and the interactions among them. BFO is meant to be domain-neutral and sufficiently abstract to be relevant across various fields. Due to its inheritance from BFO as a top-level ontology and its availability of a modular and extendable set of classes and relationships that may be connected to our domain ontology, MSDL is adequate for our purposes.

The remainder of this article is structured into the following three sections; Section 2 provides a brief overview of robotics scholars' literature studies and how capability modeling has a truly greater impact on the future of robotics. It also discusses the importance of ontologies and how they can help model robotic systems' capabilities. Section 3 emphasizes reasons why modeling robotic capabilities is critical, especially in applications in industrial Use cases. Section 4 examines the proposed approach for modeling robotic design specifications using (MSDL) and explains how we model robotic capabilities and section 5 validation of the ontology model via SPARQL at last. Section 6 prescribes upon conclusion and how we further expand this approach. Finally, This paper clarifies the significance of ontological approaches for modeling notion capability in robotics.

2. Related work

These enormous advances in robotics are about more than merely automating tasks; it is also about giving robots abilities that closely resemble, and in some cases meet or exceed human capabilities [8, 9, 10, 11]. On the other hand, the emergence of more powerful robotics integrated with cutting-edge machine learning(ML) and artificial intelligence (AI) technology has combined these distinctions [12, 13, 14, 15, 16, 17, 18]. The diverse characteristics of robotic capabilities make the modeling procedure more complex due to the notions such as; the robot's reach, precision, and repeatability, additionally, regarding utilizing robotic capabilities in various environments, scenarios, and tasks. It's essential to comprehend the concept of "capability" before diving into the specifics of robotic capabilities. According to ISO 15531-31, [19], capabilities and capacities are distinguished on a qualitative-quantitative axis, where capacity is a quantitative concept exemplified by product throughput, and capability is qualitative. According to Eric et al., "A capability of an entity is, intuitively, the potential for that entity to do something useful" [20].

The word "Capability" is frequently used in daily life as software capabilities, human capabilities, the capabilities we will acquire through learning yoga classes, and so on. Some entities can carry out actions that are useful or wanted. For example, my passport allows me to travel and meet people from different cultures. My football boots provide me with the comfort and support to play football. When choosing actions and attempting to achieve objectives, it is helpful to be aware of the possibility of such activities. Thus, it's critical to know what actions the entities accessible

---

[1] https://basic-formal-ontology.org

to us can take. Sabbagh & Ameri defined “Capability” as the inherent potential of diverse resources in generating benefits for various stakeholders [21]. While Sarkar & Sormaz argued that capability, capacity, and competency are mostly used with interconnected connotations [22]. Francesco & Stefano talks about what are capabilities and capacities, how they are similar to each other in terms of functionality, and how you differentiate as they state, “capacities essentially indicate how the corresponding capabilities can be practically implemented.” also, they perform different analysis based on using the top-level ontology DOLCE as a framework [23]. So based on these definitions, we can state that capability is ” The ability or potential of an entity, process, or product to accomplish a desired result or execute specific tasks under a set of established parameters.”

In robotics, a robot’s capability can relate to performing tasks such as lifting, placing items, navigating areas, detecting objects, or understanding voice. But these are the abilities or tasks a robot is created and programmed from the start to accomplish.

We define it as “Pre-designed capability” because what a robot can perform under actual circumstances could vary from its pre-designed capabilities mentioned in the manufacturer’s design specification or robot manual. A robot’s pre-designed capability, which could have been viewed as its fundamental function, could differ from its actual capabilities observed in practical application contexts. While these functions are addressed in the manufacturer’s design specification or robot manual, a robot’s actual capabilities may diverge dramatically from these pre-planned functions. A robot, for example, maybe pre-designed to perform a specific task in a production line, such as component assembly. Still, in practice, it may be repurposed to transport equipment across the manufacturing facility, a capability the designer or manufacturer may not have originally intended. In an entirely different setting, a robot developed for a specific function may even be used as a weight in a gym, which is a different unanticipated outcome.

3. Modeling of Robotic Capabilities is Pivotal

In this section, we describe various reasons modeling robotic capabilities is critical, especially in applications in industrial Use cases.

- Modeling these capabilities can guide the selection of appropriate robots for specific tasks, leading to improved productivity [24].
- Robots are costly, and a lack of knowledge or modeling of their capabilities can lead to inefficient usage and diminished resources [25]. For example, if a robot’s reach or precision is incorrectly represented, it may be assigned tasks that it cannot accomplish adequately, resulting in inefficiency and waste.
- Robots can endanger human beings if employed outside their capabilities or for jobs not built for that particular task[26]. For instance, understanding a robot’s lifting capability is crucial to prevent it from being overloaded, which could lead to equipment failure or even harm human operators and other equipment.
- Automated Decision-Making towards trustful and flexible manufacturing, promoting reconfiguration in production lines [27].

In the modern era of flexible production systems, robotic capability modeling has grown progressively relevant when robotics is anticipated to carry out various activities [28, 29, 30]. In this context, modeling robotic capabilities helps lead the development of adaptable robotics capable of effortlessly shifting among diverse jobs. Also, modeling robotic capabilities isn't simply an abstract activity but an important part of the industrial process. It influences robotics's development, installation, and secure functioning in industries, impacting productivity, trustfulness, cost efficiency, and security.

To design an effective robotic system or a single robot to perform a particular task, operators, engineering, or people in charge must first grasp the required capabilities of a robot. Ontologies are an excellent answer to this problem. Ontologies can accurately explain and represent complex, constantly evolving systems like robots with varying capabilities and capacities. Several recent works in the literature regarding robotics utilized ontologies to model robotics automation for modeling common concepts, robotics standards, and human-robot interaction [31, 32]. A more nuanced knowledge of what is expected from a robot, including minor skills like being able to perform complicated operations or adjust to evolving circumstances, can be provided through an ontology-based approach to robotics capability modeling. For example, consider three robots that have been trained to do certain tasks: Robot-A assembles parts, Robot-B paints final items, and Robot-C bundles them up for delivery, but when production methods evolve and additional products are added to be produced, they change the production order or add the different specification to the product. Robots existing capability information, which depends purely on pre-designed capability, does not make adapting to these new requirements simple. All robots must be reprogrammed for each new duty, which is expensive and time-consuming and causes delays in production and financial losses. However, suppose the robots can adapt to this change. In that case, they may be able to adapt to new tasks more rapidly while still preserving production efficiency and lowering costs.

To do this, we must represent the idea of capability in robotics, collecting pre-designed capabilities via the robot's manufacturer design specification or robot manual to determine the robot's factual capability. An ontological model can offer the framework for recognizing and distinguishing these capabilities, enabling researchers to develop and deploy more flexible robots.

One important thing to note before discussing the methodology and scope of the Ontology is that RCO has a broader scope in terms of attaining the objectives, which includes (Capability, Function, Quality, and Role) as this work is a part of the project CHAIKMAT [2]. But, in this paper, we stick to the notion of capability. We use the NED2 Robot[3] and its manufacturer Hardware Design Manual[4] as a use-case scenario in the manufacturing industry to model the capability of a robot. We extract some parameters such as **Payload** = 300 g, **Reach** = 440m, and **Repeatability** = 0.5 mm from the technical specifications of NED2 Robot provided by its manufacturer. We use these parameters to model Payload as picking capability, Reach as reach capability, and Repetition as repeatability capability, where the robot's essential functions are to perform handling and transportation. Besides classifying and modeling different capabilities, our ontology should provide insightful responses to important questions concerning these robot capabilities. These Competency Questions (CQ) are tested in section 5.

CQ1: Can a NED2 robot repetitively perform an operation with a precision of +- 0.5 mm? ;

---

[2] https://chaikmat-anr.enit.fr

[3] https://niryo.com/products-cobots/robot-ned-2/

[4] https://docs.niryo.com/product/ned2/v1.0.0/en/index.html

CQ2: Can a NED2 robot pick up a 300-gram item? ; **CQ3:** Can a NED2 robot pick up an item 440mmm distant from its base?

We made the choice to emphasize the practical value of our work when developing our ontology by using real-world scenario-based competence questions. The events we encountered or imagined in a real production line environment served as the basis for our research. The questions we asked, while particular, are typical of many other comparable problems that can come up when deploying robots for automation. For instance, we picked the robot NED2 for our examples because it represents the general class of robots used in comparable production situations, not because our questions are confined to this specific robot. We intended to illustrate how our ontology may address particular, practical issues that emerge when deploying robots in a production environment by concentrating on actual, concrete examples.

4. Using Manufacturing Service Description Language (MSDL) in Robotic Capability Ontology.(RCO)

4.0.1. Applying MSDL in Modeling Robot Capabilities

Key concepts that we used from MSDL are the following MSDL they defined **Capability** "A disposition in whose realization some agent has an interest"; **Engineerined Artificat** conceptualize refers to "An object or object aggregate that is deliberately created to have a certain function and is prescribed by some design specifications." Another critical factor to using MSDL is there are measurement datum for different measurement labels, which are required to model values of different values such as length, and volume; MSDL has partially aligned BFO as well as Open Biological and Biomedical Ontology Foundry (OBO)[5] AND Information Artifact Ontology (IAO)[6].

The RCO extends MSDL's structure as it can expand the collection of classes and relationships by introducing new domain-specific notions required for capturing robot capabilities, as shown in figure 1. We've defined the class RCO:**HandlingandTransportationEquipment** within the MSDL:**Equipment** class to describe equipment specially built for material handling and transportation. This class is a subclass of MSDL:**EngineeredArtifact**, which represents physical and digital items produced through engineering design and production techniques. Furthermore, we've introduced the class RCO:**Robot** as a subclass of RCO:**HandlingandTransportationEquipment**, implying that robots are specific equipment for material handling and transportation. As a result, instances inside our ontology, such as the RCO:**NED2Robot**, can be defined under the RCO:**Robot** class, indicating that it is a component of the larger domain RCO:**HandlingandTransportationEquipment**, and subsequently MSDL:**Equipment**. We've amended the MSDL's **Capability** class, a subclass of the BFO:**Disposition** class of BFO:**Entity** to depict distinct robot capabilities explicitly.

This class relates to an Objective representing an entity's ability to achieve targets connected with its overall purpose. We added the RCO:**MaterialHandlingCapability** as a subclass of MSDL:**ManufacturingCapability** and subsequently, the RCO:**RepeatabilityCapability**

---

[5] http://obofoundry.org

[6] https://www.ebi.ac.uk/ols/ontologies/iao

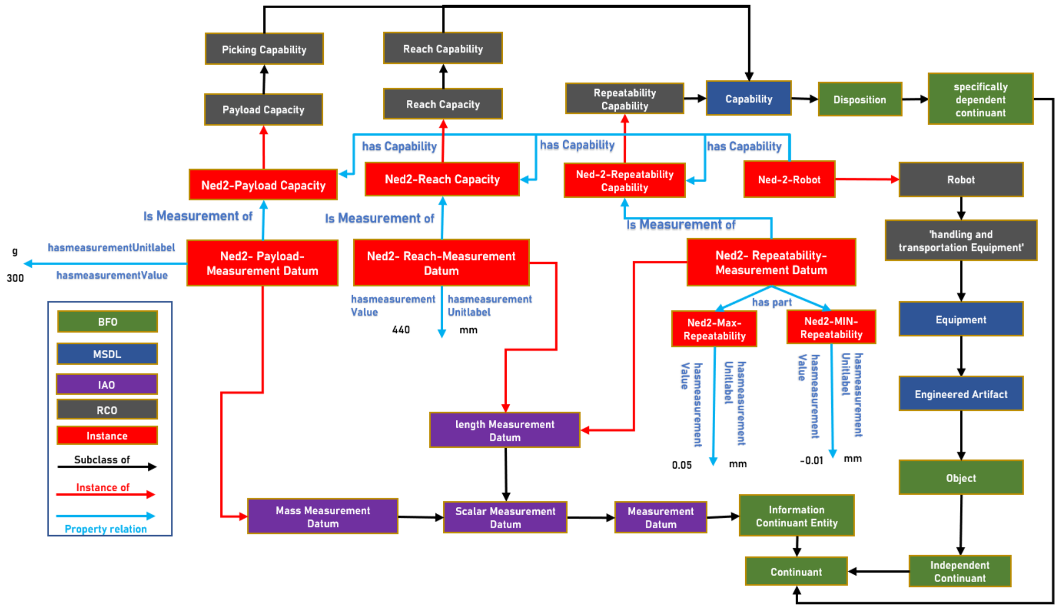
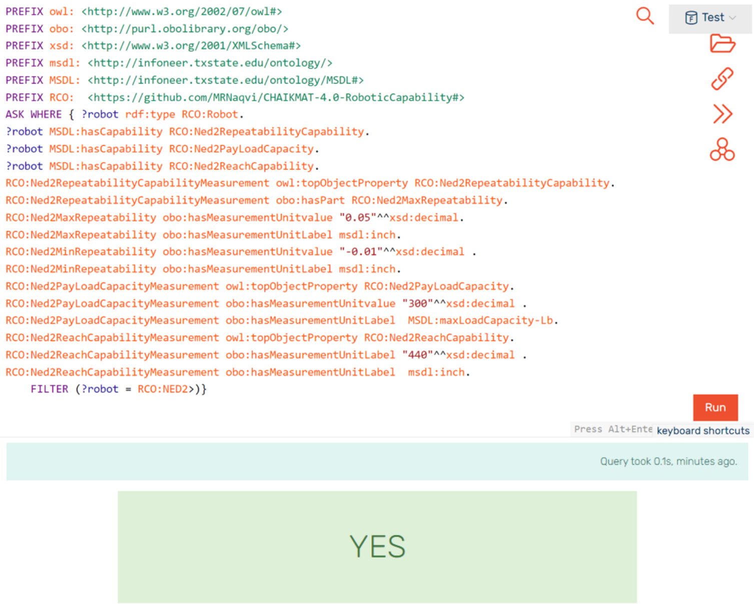


Figure 1: Modeling of NED2 Robot Repeatability Capability

class as a subclass of **MaterialHandlingCapability**. The IAO:**MeasurementDatum** class is a generic class to represent measurement data. IAO:**ScalarMeasurementDatum** is a subclass of IAO:**MeasurementDatum** , and IAO:**LengthMeasurementDatum** is a subclass of IAO:**ScalarMeasurementDatum** to properly define length-related measurement data. We developed a special instance named RCO:**NED2RepeatabilityMeasurement** within the IAO:**LengthMeasurementDatum** class to capture the repeatability measurement value. The object attribute MSDL:**hasCapability** links entities to their capabilities. Thus, using the MSDL:**hasCapability** object property, the NED2 instance is connected to the RCO:**RepeatabilityCapability**.

Moreover, the object attribute RCO:**isMeasurementOf** is developed to represent the link between measurements and capabilities. IAO:**MeasurementDatum** , a subclass of BFO:**InformationContinuantEntity**, is the domain of the RCO:**isMeasurementOf**, and the range is 'BFO:**specificallyIndependentContinuant**, representing the measurement's related specific independent continuant entity. The Basic Formal Ontology (BFO) relationship BFO:**hasPart** represents the lowest and highest values of the NED2 repeatability capability and transmits measurement values, measurement data, and parameter units. The property IOA:**hasmeasurementUnitLabel** shows the parameter unit's label, whereas IOA:**hasMeasurementValue** associates the measurement value with a specific datum. This structure results in an accurate and comprehensive depiction of robotic capabilities in ontology. This ontological framework supports the exact and exhaustive representation of robotic capabilities, emphasizing the need to use RCO in the context of robotics in the manufacturing Industry. We model payload and Reach as a capacity subclass of Capability because of its parameters of capabilities. For Payload, we use Mass Measurement Datum; for Reach, we use the exact length



```
PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX obo: <http://purl.obolibrary.org/obo/>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>
PREFIX msdl: <http://infoneer.txstate.edu/ontology/>
PREFIX MSDL: <http://infoneer.txstate.edu/ontology/MSDL#>
PREFIX RCO:  <https://github.com/MRNaqvi/CHAIKMAT-4.0-RoboticCapability#>
ASK WHERE { ?robot rdf:type RCO:Robot.
?robot MSDL:hasCapability RCO:Ned2RepeatabilityCapability.
?robot MSDL:hasCapability RCO:Ned2PayLoadCapacity.
?robot MSDL:hasCapability RCO:Ned2ReachCapability.
RCO:Ned2RepeatabilityCapabilityMeasurement owl:topObjectProperty RCO:Ned2RepeatabilityCapability.
RCO:Ned2RepeatabilityCapabilityMeasurement obo:hasPart RCO:Ned2MaxRepeatability.
RCO:Ned2MaxRepeatability obo:hasMeasurementUnitvalue "0.05"^^xsd:decimal.
RCO:Ned2MaxRepeatability obo:hasMeasurementUnitLabel msdl:inch.
RCO:Ned2MinRepeatability obo:hasMeasurementUnitvalue "-0.01"^^xsd:decimal .
RCO:Ned2MinRepeatability obo:hasMeasurementUnitLabel msdl:inch.
RCO:Ned2PayLoadCapacityMeasurement owl:topObjectProperty RCO:Ned2PayLoadCapacity.
RCO:Ned2PayLoadCapacityMeasurement obo:hasMeasurementUnitvalue "300"^^xsd:decimal .
RCO:Ned2PayLoadCapacityMeasurement obo:hasMeasurementUnitLabel  MSDL:maxLoadCapacity-Lb.
RCO:Ned2ReachCapabilityMeasurement owl:topObjectProperty RCO:Ned2ReachCapability.
RCO:Ned2ReachCapabilityMeasurement obo:hasMeasurementUnitLabel "440"^^xsd:decimal .
RCO:Ned2ReachCapabilityMeasurement obo:hasMeasurementUnitLabel  msdl:inch.
    FILTER (?robot = RCO:NED2>)}
```

```
Query took 0.1s, minutes ago.

YES
```

Figure 2: Sparql Query For Validation of CQs

measurement datum as repeatability.

5. RCO Validation Through SPARQL

We combine all 3 CQS into one: ” Can a NED2 robot repetitively operate with a precision of +- 0.5 mm, pick up a 300-gram item 440mm distant from its base?” As a result, we could answer our competence question with a binary ” Yes” or ” No,” indicating if the NED2 robot could fulfill all of the requirements at once. We used the GraphDB SPARQL API to run a single comprehensive SPARQL query, as Shown in Fig. 2, to evaluate our (RCO) Competency Questions. Knowing the precise response is essential, but understanding the query’s details and being able to respond to a variety of comparable requests are also important. Using ontologies and SPARQL queries for robotic capabilities improves knowledge modeling and interoperability while providing scalability and automation assistance, allowing for efficient, data-driven decision-making across various systems and applications. Information may be automatically retrieved and analyzed using SPARQL queries, as seen in the NED2 robot example. This can considerably minimize the amount of time and effort required to answer difficult queries concerning a robot’s capabilities. Combined with other systems, ontology and SPARQL investigations can give helpful decision-making information. A manufacturer, for example, can rapidly decide if a given robot fits a specific task based on its established capabilities. This allows for data-driven decisions, which improves efficiency and results.

6. Conclusion and Future Work

Our work demonstrates the significance of ontological models in correctly capturing robotic capabilities to support industrial flexibility. The study underlines the importance of semantically exact models as robots grow capable of performing various functions. An ontological model enables a thorough comprehension of concepts like reach, accuracy, repetition, and various robotic behaviors. The described ontology-based method has several advantages in industrial situations and provides a foundation for modeling robot design criteria. Exploiting ontological models helps select appropriate robots for specific jobs, enhances productivity, reduces inefficient usage and possible dangers, and promotes trustworthy and adaptable production by precisely capturing the capabilities of robots. Overall, using ontological modeling in robotic capability modeling advances flexible production systems and improves the creation and use of autonomous robots. Our ongoing work focuses on modeling notions such as function, quality, and role of robots to enhance the understanding and utilization of robotic capabilities in flexible manufacturing systems.

Acknowledgments

This work is performed within the CHAIKMAT project funded by the French National Research Agency (ANR) under grant agreement ” ANR-21-CE10-0004-01”.

References

[1] J. Rosak-Szyrocka, J. Żywiołek, M. Shahbaz, Quality Management, Value Creation and the Digital Economy, 2023. doi:`10.4324/9781003404682`.

[2] T. A. Kurniawan, M. H. D. Othman, X. Liang, H. H. Goh, P. Gikas, T. D. Kusworo, A. Anouzla, K. W. Chew, Decarbonization in waste recycling industry using digitalization to promote net-zero emissions and its implications on sustainability, Journal of environmental management 338 (2023). doi:`10.1016/j.jenvman.2023.117765`.

[3] K. Moulaei, K. Bahaadinbeigy, A new revolution in healthcare transformation using hyper-automation technologies, Frontiers in Health Informatics 12 (2023) 134. URL: http://ijmi.ir/index.php/IJMI/article/view/422. doi:`10.30699/fhi.v12i0.422`.

[4] K. Haricha, A. KHIAT, Y. Issaoui, A. Bahnasse, O. Hassan, Recent technological progress to empower smart manufacturing: Review and potential guidelines, IEEE Access PP (2023) 1–1. doi:`10.1109/ACCESS.2023.3246029`.

[5] K. Kennedy, Teacher education for the fourth industrial revolution–teachers, technologies, and transformation, in: Future-Proofing Teacher Education, Routledge, 2023, pp. 34–46.

[6] L. Signé, Africa’s Fourth Industrial Revolution, Cambridge University Press, 2023. doi:`10.1017/9781009200004`.

[7] F. Ameri, D. Dutta, An upper ontology for manufacturing service description, volume 2006, 2006. doi:`10.1115/DETC2006-99600`.

[8] Z. Jin, D. Qin, A. Liu, W. Zhang, L. Yu, Learning neural-shaped quadratic lyapunov

function for stable, accurate and generalizable human–robot skills transfer, Robotics and Computer-Integrated Manufacturing 82 (2023).

[9] A. Powers, S. Kiesler, S. Fussell, C. Torrey, Comparing a computer agent with a humanoid robot, in: Proceedings of the ACM/IEEE International Conference on Human-Robot Interaction, HRI '07, Association for Computing Machinery, New York, NY, USA, 2007, p. 145–152. URL: https://doi.org/10.1145/1228716.1228736. doi:`10.1145/1228716.1228736`.

[10] M. Carlson, The robotic reporter: Automated journalism and the redefinition of labor, compositional forms, and journalistic authority, Digital Journalism 3 (2015) 416–431. doi:`10.1080/21670811.2014.976412`.

[11] S. Lemaignan, M. Warnier, E. A. Sisbot, A. Clodic, R. Alami, Artificial cognition for social human–robot interaction: An implementation, Artificial Intelligence 247 (2017) 45–69. URL: https://www.sciencedirect.com/science/article/pii/S0004370216300790. doi:`https://doi.org/10.1016/j.artint.2016.07.002`, special Issue on AI and Robotics.

[12] A. S. Rajawat, R. Rawat, K. Barhanpurkar, R. N. Shaw, A. Ghosh, Chapter one - robotic process automation with increasing productivity and improving product quality using artificial intelligence and machine learning, in: R. N. Shaw, A. Ghosh, V. E. Balas, M. Bianchini (Eds.), Artificial Intelligence for Future Generation Robotics, Elsevier, 2021, pp. 1–13. URL: https://www.sciencedirect.com/science/article/pii/B9780323854986000071. doi:`https://doi.org/10.1016/B978-0-323-85498-6.00007-1`.

[13] A. de Jesús Plasencia-Salgueiro, Deep reinforcement learning for autonomous mobile robot navigation, in: A. T. Azar, A. Koubaa (Eds.), Artificial Intelligence for Robotics and Autonomous Systems Applications, volume 1093 of *Studies in Computational Intelligence*, Springer, 2023, pp. 195–237. URL: https://doi.org/10.1007/978-3-031-28715-2_7. doi:`10.1007/978-3-031-28715-2\_7`.

[14] R. R. Devaram, G. Beraldo, R. De Benedictis, M. Mongiovì, A. Cesta, Lemon: A lightweight facial emotion recognition system for assistive robotics based on dilated residual convolutional neural networks, Sensors 22 (2022). URL: https://www.mdpi.com/1424-8220/22/9/3366. doi:`10.3390/s22093366`.

[15] K. Nutonen, V. Kuts, T. Otto, Industrial robot training in the simulation using the machine learning agent, Procedia Computer Science 217 (2023) 446–455. doi:`10.1016/j.procs.2022.12.240`.

[16] A. Singh, K. Raj, T. Kumar, S. Verma, A. M. Roy, Deep learning-based cost-effective and responsive robot for autism treatment, Drones 7 (2023). URL: https://www.mdpi.com/2504-446X/7/2/81. doi:`10.3390/drones7020081`.

[17] W. Sleaman, A. Hameed, A. Jamil, Monocular vision with deep neural networks for autonomous mobile robots navigation, Optik 272 (2022) 170162. doi:`10.1016/j.ijleo.2022.170162`.

[18] M. Mansouri, F. Pecora, A robot sets a table : a case for hybrid reasoning with different types of knowledge, Journal of experimental and theoretical artificial intelligence (Print) 28 (2016) 801–821. doi:`10.1080/0952813X.2015.1132267`, funding Agency;EC 287752.

[19] E. Järvenpää, N. Siltala, O. Hylli, M. Lanz, The development of an ontology for describing the capabilities of manufacturing resources, J. Intell. Manuf. 30 (2019) 959–978. URL: https://doi.org/10.1007/s10845-018-1427-6. doi:`10.1007/s10845-018-1427-6`.

[20] E. Merrell, D. Limbaugh, P. Koch, B. Smith, Capabilities, 2022.

[21] R. Sabbagh, F. Ameri, A Framework Based on K-Means Clustering and Topic Modeling for Analyzing Unstructured Manufacturing Capability Data, Journal of Computing and Information Science in Engineering 20 (2019) 011005. URL: https://doi.org/10.1115/1.4044506. doi:10.1115/1.4044506. arXiv:https://asmedigitalcollection.asme.org/computingengineering/article-pdf/20/

[22] A. Sarkar, D. Šormaz, Ontology model for process level capabilities of manufacturing resources, Procedia Manufacturing 39 (2019) 1889–1898. URL: https://www.sciencedirect.com/science/article/pii/S2351978920303012. doi:https://doi.org/10.1016/j.promfg.2020.01.244, 25th International Conference on Production Research Manufacturing Innovation: Cyber Physical Manufacturing August 9-14, 2019 | Chicago, Illinois (USA).

[23] F. Compagno, S. Borgo, Towards a formal ontology of engineering functions, behaviours, and capabilities, Semantic Web (2023). doi:10.3233/SW-223188.

[24] Y. Qin, S. Hu, Y. Lin, W. Chen, N. Ding, G. Cui, Z. Zeng, Y. Huang, C. Xiao, C. Han, Y. R. Fung, Y. Su, H. Wang, C. Qian, R. Tian, K. Zhu, S. Liang, X. Shen, B. Xu, Z. Zhang, Y. Ye, B. Li, Z. Tang, J. Yi, Y. Zhu, Z. Dai, L. Yan, X. Cong, Y. Lu, W. Zhao, Y. Huang, J. Yan, X. Han, X. Sun, D. Li, J. Phang, C. Yang, T. Wu, H. Ji, Z. Liu, M. Sun, Tool learning with foundation models, 2023. arXiv:2304.08354.

[25] L. Bernhard, A. F. Amalanesan, O. Baumann, F. Rothmeyer, Y. Hafner, M. Berlet, D. Wilhelm, A. Knoll, Mobile service robots for the operating room wing: balancing cost and performance by optimizing robotic fleet size and composition, International Journal of Computer Assisted Radiology and Surgery 18 (2022) 195 – 204. URL: https://api.semanticscholar.org/CorpusID:252185831.

[26] S. Kreuzwieser, A. Kimmig, F. Michels, R. Bulander, V. Häfner, J. Bönsch, J. Ovtcharova, Human-Machine-Interaction in Innovative Work Environment 4.0 – A Human-Centered Approach, Springer International Publishing, 2023, p. 68–86. doi:10.1007/978-3-031-26490-0_5.

[27] A. Sarkar, M. R. Naqvi, L. Elmhadhbi, D. Sormaz, B. Archimède, H. Karray, CHAIKMAT 4.0 - Commonsense Knowledge and Hybrid Artificial Intelligence for Trusted Flexible Manufacturing, 2023, pp. 455–465. doi:10.1007/978-3-031-17629-6_47.

[28] A. Billard, D. Kragic, Trends and challenges in robot manipulation, Science 364 (2019) eaat8414. URL: https://www.science.org/doi/abs/10.1126/science.aat8414. doi:10.1126/science.aat8414. arXiv:https://www.science.org/doi/pdf/10.1126/science.aat8414.

[29] M. Javaid, A. Haleem, R. P. Singh, R. Suman, Substantial capabilities of robotics in enhancing industry 4.0 implementation, Cognitive Robotics 1 (2021) 58–75. URL: https://www.sciencedirect.com/science/article/pii/S2667241321000057. doi:https://doi.org/10.1016/j.cogr.2021.06.001.

[30] D. Han, B. Mulyana, V. Stankovic, S. Cheng, A survey on deep reinforcement learning algorithms for robotic manipulation, Sensors 23 (2023). URL: https://www.mdpi.com/1424-8220/23/7/3762. doi:10.3390/s23073762.

[31] C. Schlenoff, E. Prestes, R. Madhavan, P. Goncalves, H. Li, S. Balakirsky, T. Kramer, E. Migueláñez, An ieee standard ontology for robotics and automation, in: 2012 IEEE/RSJ

International Conference on Intelligent Robots and Systems, 2012, pp. 1337–1342. doi:10.1109/IROS.2012.6385518.

[32] J. I. Olszewska, M. Barreto, J. Bermejo-Alonso, J. Carbonera, A. Chibani, S. Fiorini, P. Goncalves, M. Habib, A. Khamis, A. Olivares, E. P. de Freitas, E. Prestes, S. V. Ragavan, S. Redfield, R. Sanz, B. Spencer, H. Li, Ontology for autonomous robotics, in: 2017 26th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN), 2017, pp. 189–194. doi:10.1109/ROMAN.2017.8172300.