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# The Internet of Robotic Things: A review of concept, added value and applications

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**Abstract**

The Internet of Robotic Things is an emerging vision that brings together pervasive sensors and objects with robotic and autonomous systems. This survey examines how the merger of robotic and Internet of Things technologies will advance the abilities of both the current Internet of Things and the current robotic systems, thus enabling the creation of new, potentially disruptive services. We discuss some of the new technological challenges created by this merger and conclude that a truly holistic view is needed but currently lacking.

**Keywords**

Internet of Things, cyber-physical systems, distributed robotics, network robot systems, autonomous systems, robot ecology

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## Introduction

The Internet of Things (IoT) and robotics communities have so far been driven by different yet highly complementary objectives, the first focused on supporting information services for pervasive sensing, tracking and monitoring; the latter on producing action, interaction and autonomous behaviour. For this reason, it is increasingly claimed that the creation of an internet of robotic things (IoRT) combining the results from the two communities will bring a strong added value.[1–3]

Early signs of the IoT-robotics convergence can be seen in distributed, heterogeneous robot control paradigms like network robot systems[4] or robot ecologies,[5] or in approaches such as ubiquitous robotics[6–8] and cloud robotics[9–12] that place resource-intensive features on the server side.[13,14] The term 'Internet of robotic things' itself was coined in a report of ABI research[1] to denote a concept where sensor data from a variety of sources are fused, processed using local and distributed intelligence and used to control and manipulate objects in the physical world. In this *cyber-physical perspective* of the IoRT, sensor and data analytics technologies from the IoT are used to give robots a wider situational awareness that leads to better task execution. use cases include intelligent transportation[15] and companion robots.[16] Later uses of the term IoRT in literature adopted alternative perspectives of this term: for example, one that focuses on the robust team communication,[17–19] and

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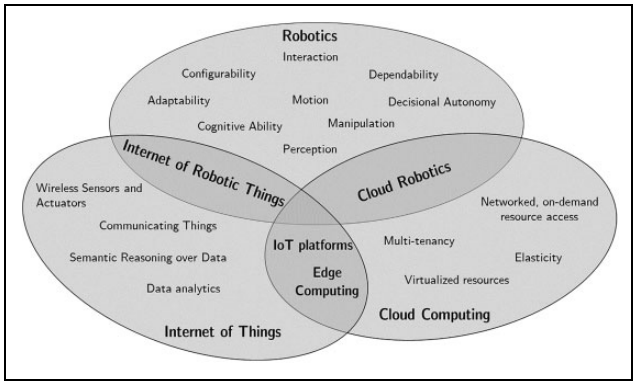


**Figure 1.** The scope of this review paper is the IoT as enabler in distributed robotic systems. IoT: Internet of Things.

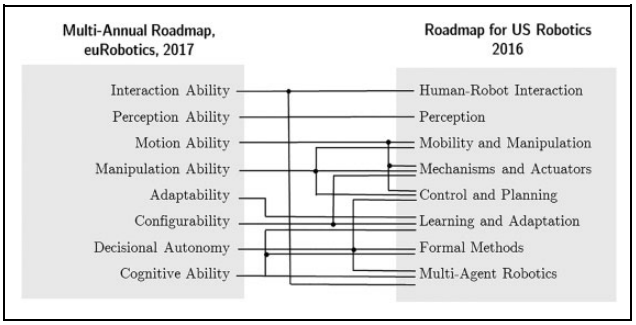


**Figure 2.** Mapping between the system abilities defined in the multi-annual roadmap of euRobotics[26] – along which this review is structured – and the research challenges identified in the roadmap for US Robotics.[27]

a 'robot-aided IoT' view where robots are just additional sensors.[20,21]

Cloud computing and the IoT are two non-robotic enablers in creating distributed robotic systems (see Figure 1). IoT technologies have three tenets[22]: (i) sensors proliferated in the environment and on our bodies; (ii) smart connected objects using machine-to-machine (M2M) communication; and (iii) data analytics and semantic technologies transforming raw sensor data. Cloud computing provides on-demand, networked access to a pool of virtualized hardware resources (processing, storage) or higher level services. Cloud infrastructure has been used by the IoT community to deploy scalable IoT platform services that govern access to (raw, processed or fused) sensor data. Processing the data streams generated by billions of IoT devices in a handful of centralized data centres brings concerns on response time latency, massive ingress bandwidth needs and data privacy. Edge computing (also referred to as fog computing, cloudlets) brings on-demand and elastic computational resources to the edge of the network, closer to the producers of data[23]. The cloud paradigm was also adopted by the robotics community, called *cloud robotics*[9–12] for offloading resource-intensive tasks,[13,14] for the sharing of data and knowledge between robots[24] and for reconfiguration of robots following an app-store model.[25] Although there is an overlap between cloud robotics and IoRT, the former paradigm is more oriented towards providing network-accessible infrastructure for computational power and storage of data and knowledge, while the latter is more focused on M2M communication and intelligent data processing. The focus of this survey is on the latter, discussing the potential added value of the IoT-robotics crossover in terms of improved system abilities, as well as the new technological challenges posed by the crossover.

As one of the goals of this survey is to inspire researchers on the potential of introducing IoT technologies in robotic systems and vice versa, we structure our discussion along the system abilities commonly found in robotic systems, regardless of specific robot embodiment or application domains. Finding a suitable taxonomy of abilities is a delicate task. In this work, we build upon an existing community effort and adopt the taxonomy of *nine system abilities*, defined in the euRobotics roadmap,[26] which shapes the robotic research agenda of the European Commission. Interestingly, these abilities are closely related to the *research challenges* identified in the US Robotics roadmap[27] (see Figure 2).

## Basic abilities

### *Perception ability*

The sensor and data analytics technologies from the IoT can clearly give robots a wider horizon compared to local, on-board sensing, in terms of space, time and type of information. Conversely, placing sensors on-board mobile robots allows to position them in a flexible and dynamic way and enables sophisticated active sensing strategies.

A key challenge of perception in an IoRT environment is that the environmental observations of the IoRT entities are spatially and temporally distributed.[28] Some techniques must be put in place to allow robots to query these distributed data. Dietrich et al.[29] propose to use local databases, one in each entity, where data are organized in a spatial hierarchy, for example, an object has a position relative to a robot, the robot is positioned in a room and so on. Other authors[30,31] propose that robots send specific observation requests to the distributed entities, for example, a region and objects of interest: this may speed up otherwise intractable sensor processing problems (see Figure 3).

A key component of robots' perception ability is getting knowledge of their own location, which includes the ability to build or update models of the environment.[32] Despite great progress in this domain, self-localization may still be challenging in crowded and/or Global Positioning System (GPS)-denied indoor environments, especially if high reliability is demanded. Simple IoT-based infrastructures such as an radio frequency identification (RFID)-enhanced floor have been used to provide reliable location information to domestic robots.[33] Other approaches use range-based techniques on signals emitted by off-board

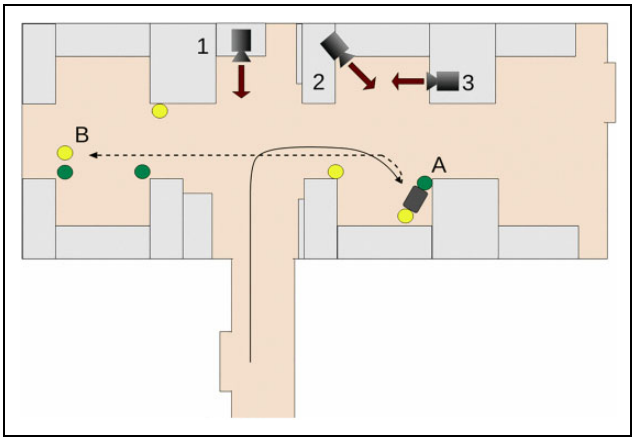


**Figure 3.** Distributed cameras assist the robot in locating a charging station in an environment. The charging station was placed between a green and yellow visual marker (location A). Visual markers of the same colours were placed elsewhere in the environment to simulate distractors. Visual processing is performed on-demand on the camera nodes to inform the robot that the charging station is at location A and not at the distracting location B (Image from Chamberlain et al.[30]) (c) 2016 IEEE.

infrastructure, such as Wi-Fi access points[34] and visible light,[35] or by IoT devices using protocols such as Ultra-Wideband (UWB),[36] Zigbee[37] or Bluetooth lowenergy.[38,39]

### *Motion ability*

The ability to move is one of the fundamental added values of robotic systems. While mechanical design is the key factor in determining the intrinsic effectiveness of robot mobility, IoT connectivity can assist mobile robots by helping them to control automatic doors and elevators, for example in assistive robotics[40] and in logistic applications.[41]

IoT platform services and M2M and networking protocols can facilitate distributed robot control architectures in large-scale applications, such as last mile delivery, precision agriculture, and environmental monitoring. FIROS[42] is a recent tool to connect mobile robots to IoT services by translating Robot Operating System (ROS)[43] messages into messages grounded in Open Mobile Alliance APIs?. Such an interface is suited for robots to act as a mobile sensor that publishes its observations and makes them available to any interested IoT service.

In application scenarios such as search and rescue, where communication infrastructure may be absent or damaged, mobile robots may need to set up ad hoc networks and use each other as forwarding nodes to maintain communication. While the routing protocols developed for mobile ad hoc networks can be readily applied in such scenarios, lower overhead and increased energy efficiency can be obtained when such protocols explicitly take into account the knowledge of robot's planned movements and activities.[44] Sliwa et al.[45] propose a similar approach to minimize path losses in robot swarms.

### *Manipulation ability*

While the core motivation of the IoT is to sense the environment, the one of robotics is to modify it. Robots can grasp, lift, hold and move objects via their end effectors. Once the robot has acquired the relevant features of an object, like its position and contours, the sequence of torques to be applied on the joints can be calculated via inverse kinematics.

The added value of IoT is in the acquisition of the object's features, including those that are not observable with the robot's sensors but have an impact on the grasping procedure, such as the distribution of mass, for example, in a filled versus an empty cup. Some researchers attached RFID tags to objects that contain information about their size, shape and grasping points[5]. Deyle et al.[46] embedded RFID reader antennas in the finger of a gripper: Differences in the signal strength across antennas were used to more accurately position the hand before touching the object. Longer range RFID tags were used to locate objects in a kitchen[47] or in smart factories,[48,49] as well as to locate the robots themselves.[50]

## Higher level abilities

### *Decisional autonomy*

Decisional autonomy refers to the ability of the system to determine the best course of action to fulfil its tasks and missions.[26] This is mostly not considered in IoT middleware:[51–53] applications just call an actuation API of so-called smart objects that hide the internal complexity.[28]

Roboticists often rely on Artificial Intelligence (AI) planning techniques[54,55] based on predictive models of the environment and of the possible actions. The quality of the plans critically depends on the quality of these models and of the estimate of the initial state. In this respect, the improved situational awareness that can be provided by an IoT environment (see "Perception ability" section) can lead to better plans. Human-aware task planners[56] use knowledge of the intentions of the humans inferred through an IoT environment to generate plans that respect constraints on human interaction (see Figure 4).

IoT also widens the scope of decisional autonomy by making more actors and actions available, such as controllable elevators and doors.[40,57] However, IoT devices may dynamically become available or unavailable,[58] which challenges classical multi-agent planning approaches. A solution is to do planning in terms of abstract services, which are mapped to actual devices at runtime.[59]

## Interaction ability

This is the ability of a robot to interact physically, cognitively and socially either with users, operators or other systems around it.[26] While M2M protocols[60] can be directly adopted in robotic software, we focus here on how

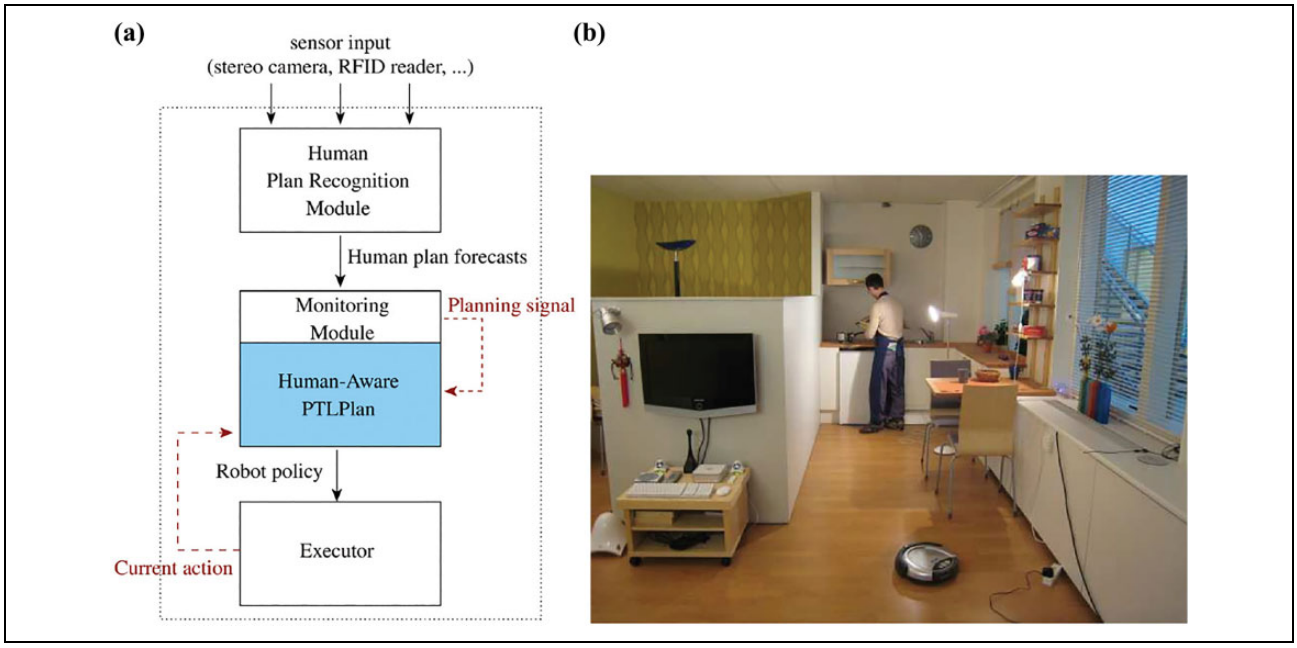


**Figure 4.** The vacuum cleaning robot adapts its plan to avoid interference in the kitchen (Figure from Cirillo et al.[56]) (c) 2010 ACM.

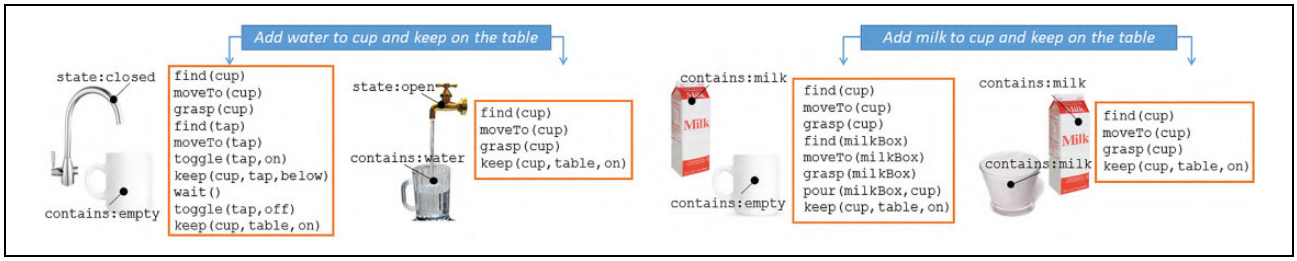


**Figure 5.** Depending on the state of the environment, a natural language instructions results in different actions to be performed (Image from Misra et al.[62]) (c) 2016 SAGE.

IoT technologies can facilitate human–robot interaction at functional (commanding and programming) and social levels, as well as a means for tele-interaction.

*Functional* pervasive IoT sensors can make the functional means of human–robot interaction more robust. Natural language instructions are a desirable way to instruct robots, especially for non-expert users, but they are often vague or contain implicit assumptions.[61,62] The IoT can provide information on the position and state of objects to disambiguate these instructions (see Figure 5). Gestures are another intuitive way to command robots, for instance, by pointing to objects. Recognition of pointing gestures from sensors on-board the robot only works within a limited field of view.[63] External cameras provide a broader scene perspective that can improve gesture recognition.[64] Wearable sensors have also been used, for example, Wolf et al.[65] demonstrated a sleeve that measures forearm muscle movements to command robot motion and manipulation.

*Social* body cues like gestures, voice or face expression can be used to estimate the user's emotional state[66] and make the robot respond to it.[67,68] The integration with body-worn IoT sensors can improve this estimate by measuring physiological signals: Leite et al.[69] measured heart rate and skin conductance to estimate engagement, motivation and attention during human–robot interaction. Others have used these estimates to adapt the robot's interaction strategy, for example, in the context of autism therapy[70] or for stress relievement.[71]

*Tele-interaction* robots have also been used besides IoT technologies for remote interaction, especially in healthcare. Chan et al.[72] communicate hugs and manipulations between persons via sensorized robots. Al-Taee et al.[73] use robots to improve the tele-monitoring of diabetes patients by reading out the glucose sensor and vocalizing the feedback from the carer (see Figure 6). Finally, in the GiraffPlus project[7], a tele-presence robot was combined with environmental sensors to provide health-related data to a remote therapist.

## Cognitive ability

By reasoning on and inferring knowledge from experience, cognitive robots are able to understand the relationship

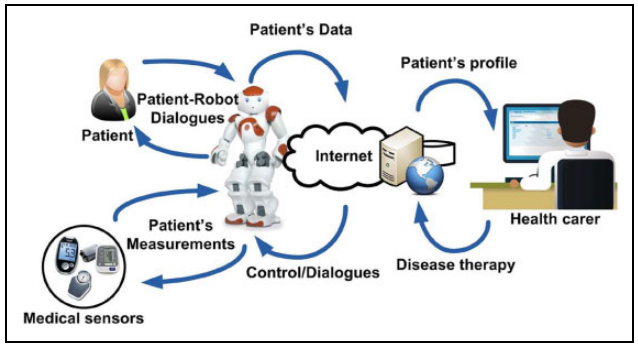


**Figure 6.** The robot acts as a master Bluetooth device that reads out glucose sensors and transfers them to the caregivers. The robot is then used to provide verbal information concerning the patient's diet, insulin bolus/intake, and so on (Image from Al-Taee et al.[73]) (c) 2017 IEEE.

between themselves and the environment, between objects, and to assess the possible impact of their actions. Some aspects of cognition were already discussed in the previous sections, for example, multi-modal perception, deliberation and social intelligence. In this section, we focus on the cognitive tasks of reasoning and learning in an IoRT multi-actor setting.

Knowledge models are important components of cognitive architectures.[74,75] Ontologies are a popular technique in both IoT and robotics for structured knowledge. Example ontologies describing the relationship between an agent and its physical environment are the Semantic Sensor Network,[76] IoT-A[77] and the IEEE Ontologies for Robotics and Automation[78] (ORA). For example, Jorge et al.[79] use the ORA ontology for spatial reasoning between two robots that must coordinate in providing a missing tool to a human. Recent works[???] harness the power of the cloud to derive knowledge from multi-modal data sources, such as human demonstrations, natural language or raw sensor data observations[?], and to provide a virtual environment for simulating robot control policies. In an IoRT environment, these knowledge engines will be able to incorporate even more sources of data.

In the IoT domain, cognitive techniques were recently proposed for the management of distributed architectures.[80,81] Here, the system self-organizes a pipeline of data analytics modules on a distributed set of sensor nodes, edge cloud and so on. To our knowledge, the inclusion of robots in these pipelines has not yet been considered. If robots subscribe themselves as additional actors in the environment, then this gives rise to a new strand of problems in distributed consensus and collaboration for the IoT, because robots typically have a larger degree of autonomy than traditional IoT 'smart' objects, and because they are able to modify the physical environment leading to complex dependencies and interactions.

## System level abilities

### *Configurability*

This is the ability of a robotic system to be configured to perform a given task or reconfigured to perform different tasks.[26]

IoT is mainly instrumental in supporting *software configurability*, in particular to orchestrate the concerted configuration of multiple devices, each contributing different capabilities and cooperating to the achievement of complex objectives. However, work in IoT does not explicitly address the requirement of IoRT systems to exchange continuous streams of data while interacting with the physical world.

This requirement is most prominent in the domains of logistic and of advanced manufacturing, where a fast reaction to disruptions is needed, together with flexible adaptation to varying production objectives.

Kousi et al.[82] developed a service-oriented architecture to support autonomous, mobile production units which can fuse data from a peripheral sensing network to detect disturbances. Michalos et al.[83] developed a distributed system for data sharing and coordination of human–robot collaborative operations, connected to a centralized task planner. Production lines have also been framed as multi-agent systems[84,85] equipped with self-descriptive capabilities to reduce set-up and changeover times.

General purpose middlewares have also been developed to support distributed task coordination and control in IoRT environments. The Ubiquitous Network Robot Platform[86] is a general purpose middleware for IoRT environments (see Figure 7). It manages the handover of functionality for services using real and virtual robots, for example reserving a real assistant robot using a virtual robot on the smartphone.

Configurability can be coupled with decision ability to lead to the ability of a system to *self-configure*. Self-configuration is especially challenging in an IoRT system since the configuration algorithms must take into account both the digital interactions between the actors and their physical interactions through the real world. The 'PEIS Ecology' framework[5] includes algorithms for the self-configuration of a robot ecology: complex functionality is achieved by composing a set of devices with sensing, acting and/or computational capabilities, including robots. A shared tuple-space blackboard allows for high level collaboration and dynamic reconfiguration.[87]

### *Adaptability*

This is the ability of the system to adapt to different work scenarios, environments and conditions.[26] This includes the ability to adapt to unforeseen events, faults, changing tasks and environments and unexpected human behaviour. The key enablers for adaptability are the perception, decisional and configuration abilities as described above. Hence, we

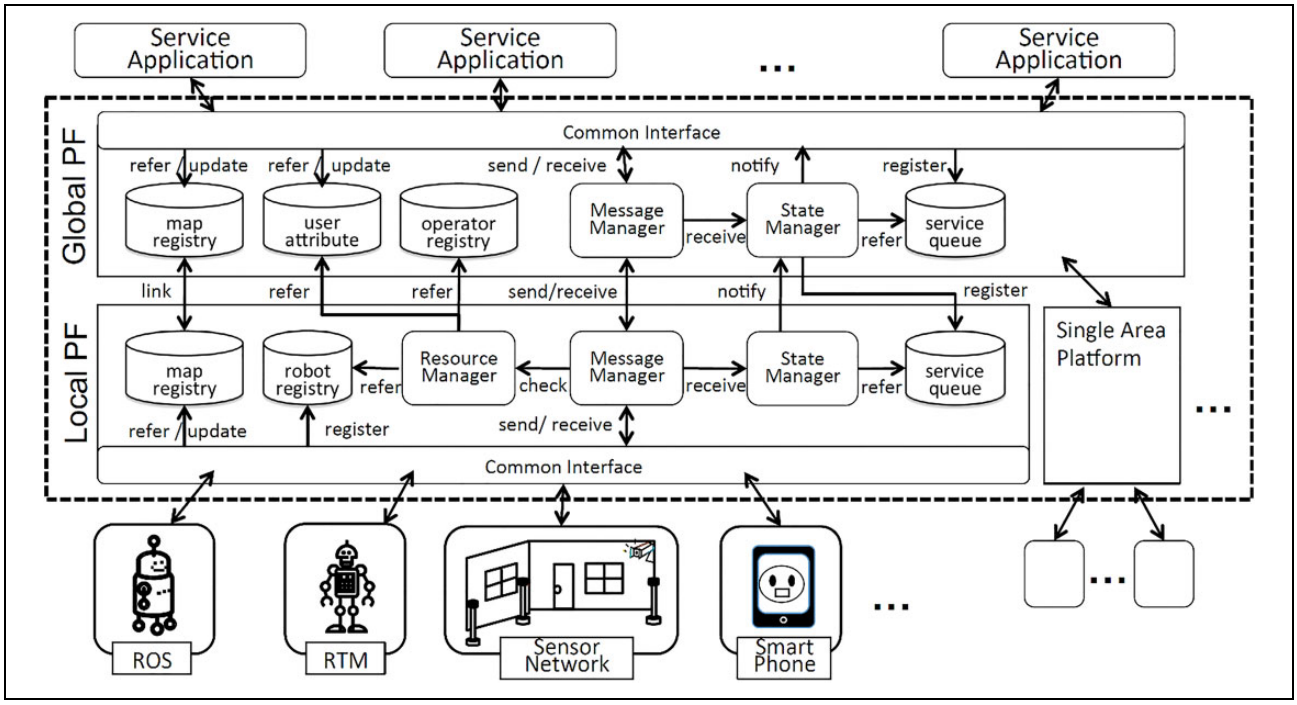


**Figure 7.** The Ubiquitous Network Robot Platform is a two-layered platform. The LPF configures a robotic system in a single area. The GPF is a middle-layer between the LPFs of different areas and the service applications (Image from Nishio et al.[86]). LPF: local platform; GPF: global platform (c) 2013 Springer-Verlag.

will now discuss relevant application domains and supporting platforms.

Mobile robots are used in precision agriculture for the deployment of herbicide, fertilizer or irrigation.[88] These robots need to adapt to spatio-temporal variations of crop and field patterns, crop sizes, light and weather conditions, soil quality, and so on.[89] Wireless Sensor Network (WSNs) can provide the necessary information,[90,91] for example, knowledge of soil moisture may be used to ensure accurate path tracking.[92,93] Gealy et al.[94] use a robot to adjust the drip rate of individual water emitters to allow for plant-level control of irrigation. This is a notable example of how robots are used to adjust IoT devices.

Some platforms supporting adaptation of IoRT have also been showcased in the context of Ambient Assisted Living (AAL). Building on OSGi, a platform for IoT home automation, AIOLOS exposes robots and IoT devices as reusable and shareable services, and automatically optimizes the runtime deployment across distributed infrastructure, for example, by placing a shared data processing service closer to the source sensor.[95,96] Bacciu et al.[97,98] deploy recurrent neural networks on distributed infrastructure to automatically learn user preferences, and to detect disruptive environmental changes like the addition of a mirror.[99]

## Dependability

Dependability is a multifaceted attribute, covering the reliability of hardware and software robotic components, safety guarantees when cooperating with humans and the degree to which systems can continue their missions when failures or other unforeseen circumstances occur.

In this section, we follow the classification of means of dependability identified by Crestani et al.[100]

A first means of dependability is to *forecast faults* or *conflicts*. For instance, robots in a manufacturing plant must stop if an operator comes too near. IoT technology can provide useful tools to realize this. Rampa et al.[101] mounted a network of small tranceivers in a robotic cell and estimated the user position from the perturbations of the radio field. Other researchers embedded sensors in clothing and on the helmet. Qian et al.[102] developed a probabilistic framework to avoid conflicts of robot and human motion, by combining observations from fixed cameras and on-board sensors with historical knowledge on human trajectories (see Figure 8).

In a marine context, acoustic sensor networks have been used to provide information on water current and ship positions to a path planner for underwater gliders, to avoid collisions when they come to the surface[103] or to preserve energy.[104]

A second means of dependability is *robust system engineering*. This can take new forms in an IoRT system. For instance, mobile wireless communication is a key enabler for industry 4.0, where both field devices, fixed machines and mobile AGV are connected. IoT protocols such as WirelessHart or Zigbee Pro were designed to address the industry concerns on reliability, security and cost.[105] When

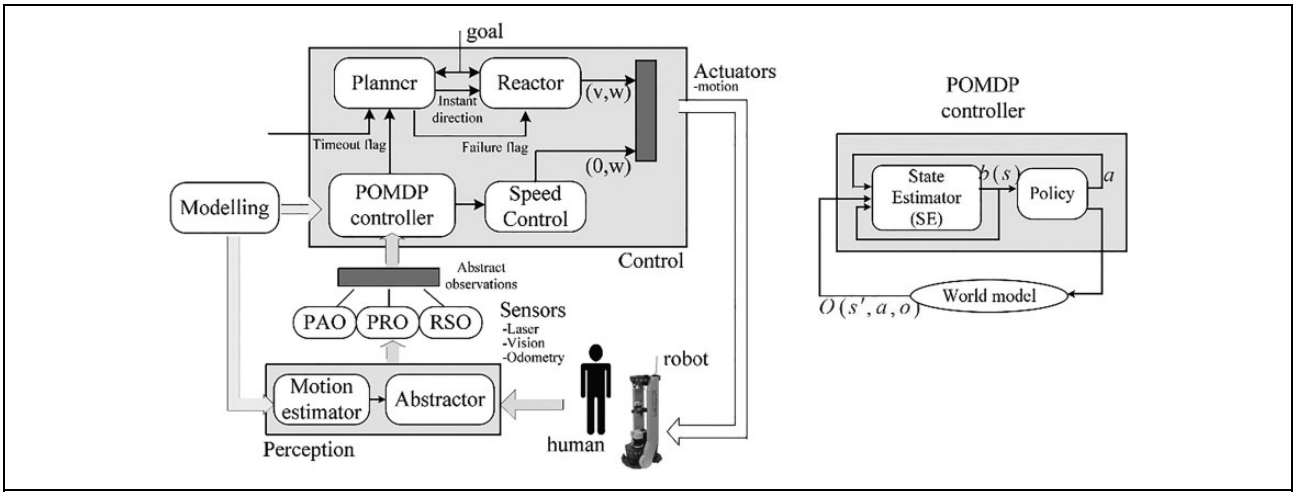


**Figure 8.** Sensory data from laser and global cameras are fed to the perception module, together with human motion patterns learned by the modelling module. Then three types of abstracted observations are inputted to the controller: PAO, PRO and RSO. Using a Partially Observable Markov Decision Process, a suitable navigational policy is generated (Image from Qian et al.[102]). PAO: people's action observation; PRO: people-robot relation observation; RSO: robot state observation (c) 2013 SAGE.

mobility is involved, however, these protocols must be complemented by meshing technologies to cope with handovers and with the massive presence of metal.[106,107]

The last means is *fault tolerance*, which allows the system to keep working even when components fail. Redundancy is key to fault tolerance, and the IoRT enables redundancy of sensors, information and actuation. Data fusion from both on-board and environment sensors, however, requires a good understanding of the spatial and temporal relationship between the observations from different sensors. Such relationships have been explicitly modelled, for example, in the Positioning Ontology[79] (POS), or implicitly learned as part of modular deep neural network controller.[108]

## Conclusion

Robotics and IoT are two terms each covering a myriad of technologies and concepts. In this review, we have unravelled the added value of the crossover of both technology domains into nine system abilities. The IoT advantages exploited by roboticists are mostly distributed perception and M2M protocols. Conversely, the IoT has so far mostly exploited robots for active sensing strategies. Current IoRT incarnations are almost uniquely found in vertical application domains, notably AAL, precision agriculture and Industry 4.0. Domain-agnostic solutions, for example, to integrate robots in IoT middleware platforms, are only emerging. It is our conviction that the IoRT should go beyond the readings of 'IoT-aided robots' or 'Robot-enhanced IoT'. We hope that this survey may stimulate researchers from both disciplines to start work towards an ecosystem of IoT agents, robots and the cloud that combines both the above readings in a holistic way.

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### References

1. Kara D and Carlaw S. The Internet of Robotic Things. Technical Report, ABI Research, 2014.
2. Vermesan O, Bröring A, Tragos E, et al. Internet of robotic things: converging sensing/actuating, hypoconnectivity, artificial intelligence and IoT platforms. In: Vermesan O and Bacquet J (eds) *Cognitive hyperconnected digital transformation: internet of things intelligence evolution*, Norway, Belgium: River Publishers Series, 2017, pp. 1–35.
3. Ray PP.Internet of robotic things: concept, technologies, and challenges. *IEEE Access* 2016; 4: 9489–9500.
4. Sanfeliu A, Hagita N and Saffiotti A. Network robot systems. *Robot Auton Syst* 2008; 56(10): 793–797.
5. Saffiotti A, Broxvall M, Gritti M, et al. The PEIS-ecology project: vision and results. In: *IEEE/RSJ international conference on intelligent robots and systems, 2008. IROS 2008*, Nice, France, 22–26 September 2008, pp. 2329–2335. IEEE.
6. Kim JH, Lee KH, Kim YD, et al. Ubiquitous robot: a new paradigm for integrated services. In: *2007 IEEE international conference on robotics and automation*, Roma, Italy, 10–14 April 2007, pp. 2853–2858. IEEE.

7. Kim JH.Ubiquitous robot. In: Bernd R (ed) *Computational Intelligence, Theory and Applications*. Berlin, Heidelberg: Springer Berlin Heidelberg, 2005, pp. 451–459.
8. Ha YG, Sohn JC, Cho YJ, et al. Towards ubiquitous robotic companion: design and implementation of ubiquitous robotic service framework. *ETRI J* 2005; 27(6): 666–676.
9. Kehoe B, Patil S, Abbeel P, et al. A survey of research on cloud robotics and automation. *IEEE Trans Autom Sci Eng* 2015; 12(2): 398–409.
10. Hu G, Tay WP and Wen Y. Cloud robotics: architecture, challenges and applications. *IEEE Network* 2012; 26(3): 21–28.
11. Qureshi B and Koubâa A. Five traits of performance enhancement using cloud robotics: a survey. *Procedia Comput Sci* 2014; 37: 220–227.
12. Kamei K, Nishio S, Hagita N, et al. Cloud networked robotics. *IEEE Network* 2012; 26(3): 28–34.
13. Mohanarajah G, Hunziker D, D'Andrea R, et al. Rapyuta: a cloud robotics platform. *IEEE Trans Autom Sci Eng* 2015; 12(2): 481–493.
14. Salmerón-Garcı J, Íñigo-Blasco P, Díaz del Río F, et al. A tradeoff analysis of a cloud-based robot navigation assistant using stereo image processing. *IEEE Trans Autom Sci Eng* 2015; 12(2): 444–454.
15. Chowdhury AR. IoT and robotics: a synergy. *PeerJ Preprints* 2017; 5: e2760v1.
16. Simoens P, Mahieu C, Ongenae F, et al. Internet of robotic things: context-aware and personalized interventions of assistive social robots. In: *5e IEEE international conference on cloud networking (IEEECloudNet 2016)* (ed Giordano S), Pisa, Italy, 3–5 October 2016, pp. 1–4. IEEE.
17. Bhavanam P and Jami MT. Performance assessment in internet of robotic things based on IoT. *IJITR* 2017; 5(3): 6459–6462.
18. Bharathi K and Anbarasan K. Design of multi robot system using fuzzy based IoT. *Int J Res Sci Eng* 2017. 21 December 2017. Available at: www.ijrse.org.
19. Razafimandimby C, Loscri V and Vegni AM. A neural network and IoT based scheme for performance assessment in internet of robotic things. In: *2016 IEEE first international conference on Internet-of-Things Design and Implementation (IoTDI)*, Berlin, Germany, 4–8 April 2016, pp. 241–246. IEEE.
20. Oh J, Park Y, Choi J, et al. A rule-based context transforming model for robot services in internet of things environment. In: *2017 14th international conference on, ubiquitous robots and ambient intelligence (URAI)*, pp. 331–336. IEEE.
21. Scilimati V, Petitti A, Boccadoro P, et al. Industrial internet of things at work: a case study analysis in robotic-aided environmental monitoring. *IET Wireless Sen Syst* 2017; 7(5): 155–162.
22. Atzori L, Iera A and Morabito G. The internet of things: a survey. *Comput Networks* 2010; 54(15): 2787–2805.
23. Shi W, Cao J, Zhang Q, et al. Edge computing: vision and challenges. *IEEE Internet of Things Journal* 2016; 3(5): 637–646. DOI: 10.1109/JIOT.2016.2579198.
24. Cieslewski T, Lynen S, Dymczyk M, et al. Map API-scalable decentralized map building for robots. In: *2015 IEEE international conference on robotics and automation (ICRA)*, Seattle, WA, USA, 26–30 May 2015, pp. 6241–6247. IEEE.
25. Szlenk M, Zieliński C, Figat M, et al. Reconfigurable agent architecture for robots utilising cloud computing. In: Szewczyk R, Zielinsky C and Kaliczynska M (eds) *Progress in automation, robotics and measuring techniques*. Cham: Springer, 2015, pp. 253–264.
26. Multi-annual roadmap for horizon. 2020. *SPARC Robotics, euRobotics AISBL*, Brussels, Belgium, 21 December 2017, https://www.eu-robotics.net/sparc.
27. Christensen H. A roadmap for US robotics, from internet to robotics. National Robotics Initiative 2.0, 2016. 21 December 2017. Online at http://cra.org/ccc.
28. Remy SL and Blake MB. Distributed service-oriented robotics. *IEEE Int Comput* 2011; 15(2): 70–74.
29. Dietrich A, Zug S, Mohammad S, et al. Distributed management and representation of data and context in robotic applications. In: *2014 IEEE/RSJ international conference on intelligent robots and systems (IROS 2014)*, Chicago, IL, USA, 14–18 September 2014, pp. 1133–1140. IEEE.
30. Chamberlain W, Leitner J, Drummond T, et al. A distributed robotic vision service. In: *2016 IEEE international conference on robotics and automation (ICRA)*, Stockholm, Sweden, 16–21 May 2016, pp. 2494–2499. IEEE.
31. Sprute D, Pörtner A, Rasch R, et al. Ambient assisted robot object search. In: Mokhtari M, Abdulrazak B and Aloulou H (eds) *International conference on smart homes and health telematics*. Cham: Springer, pp. 112–123.
32. Thrun S and Leonard JJ. Simultaneous localization and mapping. In: Siciliano B and Khatib O (eds) *Springer handbook of robotics*. Cham: Springer, 2008, pp. 871–889.
33. Khaliq AA, Pecora F and Saffiotti A. Inexpensive, reliable and localization-free navigation using an RFID floor. In: *2015 European conference on mobile robots (ECMR)*, Lincoln, UK, 2–4 September 2015, pp. 1–7. IEEE.
34. He S and Chan SHG. Wi-fi fingerprint-based indoor positioning: recent advances and comparisons. *IEEE Commun Surv Tutor* 2016; 18(1): 466–490.
35. Hassan NU, Naeem A, Pasha MA, et al. Indoor positioning using visible led lights: a survey. *ACM Comput Surv (CSUR)* 2015; 48(2): 20.
36. Karbownik P, Krukar G, Shaporova A, et al. Evaluation of indoor real time localization systems on the UWB based system case. In: *2015 international conference on indoor positioning and indoor navigation (IPIN2015) Banff, Canada*, Jeju, South Korea, 28 June–1 July 2017.
37. Luoh L. Zigbee-based intelligent indoor positioning system soft computing. *Soft Comput* 2014; 18(3): 443–456.
38. Bonaccorsi M, Fiorini L, Cavallo F, et al. A cloud robotics solution to improve social assistive robots for active and healthy aging. *Int J Soc Robot* 2016; 8(3): 393–408.
39. Jadidi MG, Patel M and Miro JV. Gaussian processes online observation classification for RSSI-based low-cost indoor

positioning systems. In: *2017 IEEE international conference on, robotics and automation (ICRA)*, Singapore, 29 May–3 June 2017, pp. 6269–6275. IEEE.
40. Cavallo F, Limosani R, Manzi A, et al. Development of a socially believable multi-robot solution from town to home. *Cogn Comput* 2014; 6(4): 954–967.
41. Mutlu B and Forlizzi J. Robots in organizations: the role of workflow, social, and environmental factors in human-robot interaction. In: *ACM/IEEE international conference on human-robot interaction (HRI)*, Amsterdam, The Netherlands, 12–15 March 2008, pp. 287–294. ACM. DOI: 10.1145/1349822.1349860.
42. FIROS. http://docs.firos.apiary.io/#reference/0/connect-robot/ (accessed 9 September 2017).
43. Quigley M, Conley K, Gerkey B, et al. ROS: an open-source robot operating system. In: *ICRA workshop on open source software*, vol. 3. Kobe, Japan, 12–17 May 2009, p. 5. IEEE.
44. Das SM, Hu YC, Lee CG, et al. Mobility-aware ad hoc routing protocols for networking mobile robot teams. *J Commun Networks* 2007; 9(3): 296–311.
45. Sliwa B, Ide C and Wietfeld C. An omnet++ based framework for mobility-aware routing in mobile robotic networks. *CoRR* 2016; abs/1609.05351. 21 December 2017. http://arxiv.org/abs/1609.05351.
46. Deyle T, Tralie CJ, Reynolds MS, et al. In-hand radio frequency identification (RFID) for robotic manipulation. In: *2013 IEEE international conference on robotics and automation (ICRA)*, Karlsruhe, Germany, 6–10 May 2013, pp. 1234–1241. IEEE.
47. Rusu RB, Gerkey B and Beetz M. Robots in the kitchen: exploiting ubiquitous sensing and actuation. *Robot Auton Syst* 2008; 56(10): 844–856.
48. Zhong RY, Dai Q, Qu T, et al. RFID-enabled real-time manufacturing execution system for mass-customization production. *Robot Comput Int Manuf* 2013; 29(2): 283–292.
49. Wan J, Tang S, Hua Q, et al. Context-aware cloud robotics for material handling in cognitive industrial internet of things. *IEEE Int Things J* 2017 http://ieeexplore.ieee.org/document/7983343/.
50. Deyle T, Nguyen H, Reynolds M, et al. RFID-guided robots for pervasive automation. *IEEE Pervasive Comput* 2010; 9(2): 37–45.
51. Fortino G, Guerrieri A, Russo W, et al. Middlewares for smart objects and smart environments: overview and comparison. In: Fortino G and Trunfio P (eds) *Internet of Things Based on Smart Objects*. Cham: Springer, 2014, pp. 1–27.
52. Han SN, Khan I, Lee GM, et al. Service composition for IP smart object using realtime web protocols: concept and research challenges. *Comput Stand Interf* 2016; 43: 79–90.
53. Guerrieri A, Loscri V, Rovella A, et al. *Management of cyber physical objects in the future internet of things: methods, architectures and applications*. Cham: Springer, 2016.
54. Ghallab M, Nau D and Traverso P. *Automated Planning: Theory and Practice. Elsevier*, 2004.
55. Cashmore M, Fox M, Long D, et al. Rosplan: planning in the robot operating system. In: *ICAPS*, Austin Texas, USA, 25–30 January 2015, pp. 333–341. AAAI.
56. Cirillo M, Karlsson L and Saffiotti A. Human-aware task planning: an application to mobile robots. *ACM Trans Intell Syst Technol (TIST)* 2010; 1(2): 15:1–15:26, https://dl.acm.org/citation.cfm?id=1869404.
57. Kovacs DL. A multi-agent extension of PDDL3.1. In: *Proceedings of the 3rd workshop on the international planning competition (IPC), ICAPS-2012* (eds Seilva JR and Bonet B), Atibaia, Brazil, 25–29 June 2012, pp. 19–27. Brazil: University of Sao Paulo.
58. Alterovitz R, Koenig S and Likhachev M. Robot planning in the real world: research challenges and opportunities. *AI Magazine* 2016; 37(2): 76–84.
59. Bidot J and Biundo S. Artificial intelligence planning for ambient environments. In: Ultes S, Nothdurft F, Heinroth T, et al *Next Generation Intelligent Environments*. 2011, Cham: Springer, pp. 195–225.
60. Kim J, Lee J, Kim J, et al. M2M service platforms: survey, issues, and enabling technologies. *IEEE Commun Surv Tutor* 2014; 16(1): 61–76.
61. Yazdani F, , Brieber B and Beetz M. Cognition-enabled robot control for mixed human-robot rescue teams. In: Menegatti E, Michael N, Berns K, et al (eds) *Intelligent Autonomous Systems* 13. Cham: Springer, 2016, pp. 1357–1369.
62. Misra DK, Sung J, Lee K, et al. Tell me dave: context-sensitive grounding of natural language to manipulation instructions. *Int J Robot Res* 2016; 35(1–3): 281–300.
63. Wachs JP, Kölsch M, Stern H, et al. Vision-based hand-gesture applications. *Commun ACM* 2011; 54(2): 60–71.
64. Hawkins KP, Vo N, Bansal S, et al. Probabilistic human action prediction and wait-sensitive planning for responsive human-robot collaboration. In: *2013 13th IEEE-RAS international conference on, humanoid robots (Humanoids)*, Atlanta, GA, USA, 15–17 October 2013, pp. 499–506. IEEE.
65. Wolf MT, Assad C, Vernacchia MT, et al. Gesture-based robot control with variable autonomy from the JPL biosleeve. In: *2013 IEEE international conference on, robotics and automation (ICRA)*, Karlsruhe, Germany, 6–10 May 2013, pp. 1160–1165. IEEE.
66. Cambria E. Affective computing and sentiment analysis. *IEEE Intell Syst* 2016; 31(2): 102–107.
67. De Ruyter B, Saini P, Markopoulos P, et al. Assessing the effects of building social intelligence in a robotic interface for the home. *Int comput* 2005; 17(5): 522–541.
68. McColl D, Hong A, Hatakeyama N, et al. A survey of autonomous human affect detection methods for social robots engaged in natural HRI. *J Intell Robot Syst* 2016; 82(1): 101–133.
69. Leite I, Henriques R, Martinho C, et al. Sensors in the wild: exploring electrodermal activity in child-robot interaction. In: *2013 8th ACM/IEEE international conference on human-robot interaction (HRI)*, Tokyo, Japan, 3–6 March 2013, pp. 41–48. IEEE. DOI: 10.1109/HRI.2013. 6483500.

70. Bekele E and Sarkar N. Psychophysiological feedback for adaptive human–robot interaction (HRI). In: *Advances in physiological computing*. Springer, 2014, pp. 141–167.
71. Tapus A and Thi-Hai-Ha D. Stress game: The role of motivational robotic assistance in reducing users task stress. *Int J Soc Robot* 2015; 7(2): 227–240.
72. Chen M, Ma Y, Hao Y, et al. Cp-robot: cloud-assisted pillow robot for emotion sensing and interaction. In: *International conference on industrial IoT technologies and applications* (eds Wan J, Humar I and Zhang D). Cham: Springer, pp. 81–93.
73. Al-Taee MA, Al-Nuaimy W, Muhsin ZJ, et al. Robot assistant in management of diabetes in children based on the internet of things. *IEEE Int Things J* 2017; 4(2): 437–445.
74. Lieto A. Representational limits in cognitive architectures. *Proceedings of EUCognition 2016. Cogn Robot Arch*, Vienna, Austria, 8–9 December 2016, pp. 16–20. European Society for Cognitive Systems.
75. Oltramari A and Lebiere C. Pursuing artificial general intelligence by leveraging the knowledge capabilities of ACTR. In: Bach J, Goertzel B and Iklé M (eds) *AGI*. Berlin, Heidelberg: Springer-Verlag Berlin, pp. 199–208.
76. Compton M, Barnaghi P, Bermudez L, et al. The SSN ontology of the W3C semantic sensor network incubator group. *Web Semant Sci Serv Agents World Wide Web* 2012; 17: 25–32.
77. Seydoux N, Drira K, Hernandez N, et al. *IoT-O, a Core-Domain IoT Ontology to Represent Connected Devices Networks*, 21 December 2017. Cham: Springer International Publishing. ISBN 978-3-319-49004-5, 2016, pp. 561–576. DOI: 10.1007/978-3-319-49004-5 36.
78. Prestes E, Carbonera JL, Fiorini SR, et al. Towards a core ontology for robotics and automation. *Robot Auton Syst* 2013; 61(11): 1193–1204.
79. Jorge VA, Rey VF, Maffei R, et al. Exploring the IEEE ontology for robotics and automation for heterogeneous agent interaction. *Robot Comput Int Manuf* 2015; 33: 12–20.
80. Foteinos V, Kelaidonis D, Poulios G, et al. Cognitive management for the internet of things: a framework for enabling autonomous applications. *IEEE Vehic Technol Magaz* 2013; 8(4): 90–99.
81. Mezghani E, Exposito E and Drira K. A model-driven methodology for the design of autonomic and cognitive IoT-based systems: application to healthcare. *IEEE Trans Emerg Topics Comput Intell* 2017; 1(3): 224–234.
82. Kousi N, Koukas S, Michalos G, et al. Service oriented architecture for dynamic scheduling of mobile robots for material supply. *Procedia CIRP* 2016; 55: 18–22.
83. Michalos G, Makris S, Aivaliotis P, et al. Autonomous production systems using open architectures and mobile robotic structures. *Procedia CIRP* 2015; 28: 119–124.
84. Reis J. Towards an industrial agent oriented approach for conflict resolution. In: *9th Doctoral Symposium in Informatics Engineering (DSIE)* (eds Oliveira E and Souse A), Porto, Portugal, 30–31 January 2014, pp. 9–20. University of Porto.
85. Järvenpää E, Siltala N and Lanz M. Formal resource and capability descriptions supporting rapid reconfiguration of assembly systems. In: *2016 IEEE international symposium on, assembly and manufacturing (ISAM)*, Fort Worth, TX, USA, 21–22 August 2016, pp. 120–125. IEEE.
86. Nishio S, Kamei K and Hagita N. Ubiquitous network robot platform for realizing integrated robotic applications. *Intell Auton Syst* 2013; 12: 477–484.
87. Broxvall M. The PEIS kernel: a middleware for ubiquitous robotics. In: *Proceedings of the IROS-07 workshop on ubiquitous robotic space design and applications*, San Diego, CA, USA, October 29–November 02 2007, pp. 212–218. IEEE.
88. Emmi L, Gonzalez-de Soto M, Pajares G, et al. New trends in robotics for agriculture: integration and assessment of a real fleet of robots. *Sci World J* 2014; 2014: 21.
89. Bac CW, Henten EJ, Hemming J, et al. Harvesting robots for high-value crops: State-of-the-art review and challenges ahead. *J Field Robot* 2014; 31(6): 888–911.
90. Ojha T, Misra S and Raghuwanshi NS. Wireless sensor networks for agriculture: The state-of-the-art in practice and future challenges. *Comput Electron Agric* 2015; 118: 66–84.
91. Srbinovska M, Gavrovski C, Dimcev V, et al. Environmental parameters monitoring in precision agriculture using wireless sensor networks. *J Clean Product* 2015; 88: 297–307.
92. Han XZ, Kim HJ, Kim JY, et al. Path-tracking simulation and field tests for an auto-guidance tillage tractor for a paddy field. *Comput Electron Agric* 2015; 112: 161–171.
93. Matveev AS, Hoy M, Katupitiya J, et al. Nonlinear sliding mode control of an unmanned agricultural tractor in the presence of sliding and control saturation. *Robot Auton Syst* 2013; 61(9): 973–987.
94. Gealy DV, McKinley S, Guo M, et al. Date: A handheld co-robotic device for automated tuning of emitters to enable precision irrigation. In: *2016 IEEE international conference on, automation science and engineering (CASE)*, Fort Wort,TX, USA, 21–25 August 2016, pp. 922–927. IEEE.
95. Verbelen T, Simoens P, De Turck F, et al. AIOLOS: middleware for improving mobile application performance through cyber foraging. *J Syst Software* 2012; 85(11): 2629–2639.
96. De Coninck E, Bohez S, Leroux S, et al. Middleware platform for distributed applications incorporating robots, sensors and the cloud. In: *2016 5th IEEE international conference on, cloud networking (Cloudnet)*, pp. 218–223. IEEE.
97. Bacciu D, Chessa S, Gallicchio C, et al. A general purpose distributed learning model for robotic ecologies. *IFAC Proc Vol* 2012; 45(22): 435–440.
98. Verstraeten D, Schrauwen B, D'Haene M, et al. An experimental unification of reservoir computing methods. *Neural Netw* 2007; 20(3): 391–403. DOI: 10.1016/j.neunet.2007.04.003. http://www.sciencedirect.com/science/article/pii/S0893608007000038X (accessed 21 December 2017). Echo State Networks and Liquid State Machines.
99. Bacciu D, Gallicchio C, Micheli A, et al. Learning context-aware mobile robot navigation in home environments. In: *The*

*5th international conference on, information, intelligence, systems and applications, IISA 2014*, Chania, Greece, 7–9 July 2014, pp. 57–62. IEEE.

100. Crestani D, Godary-Dejean K and Lapierre L. Enhancing fault tolerance of autonomous mobile robots. *Robot Auton Syst* 2015; 68: 140–155.
101. Rampa V, Vicentini F, Savazzi S, et al. Safe human-robot cooperation through sensor-less radio localization. In: *2014 12th IEEE international conference on, industrial informatics (INDIN)*, Porto Alegre, Brazil, 27–30 July 2014, pp. 683–689. IEEE.
102. Qian K, Ma X, Dai X, et al. Decision-theoretical navigation of service robots using POMDPs with human-robot co-occurrence prediction. *Int J Adv Robot Syst* 2013; 10(2): 143.
103. Pereira AA, Binney J, Jones BH, et al. Toward risk aware mission planning for autonomous underwater vehicles. In: *2011 IEEE/RSJ international conference on, intelligent robots and systems (IROS)*, San Francisco, CA, USA, 25–30 September 2011, pp. 3147–3153. IEEE.
104. Zhang Y, Chen H, Xu W, et al. Spatiotemporal tracking of ocean current field with distributed acoustic sensor network. *IEEE J Ocean Eng* 2017; 42(3): 681–696.
105. Wang Q and Jiang J. Comparative examination on architecture and protocol of industrial wireless sensor network standards. *IEEE Commun Surv Tutor* 2016; 18(3): 2197–2219.
106. Jarchlo EA, Haxhibeqiri J, Moerman I, et al. To mesh or not to mesh: flexible wireless indoor communication among mobile robots in industrial environments. In: Mitton N, Loscri V and Mouradian A (eds) *International conference on ad-hoc networks and wireless*. Cham: Springer, pp. 325–338.
107. Lindhorst T and Nett E. Dependable communication for mobile robots in industrial wireless mesh networks. In: Koubâa A and Dios J Ramiro- Martinez-de (eds) *Cooperative Robots and Sensor Networks 2015*. Cham: Springer, 2015, pp. 207–227.
108. Bohez S, Verbelen T, De Coninck E, et al. Sensor fusion for robot control through deep reinforcement learning. *arXiv preprint arXiv:170304550* 2017.