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Internet of Robotic Things – Converging Sensing/Actuating, Hyperconnectivity, Artificial Intelligence and IoT Platforms

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Abstract

The Internet of Things (IoT) concept is evolving rapidly and influencing new developments in various application domains, such as the Internet of Mobile Things (IoMT), Autonomous Internet of Things (A-IoT), Autonomous System of Things (ASoT), Internet of Autonomous Things (IoAT), Internet of Things Clouds (IoT-C) and the Internet of Robotic Things (IoRT) etc. that are progressing/advancing by using IoT technology. The IoT influence represents new development and deployment challenges in different areas such as seamless platform integration, context based cognitive network integration, new mobile sensor/actuator network paradigms, things identification (addressing, naming in IoT) and dynamic things discoverability and many others. The IoRT represents new convergence challenges and their need

to be addressed, in one side the programmability and the communication of multiple heterogeneous mobile/autonomous/robotic things for cooperating, their coordination, configuration, exchange of information, security, safety and protection. Developments in IoT heterogeneous parallel processing/communication and dynamic systems based on parallelism and concurrency require new ideas for integrating the intelligent “devices”, collaborative robots (COBOTS), into IoT applications. Dynamic maintainability, self-healing, self-repair of resources, changing resource state, (re-) configuration and context based IoT systems for service implementation and integration with IoT network service composition are of paramount importance when new “cognitive devices” are becoming active participants in IoT applications. This chapter aims to be an overview of the IoRT concept, technologies, architectures and applications and to provide a comprehensive coverage of future challenges, developments and applications.

4.1 Internet of Robotic Things Concept

Artificial intelligence (AI), robotics, machine learning, and swarm technologies will provide the next phase of development of IoT applications.

Robotics systems traditionally provide the programmable dimension to machines designed to be involved in labour intensive and repetitive work, as well as a rich set of technologies to make these machines sense their environment and act upon it, while artificial intelligence and machine learning allow/empower these machines to function using decision making and learning algorithms instead of programming. The combination of these scientific disciplines opens the developments of autonomous programmable systems, combining robotics and machine learning for designing robotic systems to be autonomous.

Machine learning is part of an advanced state of intelligence using statistical pattern recognition, parametric/non-parametric algorithms, neural networks, recommender systems, swarm technologies etc. to perform autonomous tasks. In addition, the industrial IoT is a subset of the IoT, where edge devices, processing units and networks interact with their environments to generate data to improve processes [1]. It is in this area where autonomous functions and IoT can realistically allocate IoRT technology.

The use of communication-centred robots using wireless communication and connectivity with sensors and other network resources has been a growing and converging trend in robotics. A connected or “networked robot”

is a robotic device connected to a communications network such as the Internet or LAN. The network could be wired or wireless, and based on any of a variety of protocols such as TCP, UDP, or 802.11. Many new applications are now being developed ranging from automation to exploration [64]. IEEE Society of Robotics and Automation's Technical Committee on Networked Robots [10] defines two subclasses of networked robots:

- Tele-operated robots, where human supervisors send commands and receive feedback via the network. Such systems support research, education, and public awareness by making valuable resources accessible to broad audiences.
- Autonomous robots, where robots and sensors exchange data via the network with minimum human intervention. In such systems, the sensor network extends the effective sensing range of the robots, allowing them to communicate with each other over long distances to coordinate their activity. The robots in turn can deploy, repair, and maintain the sensor network to increase its longevity, and utility.

A common challenge in the two subclasses of networked robots is to develop a science base that connect communication for controlling and enabling new capabilities, normally a robot is a closed system(s) with high capacities and where upgrades in functionality and operation (remote and/or local) requires expertise and usually long maintenance periods and where usually there is no open interfaces nor open communication channels and this is a way to guarantee security and control of efficiency.

Networked robots require wireless networks for sharing data among multiple robots, and to communicate with other, more powerful workstations used for computationally expensive and offline processing such as the creation of globally consistent maps of the robot's environment. This connectivity has strong implications for the sharing of tasks among robots, e.g. allowing tele-operation, as well as for human-robot interaction (HRI) and for on-the-fly reprogramming and adaptation of the robots on the network [16]. The evolution of these systems has now reached the consumer market, for instance, to support remote meetings and as tele-presence health-care tools. Cloud robotic systems have also emerged, to overcome the limitations of networked robotics through the provision of elastic resources from cloud infrastructure [9], and to exploit shared knowledge repositories over the Internet, making robots able to share information and learn from each other [34].

All these approaches pose several technical challenges related to network noise, reliability, congestion, fixed and variable time delay, stability,

passivity, range and power limitations, deployment, coverage, safety, localization, sensor and actuation fusion, and user interface design. New capabilities arise frequently with the introduction of new hardware, software, and protocol standards.

The IoT technologies and applications are bringing fundamental changes in individuals' and society's view of how technology and business work in the world. Citizen centric IoT open environments require tackling new technological trends and challenges. In this context, the future developments where IoT infrastructure and services intersect with robotic and autonomous system technologies to deliver advanced functionality, along with novel applications, and new business models and investment opportunities, requires new IoT architectures, concepts and tools to be integrated into the open IoT platforms design and development.

The concept of IoRT goes beyond networked and collaborative/cloud robotics and integrates heterogenous intelligent devices into a distributed architecture of platforms operating both in the cloud and at the edge. IoRT addresses the many ways IoT today technologies and robotic "devices" convergence to provide advanced robotic capabilities, enabling aggregated IoT functionality along with novel applications, and by extension, new business, and investment opportunities [6] not only in industrial domains but in almost every sector where robotic assistance and IoT technology and applications can be imagined (home, city, buildings, infrastructures, health, etc.).

At the technology side, the proliferation of multi-radio access technology to connect intelligent devices at the edge has generated heterogeneous mobile networks that need complex configuration, management and maintenance to cope with the robotic things. Artificial intelligence (AI) techniques enable IoT robotic cognitive systems to be integrated with IoT applications almost seamlessly for creating optimized solutions and for particular applications. Cognitive IoT technologies allows embedding intelligence into systems and processes, allowing businesses to increase efficiency, find new business opportunities, and to anticipate risks and threats thus IoRT systems are better prepare to address the multiple requirements in the expected more IoT complex environment as it is depicted in Figure 4.1.

The combination of advanced sensing/actuating, communication, local and distributed processing, take the original vision for the IoT to a wholly different level, and one that opens completely new classes of opportunities for IoT and robotics solution providers, as well as users of their products. The concept enable baseline characteristics [1] that can be summarized as follow:

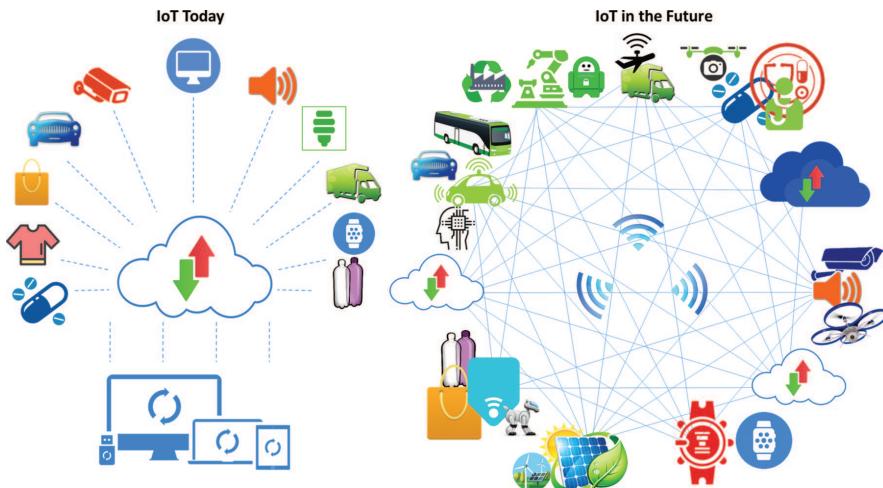


Figure 4.1 From a centralised cloud to distributed edge IoT platforms and applications.

- Define and describe the characteristics of robotics technologies that distinguish them as a separate, unique class of IoT objects, and one that differs considerably from the common understanding of IoT edge nodes as simple, passive devices.
- Reveal how the key features of robotics technology, namely movement, mobility, manipulation, intelligence and autonomy, are enhanced by the IoT paradigm, and how, in turn the IoT is augmented by robotic “objects” as “intelligent” edge devices.
- Illustrate how IoT and robotics technologies combine to provide for ambient sensing, ambient intelligence and ambient localization, which can be utilised by new classes of applications to deliver value.

IoT, cognitive computing and artificial intelligence technologies integration is part of the new developments foreseen for IoT applications in various smart environments.

4.2 Emerging IoRT Technologies

The definition of Internet of Things used in [3] states that IoT is “A dynamic global network infrastructure with self-configuring capabilities based on standard and interoperable communication protocols where physical and virtual “things” have identities, physical attributes, and virtual personalities and use intelligent interfaces, and are seamlessly integrated into the

information network”. The “things” are heterogeneous, have different levels of complexity, sensing/actuating, communication, processing, intelligence, mobility and are integrated into different platforms. The “robotic” things are a class of complex, intelligent, autonomous “things” that combine methods from robotics and from artificial intelligence [82] and are integrated to edge computing and cloud IoT based platforms. IORT combines the features of a dynamic global network infrastructure with self-configuring capabilities with the autonomous, self-learning behaviour of connected robotic things creating a system of systems that learn itself using path- and motion-planning and motion control to create services and provide solutions to specific tasks. In this context, the IoT architecture integrates the autonomous system architecture based on six main characteristics:

- Sensing is a common characteristic of the IoT and Robotic systems and this is considered as the main characteristic to enable the interaction of devices “Things” with other IoT devices and people, most of the times only in the way device to human, from here the term “sensing”, thus empowering people to be part of the ecosystem in the context of their IoT concept or service paradigm. This feature has been extensible investigated and “Sensing-as-a-Service” has been implemented among different solutions in IoT market.
- Actuating based on a holistic approach is the characteristics to enable devices “things” to action over physical and/or virtual activities, a feature or function that is well known in the IoT verticals but that is not currently available in the IoT open market. Actuating needs to look for a trusted, protected and secured development, deployment and operation of open multi-vendor IoT applications services. Actuating should be enabled on novel deployments as result of research efforts enabling “Actuation-as-a-Service” as a new paradigm for IoT enabling usability that ensure end user acceptance and engagement for controlled IoT devices.
- Control is an organised sequence of operations (mainly application layer) where functions and services are defined by a “loop” or a sequence of “loops” a.k.a. “Control Loops”. The interfaces have to be defined to provide access to sensing information as well as to provide access to required control mechanisms and the comprehensive security concepts of the architecture have to be reflected in the interface definitions to enable the required sequencing mechanisms. The Control loop can be mapped virtually to anything, from applications to services in the cloud

to networks devices in the networks infrastructure, if this last is possible then it is not difficult to believe the Internet of Things can be virtualized and represented by autonomic principles.

- Planning is an offered capability to orchestration-organize logic that coordinates the internal platform components for satisfying service requests and assuring that agreed quality levels are met throughout services life-cycle in the IoT application. The orchestration logic should align service requests with available resources, information handling and knowledge entities, and their platform-specific representation. Based on logic, planning relies on an automated workflow engine to instantiate the required functionality on a per service request basis. The orchestration logic will also maintain user-defined representations of information and resources to facilitate the process of service definition.
- Perception is known as the interdisciplinary approach in robotics where combining sensor information and knowledge modelling, robots aim to establish a robot-human interaction, by using human-interaction design, software engineering, service-based, cloud-based and data analytics architectures, multi-agent systems, machine sensor systems and sometimes artificial intelligence. Using perception robots become aware of the environment(s) enabling in this way a more particular activity for individual humans.
- Cognition, using this characteristic the device (robot) is intelligent in the sense that it has embedded monitoring (and sensing) capabilities and at the same time can get sensor data from other sources, which are fused for the “acting” purpose of the device. A second ‘intelligent’ part is that the device can leverage local and distributed “intelligence”. In other words, it can analyse the data from the events it monitors (which means a presence of edge computing or fog computing in many circumstance) and has access to (analysed) data. Finally, both prior components serve the third one which consists of (autonomously) determining what action to take and when, whereby an action can be the control or manipulation of a physical object in the physical world and, if its purpose is to do so and it has been designed to be able to, the device or robot can also move in that physical world. In this stage ‘notifying’ or ‘alerting’, based upon the analysis of ‘physical event’ can be included.

The IoRT technologies that enable the development, implementation and deployment of IoRT applications are briefly described in the following subsections.

4.2.1 Sensors and Actuators

The two baseline technologies in IoT and robotics that are well defined and identified are sensors devices and actuators, both are always crucial components for implemented IoRT systems both with well-defined interfaces (e.g. for Identification or a Reaction) and for offering these functionalities to the IoRT platform via interaction components. Different from the IoT Sensors and Actuators compose the useful functionality in and out of the IoRT building blocks. Robotic Interaction Services (RoIS) defines also the use of external of the building block and abstracts the hardware in the service robot and the Human-Robot interaction (HRI) functions provided by the robot. Calling each of the HRI functions provided by a robotic system such as a service robot or an intelligent sensing system a “functional implementation”, a robotic system can be expressed as a set of one or more functional sensor and actuator services implementations. These functional implementations (e.g. face recognition, wheel control) are usually provided in a form that is dependent on robot hardware such as sensors and actuators, examples of these sensors and actuators services are Radar, Lidar, Camera, Microphones, etc. HRI components (e.g. person detection, person identification) are logical functional elements, realized through physical units such as sensors placed on the robot and/or in the environment. The interesting part of this standard is that it allows to build applications that can be deployed on both gateways and devices, yet it is mainly focusing on HRI scenarios.

Robotic things inherit the potential for varied and complex sensing and actuation from the long tradition of robotics. From the sensing side, robotic science and technology provides methods and algorithms to use both simple and sophisticated sensors, including inertial sensors (accelerometer, compass, gyro), ranging sensors (sonar, radar, LIDAR – Light Detection and Ranging), 3D sensors (3D laser or RGBD camera), as well more common sensors like cameras, microphones and force sensors [79]. Mobile robots or multiple robots can collect sensor data from multiple pose and/or at multiple times, and techniques exist to combine these data in a coherent picture of the environment and of its evolution in time [80]. From the actuation side, the ability to modify the physical environment is arguably the most unique aspect of robotic things. Actuation can take a wide range of forms, from to operation of simple devices like an automatic door to the transportation of goods and people and to the manipulation of objects. An impressive range of techniques for actuation have been developed in the robotics field, including techniques for autonomous planning and execution of actions by single or multiple robots [81].

The IoRT applications require low-cost solid state semiconductor (CMOS) imaging sensors based on active illumination (laser based) that are robust in different environmental conditions such as sunlight, darkness, rain, fog, dust, etc. The sensors need to provide both road surface scanning (horizontal projection) and object detection (vertical projection) with high resolution and accuracy.

Current sensors mainly provide 2D sensing information and the sensors fusion (=environment model) is focused on 2D representation. Future IoRT functions require additional height information, 3D mapping and sensors/actuators fusion. The robotic things require a 3D environment model based on or adapted to existing/new sensor technologies to allow a highly accurate and reliable scene interpretation and collaboration with other robotic things, by finding the optimized representation of 3D environmental information as trade-off between resource demand and optimized performance.

The 360° vision in complex autonomous robotic things/vehicles is assure by LIDAR systems that provides the all-around view by using a rotating, scanning mirror. The LIDAR system provides accurate 3D information on the surrounding environment in order to enable the very fast decision-making needed for self-driving autonomous robotic thing, which is processed and used for object identification, motion vector determination, collision prediction, obstacle avoidance strategies.

In the case of close-in control, the LIDAR systems are not effective and the autonomous robotic things/vehicles need to equipped with radars. Operating frequency for the radar is usually in the range of 76–81 GHz, which is allocated for this use, has RF propagation characteristics, and provides the required resolution. Other advantages of the 76–81 GHz frequency range (79 GHz band) are that the radar devices are small, while the risk of mutual interference is reduced due the smaller emission power required. Radar scanning is a promising technology for collision avoidance, especially when the environment is obscured with smoke, dust, or other weather conditions.

4.2.2 Communication Technologies

The communication architecture of IoRT needs new approaches enabling shared real-time computation and the exchange of data streams (necessary for 3D-awareness and vision systems) combined with internal communication, and edge computing to enable the virtualization of functions on the existing computing engines, while enabling the ease of use of such infrastructures in many domains. The communication infrastructure and the IoRT external

communication need to be able to perform time critical communication to ensure collision prevention becomes possible, thus heavily reducing accidents and collisions.

IoRT uses typically networking technologies for local robots operation and white spectrum frequencies assigned for remote operation. IoT uses machine to machine communication and implement on standards like 4G, Wi-Fi, Bluetooth, and emergent ones like LoRa and SIGFOX, Open challenges in IoRT is achieving interoperability and establishing services at this level which is much more challenging and requires semantic knowledge from different domains and the ability to discover and classify services of things in general. This is difficult to achieve mainly because the conditions in IoRT changes rapidly and is dependent on applications, locations and use cases.

Communication protocols are the backbone of IoRT systems and enable network connectivity and integration to applications. Different communication protocols as presented in Figure 4.2 are used by the edge devices and robotic things to exchange data over the network by defining the data exchange formats, data encoding, addressing schemes for devices and routing of packets from source to destination. The protocols used are 802.11 – Wi-Fi which includes different Wireless Local Area Network (WLAN) communication standards (i.e. 802.11a that operates in the 5 GHz band, 802.11b and 802.11g operate in the 2.4 GHz band, 802.11n operates in the 2.4/5 GHz bands, 802.11ac operates in the 5 GHz band and 802.11ad operates in the 60 GHz band). The standards provide data rates from 1 Mb/s to 6.75 Gb/s and communication range in the order of 20 m (indoor) to 100 m (outdoor).

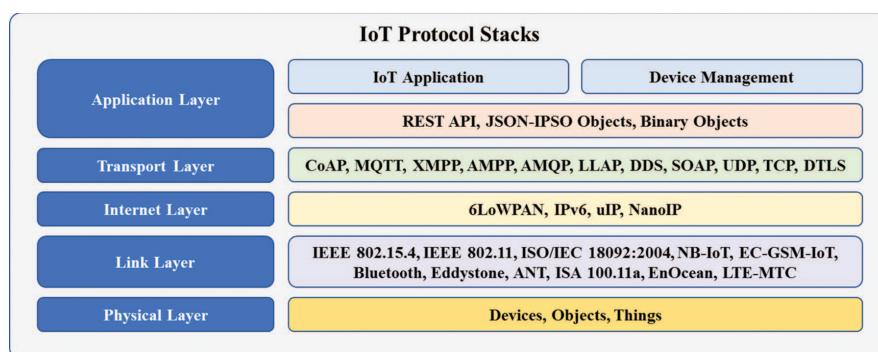


Figure 4.2 Communication protocols used by different IoRT applications.

The 802.15.4 – LR-WPAN IEEE 802.15.4 is a set of Low-Rate Wireless Personal Area Networks (LR-WPAN) standards based on the specifications for high level communications protocols such as ZigBee. LR-WPAN standards provide data rates from 40 Kb/s to 250 Kb/s. The standards provide low-cost and low-speed communication to power constrained devices and operates at 868/915 MHz and 2.4 GHz frequencies at low and high data rates, respectively.

The 2G/3G/4G and future 5G – mobile communication are different generations of mobile communication standards including second generation (2G including GSM and CDMA), third generation (3G-including UMTS, CDMA2000) and fourth generation (4G-including LTE).

IoT devices based on these standards can communicate over mobile networks with data rates ranging from 9.6 Kb/s (2G) to 100 Mb/s (4G).

The Narrowband IoT (NB-IoT) low power wide areas (LPWA) technology for IoT applications, use the existing 4G/LTE network and is based on 3GPP specifications [86]. The NB-IoT and LTE coexistence, the re-use of the LTE physical layer and higher protocol layers benefits the technology implementation. NB-IoT has been designed for extended range, and the uplink capacity can be improved in bad coverage areas. NB-IoT devices support three different operation modes [86]:

- Stand-alone operation: Utilizing one or more GSM carriers (bandwidth of 200 kHz replacements).
- Guard band operation: Utilizing the unused resource blocks within a LTE carriers' guard-band (frequency bands to prevent interference).
- In-band operation: Utilizing resource blocks within a normal LTE carrier.

For a wide range of applications, ten years battery lifetime and low cost devices will be available, and support a huge numbers of low-throughput things.

802.15.1 – Bluetooth is based on the IEEE 802.15.1 standard and offer a low power, low cost wireless communication technology for data transmission between mobile devices over a short range (8–10 m used in personal area network (PAN) communication. Bluetooth operates in 2.4 GHz band with data rate ranging from 1 Mb/s to 24 Mb/s. The ultra-low power, low cost version is called Bluetooth Low Energy (BLE which was merged with Bluetooth standard v4.0).

LoRaWAN R1.0 – LoRa is a long-range communication protocol that defines the Low Power Wide Area Networks (LPWAN) standard to enable IoT with data rates ranging from 0.3 kb/s to 50 kb/s. LoRa operates

in 868 and 900 MHz ISM bands. LoRa communicates between the connected nodes within 30kms range, in unobstructed environments. The basis is the LoRa modulation, a wireless modulation for long-range radio, low power, low data rate applications, based on a chirp spread spectrum (CSS) technology. According to the LoRa Alliance [85], LoRa can demodulates signals 19.5 dB below the noise floor, while most frequency shift keying (FSK) systems need a signal power of 8–10 dB above the noise floor. Switching between LoRa CSS and FSK modulation are also facilitated. LoRaWAN is the network protocol optimized for battery-powered end-nodes. Battery life for the attached node is normally very long, up to 10 years.

The network server hosts the system intelligence and complexity (e.g., duplicate packets elimination, acknowledgement scheduling, data rate adapting). All connections are bidirectional, support multicast operation, and forms a star of stars topology. To serve different applications, the end-nodes are classified in three different classes, which trade off communication latency versus power consumption. Class A is the most energy efficient, and is implemented in all end-nodes. Class B and C are optional and must be class A compatible. A spreading factor (SF) is used to increase the network capacity. Higher SF gives longer communication range, but also imply decreased data rate and increased energy consumption. For frequent data sampling, LoRa systems use an SF as small as possible to limit the airtime, which requires end-nodes located closer to the gateways.

4.2.3 Processing and Sensors/Actuators Data Fusion

Connected robotic things can share their sensor data, fuse them, and reason collectively about them. The mobility and autonomy capabilities of robotic brings the problem of sensor fusion in IoT platforms to an entirely new level of complexity, and adds entirely new possibilities. Complexity is increased because of the great amount and variety of sensor data that robotic things can provide, and because the location of the sensing devices is not fixed and often is not known with certainty. New possibilities are enabled because of the ability of robotic things to autonomously move to specific locations to collect specific sensory input, based on the analysis of the currently available data and of the modelling and reasoning goals. The field of robotics has developed a wide array of technologies for multi-robot sensor fusion [65–67], as well as for active and goal-directed perception [68, 69]. These techniques would enable IoRT systems to dynamically and proactively collect wide ranges of data from the physical environment, and to interpret them in semantically meaningful ways.

4.2.4 Environments, Objects, Things Modelling and Dynamic Mapping

Robotic things need to maintain an internal model of their physical environment and of their own position within it. The model must be continuously updated to reflect the dynamicity of the environment. The problem of creating and maintaining this model while the position of the robots are changing is known as SLAM, for “simultaneous localization and map building”, and it has been an active area of research in robotics for the past 20 years [70]. Techniques for metric 2D SLAM are now mature, and the field of robotics is now focusing on extending these techniques to build 3D maps [71], temporal dynamic maps [72], and semantic maps [73]. The latter are of special interest to IoRT systems, since they enrich purely metric information with semantic information about the objects and location in the environment, including their functionalities, affordances and relations.

4.2.5 Virtual and Augmented Reality

Robot-assisted surgery systems are applications that are integrating virtual reality (VR) and augmented reality (AR) technology in the operating room. Live and virtual imaging featured on robot-assisted user interfaces assist surgeon’s manipulation of robotic instruments and represent an open platform for the addition of VR and AR capabilities. Live surgical imaging is used to enhance on robot-assisted surgery systems through image injection or the superimposition of location-specific objects. The application of VR/AR technology in robot-assisted surgery is motion tracking of robotic instruments within an interactive model of patient anatomy displayed on a console screen.

The techniques and technology can be extended to IoRT applications with fleets of robots using VR/AR for learning, navigation and supporting functions.

Augmented reality as technology enhances the real world by superimposing computer-generated information on top of it, augmented reality provides a medium in which digital information is overlaid on the physical world that is in both spatial and temporal registration with the physical world and that is interactive in real time [17].

The augmented reality tools allow cognitive robotics modelers to construct, at real-time, complex planning scenarios for robots, eliminating the need to model the dynamics of both the robot and the real environment as it would be required by whole simulation environments. Such frameworks build a world model representation that serves as ground truth for training

and validating algorithms for vision, motion planning and control. The AR-based framework is applied to evaluate the capability of the robot to plan safe paths to goal locations in real outdoor scenarios, while the planning scene dynamically changes, being augmented by virtual objects [18].

4.2.6 Voice Recognition, Voice Control

Today, the conversational interfaces are focused on chatbots and microphone-enabled devices. The development of IoRT applications and the digital mesh encompasses an expanding set of endpoints with which humans and robotic things interact. As the IoRT mesh evolves, cooperative interaction between robotic things emerge, creating the framework for new continuous and ambient digital experience where robotic things and humans are collaborating.

The fleets of robots used in IoRT applications such as tour guiding, elder care, rehabilitation, search and rescue, surveillance, education, general assistance in everyday situations, assistants in factories, offices and homes require new and more intuitive ways for interactions with people and other robots using simple easy-to-use interfaces for human-robot interaction (HRI). The multimodality of these interfaces that address motion detection, sound localization, people tracking, user (or other person/robot) localization, and the fusion of these modalities is an important development for IoRT applications.

In this context, voice recognition and voice control requires robust methods for eliminating the noise by using information on the robot's own motions and postures, because a type of motion and gesture produces almost the same pattern of noise every time. The quality of the microphone is important for automatic speech recognition in order to reduce the pickup of ambient noise. The voice recognition control system for robots can robustly recognize voice by adults and children in noisy environments, where voice is captured using wireless microphones. To suppress interference and noise and to attenuate reverberation, the implementation uses a multi-channel system consisting of an outlier-robust generalized side-lobe canceller technique and a feature-space noise suppression criteria [19].

4.2.7 Orchestration

Smart behaviour and cooperation among sensing and actuating robotic things are not yet considered in the domains usually addressed with orchestration and dynamic composition of web-services in IoT platforms. An overview

of middleware for prototyping of smart object environments was reported in [58]. The authors conclude that existing efforts are limited in the management of a huge number of cooperative SOs and that a cognitive-autonomic management is needed (typically agent-based) to fulfil IoT expectations regarding context-awareness and user-tailored content management by means of interoperability, abstraction, collective intelligence, dynamisms and experience-based learning. In addition, cloud and edge computing capabilities should complement the multi-agent management for data integration and fusion and novel software engineering methodologies need to be defined.

In general, existing IoT orchestration mechanisms have been designed to satisfy the requirements of sensing and information services – not those of physical robotic things sharing information and acting in the physical environment. Furthermore, these approaches cannot be directly mapped to embedded networks and industrial control applications, because of the hard boundary conditions, such as limited resources and real-time requirements [45]. Fortunately, robotic R&D has produced some prominent approaches to self-configuration of robotic networked robotic systems. Most noticeably, both the ASyMTRe system [40], and the system by Lundh et al. [41] consider a set of robots and devices, with a set of corresponding software modules, and define automatic ways to deploy and connect these modules in a “configuration” that achieves a given goal. These frameworks leverage concepts of classical planning, together with novel methods to reason about configurations for interconnecting modules. The approach by Lundh et al is more general, in that it considers highly heterogeneous devices, including simple wireless sensor network (WSN) nodes and smart objects. An extension of this approach, based on constraint-based planning [42], was developed in the FP7 projects RUBICON [43] and RobotEra [44]. The approach leverages an online planning and execution framework that incorporates explicit temporal reasoning, and which is thus able to take into account multiple types of knowledge and constraints characteristic of highly heterogeneous systems of robotic devices operating in open and dynamic environments.

4.2.8 Decentralised Cloud

One form of orchestration is computational harvesting, i.e. offloading of computational workload using decentralised cloud solutions. This can operate in two ways. First, from a resource-constrained device to an edge cloud. There is challenging energy-performance trade-off between on-board computation and the increased communication cost, while considering network

latency [48]. This approach has been mainly studied in the context of offloading video processing workloads from smartphones and smart glasses [49]. AIOLOS is a middleware supporting dynamic offloading [50, 51], recently extended with a Thing Abstraction Layer, which advertises robots and IoT devices as OSGi-services that can be used in modular services [52].

Computational offloading has also found its way for robotics workloads. In the context of the H2020 MARIO (www.mario-project.eu) and H2020 RAPP (rapp-project.eu) projects, a framework was developed [59] where developers can create robotic applications, consisting of one Dynamic Agent (running on the robot) and one or more Cloud Agents. Cloud Agents must be delivered as a Docker container. The Dynamic Agents are developed in ROS, and need to implement a HOP web server to communicate with the Cloud Agents. Overall, the concept is mainly focused on offloading scenarios. For example, there is no support for public Cloud Agents: there is a one-to-one connection between a Cloud Agent and a Dynamic Agent. Targeted use cases are e.g. offloading of computationally intensive parts like SLAM. Similar work was done in the context of the European projects RoboEarth and follow-up RoboHow. All these frameworks are mainly oriented to allow the development of cloud-robot distributed applications and provide no integration or functionality for integration in the IoT [60].

Secondly, self-orchestration on edge clouds is related to the opposite direction, i.e. to shift (computational or storage) workloads from the centralized cloud closer to the endpoints (often the sources of data). This allows to reduce latency of control loops, or to mitigate the ingress bandwidth towards centralized servers, as recently specified by the Industrial Internet Consortium (IIC) for 3-tiers (edge, gateway, cloud) IoT architectures. Noticeable examples of such an approach include SAP Leonardo [53], GE Digital's Predix Machine [54], IBM Watson IoT [55], and GreenGrass [56] by Amazon Web Services (AWS).

4.2.9 Adaptation

Current IoT platforms do not provide sufficient support for adaptability. Rather, adaptation must be addressed for each application, and usually relies on pre-programmed, static and brittle domain knowledge. This is further exacerbated in applications that need to smoothly adapt to hard-to-predict and evolving human activity, which is particularly the case for IoRT applications. Even with adaptation logic built-in the application, the only feasible approach is the applications leveraging on contextual knowledge and experience that is provided by the platform on which the application is deployed.

The need for adaptation is even more pronounced in an IoRT platform:

- Compared to sensor-based smart objects, the **number of contexts in which smart robotic things operate is a multiple**. A large share of robots is mobile and thus enters and leaves different operational contexts. These contexts may be demarcated by the communication range of sensors, by operational constraints (e.g. leaving a Wi-Fi access point, making some services inaccessible when connected to 4G). Also, non-mobile robots need to be flexibly reconfigured in terms of software and communication with other entities, e.g. in agile Industry 4.0 manufacturing. Future robotic things will be flexible in their actuation capabilities (i.e. not limited to a single pre-programmed functionality).
- While the co-habitation of multiple applications building on the same sensor data is conceptually straightforward (could be seen as the analogue to parallel reading operations of data in a OS), this claim is not sustainable in actuation (which could be somewhat seen as “write” operations). We see three different types of situations that may arise between actors in the IoRT: competitive (non-shareable, requires locking or reservation), cooperative (robots doing two tasks at the same time instead of executing them sequentially) and adversarial (two applications require opposite end-effects of the actuators).
- IoRT applications will often be deployed in large-scale environments which are open-ended in several dimensions: human expectations and preferences, tasks to be executed, number and type of (non-connected) objects that may appear in physical space. As argued above, adaptation in today’s IoT (even when augmented with single-purpose actuators like smart automation) is a tedious procedure for which only limited platform support exists, but it must only be done once. In the IoRT, a more continuous adaptation is needed, because robots operate in open-ended, dynamic environments and are versatile actuators.
- Robotic devices are required to maintain a certain degree of autonomy. They should be given relatively high-level instructions (“Go to place X and deliver object Y i.e. they are not ideally suited for a more centralized orchestration approach to adaptation. These mandates a distributed setting with choreography between the different actors in the IoRT.

Considering all above elements, the IoRT objectives related to adaptation are truly novel. First, application developers must be provided with powerful tools to access *contextual learning* services that can provide up-to-date information and historic experience on the operational environment. Second, the

platform must allow applications to self-configure in the distributed setting introduced above, i.e. by taking the responsibility and delivering the necessary abstraction to e.g. offload or on load operations; The platform’s learning services may also publish triggers to which the application components can react in a choreography.

An important research question is how to incentivize application developers to embed their self-adapting capabilities of the IoRT ecosystem. One important consideration is that if applications are “absorbed” in the ecosystem, users might no longer be able to accredit added value to a specific service, which might decrease their willingness to pay (a negative effect for developers).

4.2.10 Machine Learning as Enabler for Adaptive Mechanisms

The IoT community is increasingly experiencing the need to exploit the potential of Machine Learning (ML) methodologies, progressively including them as part of the “things” of the IoT, and contributing to define the contours of a growing need for ML as a distributed service for the IoT. Such a need is mainly motivated by the necessity of making sense of the vast volumes of noisy and heterogeneous streams of sensorial data that can be generated by the nodes in the IoRT, and to approach the challenges posed by its many application domains. Under a general perspective, the convergence between IoT and ML would allow to systematically provide to the IoRT solutions the ability to adapt to changing contexts, at the same time providing high degree of personalization and enabling IoRT applications as well as the very same process management and service organization components of the IoRT architecture to learn from their settings and experience.

The ML service should not only be distributed, whereas it needs allowing embedding intelligence on each node of the IoRT, even at the edge of the network. Such a distributed and embedded intelligence will then be able to perform early data fusion and predictive analyses to generate high-level/aggregated information from low-level data close to where this raw data is produced by the device/sensor or close to where the application consumes the predictions. Such aggregated predictions may, in turn, become an input to another learning model located on a different network node where further predictions and data fusion operations are performed, ultimately constructing an intelligent network of learning models performing incremental aggregations of the sensed data.

Figure 4.3 shows a high-level description of how such a distributed learning architecture maps to a network of intelligent robotic things, highlighting the learning models embedded on the IoRT devices, with different computational, sensing and actuation capabilities (depicted by different colours and sizes in the figure). Figure 4.3 shows how the sizing of the learning models needs to be adjusted to the computational capabilities of the hosting device: some devices might only serve as input data providers for remote learning models. More powerful computing facilities, e.g. cloud services, can be used to deploy larger and more complex learning models, for instance aggregating predictions from several distributed learning models to provide higher-level predictions (e.g. at the level of regional gateways).

Learning service predictions need to be provided through specialized interfaces for applications and IoRT services, implementing different access policies to the learning mechanisms. One of the key functionalities such a service will need to offer, is the possibility of dynamically allocating new predictive learning tasks upon request, and the deployment of the associated learning modules, based on example/historical data supplied by the IoRT

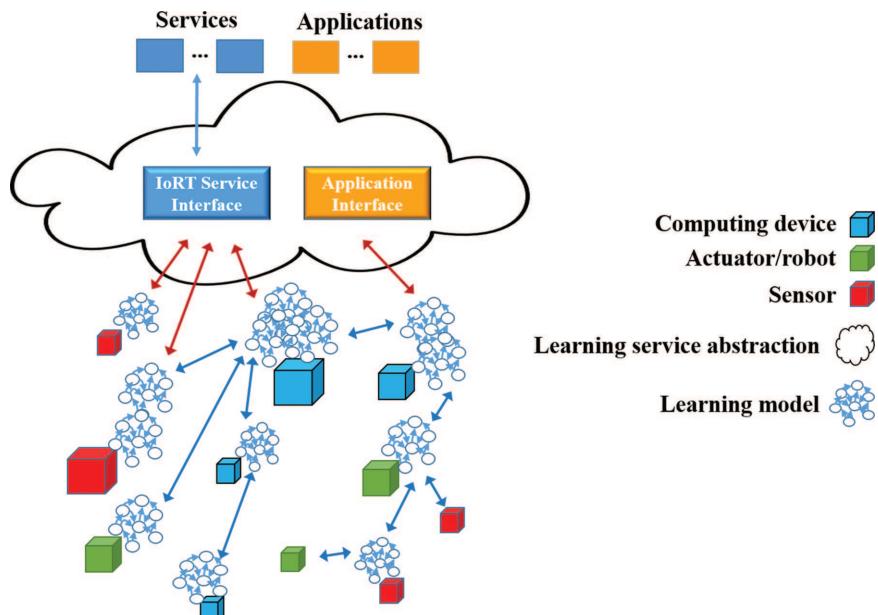


Figure 4.3 Architecture of an IoRT learning system highlighting the distributed nature of the service and the thing-embedded learning models.

applications or the platform services. Altogether such interfaces serve to realize an abstraction (depicted by the cloud in Figure 4.3) for the functionalities of the learning service which hinders the complexity of learning task deployment and execution as well as the distributed nature of the system.

From a scientific perspective, the overarching challenge is how to support applications and platform services in their self-adaptivity throughout distributed machine learning on IoT data. Fundamental challenges regarding interoperability need to be addressed, such as how can applications and services formulate data processing requests for currently missing knowledge and how these are translated into appropriate deployment strategies (What learning model to use? Where to deploy trained learning module?). Resource reasoning is another aspect to be carefully addressed: resource consumption needs to consider when determining the deployment of a trained learning module, or *predictor*, and should be constantly monitored (e.g. to dynamically transfer a predictor if resources are insufficient or critical).

Key scientific challenges also relate to the design of the learning models and machinery at the core of an IoRT learning service. These must be designed to cope with the heterogeneity of the computational resources available in the networks nodes and need to be tailored to the specific nature of the low-level data to be processed and aggregated. The latter typically characterizes as fast-flowing time-series information with widely varying semantics, properties and generation dynamics produced by the heterogeneous sensors deployed in the IoRT environment. Based on these considerations, the family of recurrent neural network models from the Reservoir Computing (RC) [12] paradigm can be thought of as particularly suitable to be considered as a ground for the design of the learning modules in an IoRT learning service. RC networks are characterized by an excellent trade-off between the ability to process noisy sensor streams and a computational and memory fingerprint, which allows their embedding on very low power devices [13]. Besides the great applicative success in approaching a huge variety of problems in the area of temporal sequence processing (see e.g. [14]), here we find particularly relevant to point out that RC models have been the key methodologies for building the Learning Layer system of the EU-FP7 RUBICON project [15], enabling the realization of a distributed intelligent sensor network supporting self-adaptivity and self-organization for robotic ecologies. The approach developed in RUBICON can be seen as a stepping stone upon which to build an IoRT learning service, by extending it to deal with the larger scale, increased complexity and heterogeneity of the IoRT environment with respect to that of a more controlled robotic ecology.

4.2.11 End to End Operation and Information Technologies Safety and Security Framework

At IoRT systems it is a real challenge increasing safety and security and at the same time implement the cooperation between networks of cameras, sensors and robots, which can be used for simple courier services, and also to include information coming from continuously patrol the environment and to check for suspicious/anomalous event patterns, and avoid the multiple possible security breaches.

IoRT End to end services must take into consideration that increasing users' comfort and energy efficiency is required. End to end safety and security services need to enable accounting for groups of users the requirements, remembering them across repeated visits, and seamlessly incorporating them into the building's heating and cooling policies, and by exploiting service robots to provide feedback on energy usage and to ensure that all the sensors in the building are calibrated and in working conditions.

IoRT challenge is to guarantee that the types, amount, and specificity of data gathered by robots and the number of billions of devices creates concerns among individuals about their privacy and among organizations about the confidentiality and integrity of their data. Providers of IoRT enabled products and services should create compelling value propositions for data to be collected and used, provide transparency into what data are used and how they are being used, and ensure that the data are appropriately protected.

IoRT poses a challenge for organizations that gather data from robotic systems and billions of devices that need to be able to protect data from unauthorized access, but they will also need to deal with new categories of risk that the having the Internet of Robotic Things connected to the Internet permanently can introduce. Extending information technology (IT) systems to new devices creates many more opportunities for potential breaches, which must be managed. Furthermore, when IoRT is deployed control of physical assets is required thus the consequences associated with a breach in security extend beyond the unauthorized release of information because potentially cause of the potential physical harm to individuals.

4.2.12 Blockchain

Blockchain technologies, including distributed ledgers and smart contracts, allow IoRT technologies and applications to scale securely, converge, combine and interact across various industrial sectors. The technology enables a decentralised and automated IoT infrastructure that allows trust less

decentralized and autonomous applications to interact and exchange data and services. The ability of blockchains and other distributed technologies to enable automated and intelligent machine to machine (robotic things) networks are transforming the design, manufacturing, distribution, logistics, retail, commerce and health applications. This will impact almost every supply chain from health to construction and manufacturing.

Figure 4.4 depicts the distributed ledger technology of blockchain that allows that in each stage of a transaction is generating a set of data, which are called blocks and as the transaction progresses, blocks are added, forming a chain, while encryption software guarantees that the blocks cannot be deleted or changed. Blockchain relies on peer-to-peer agreement (not a central authority) to validate a transaction and the transacting stakeholders rely on an open register, the ledger, to validate the transaction.

The blockchain software is installed on different computing nodes across a network and each transaction is shared to these nodes in the network and the nodes compete to verify the transaction, since the first that verifies, adds the block of data to the chain and gets an incentive, while the other nodes check the transaction, agree on about its correctness, replicate the block, and keep an updated copy of the ledger, as a form of proof that the transaction occurred.

The blockchain integrated into IoRT allows AI-based edge and cloud intelligence solutions for robotic things, using secure low latency communications technology. This allows the training and machine to machine learning

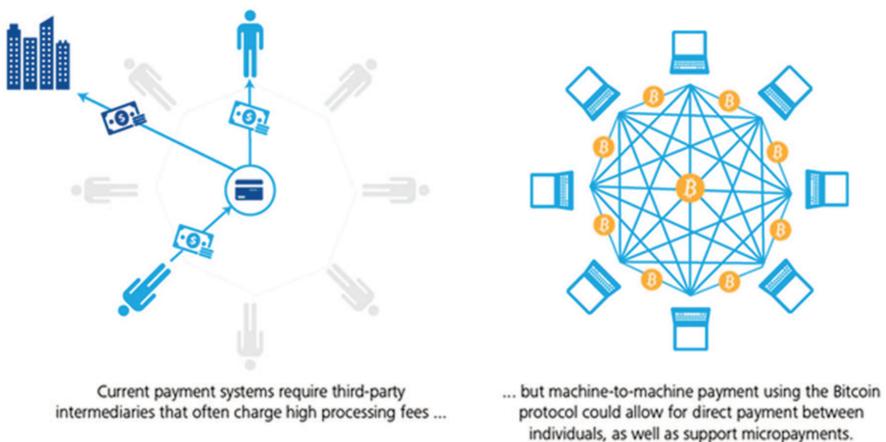


Figure 4.4 Blockchain – Payment process – Current vs Bitcoin [21].

not only one by one but training many robotic things by having edge and cloud intelligence that update in real-time in the field the robotic things with new and improved skills. The extended capabilities can use virtual reality and augmented reality for secure training.

A blockchain-enabled convergence framework is presented in Figure 4.5 to visualise the trends as a cohesive stack. The bottom data collection layer includes any sensor or hardware connected to the Internet receiving and transmitting data. This is essentially the IoT and includes devices, smartphones, drones, autonomous vehicles, 3D printers, augmented and virtual reality headsets, and connected home appliances.

The data is fed into the data management layer, with the role to manage the data being collected and the layer has different components of a decentralised architecture. The specific products can be swapped in and out, using a file system and storage component, a processing and database component and a ledger component.

These components are part of one single platform or best-of-breed for each. The data automation layer uses the data to automate business process and decision making. The automation will come from smart contracts utilizing other data directly from the ledger or smart contracts using oracles to pull data from outside of the system. Artificial narrow intelligence (ANI) can be integrated directly into the smart contract or can be the oracle itself. The higher layer is the organisational structure that directs the activity in the below layers.

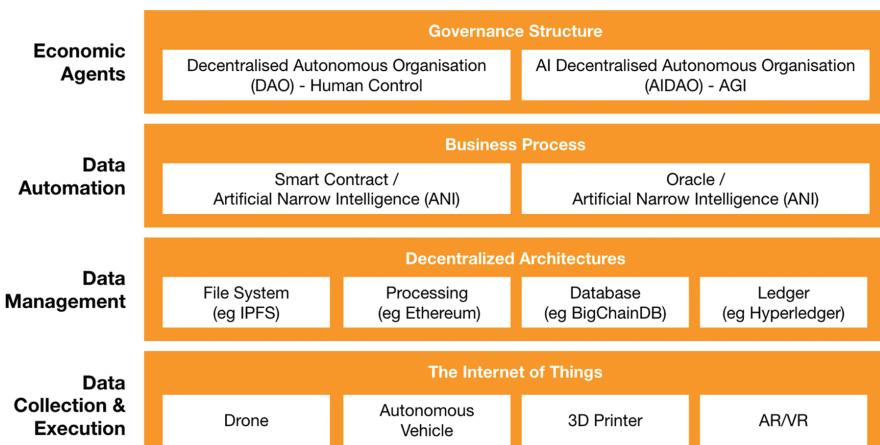


Figure 4.5 Blockchain-Enabled convergence framework [11].

The whole stack can be governed by a decentralised autonomous organisation controlled by human actors, or at some point in the future, the entire stack can be managed by an AI DAO, which may or may not constitute an artificial general intelligence (AGI). Blockchains, artificial intelligence, IoT, autonomous robotics, 3D printing, and virtual and augmented reality are all converging to significantly disrupt existing industries and create whole new markets and economic models [11]. The framework presented need to be integrated as part of the IoT open platforms architecture presented in Section 4.3.

Blockchain-based data marketplace provides a way to share and monetize data and new business models can be created so that data providers can rent their data for a specific experiment, or time period, or even based on outcomes. Autonomous robots are machines that are the mechanical manifestation of artificial intelligence and they use machine learning techniques to make decisions without needing to be pre-programmed.

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The blockchain can use to for different purposes as presented in Figure 4.6. The three levels are described as following [63]:

- Store digital records: where blockchain uses advanced cryptography and distributed programming to achieve a secure, transparent, immutable repository of truth – one designed to be highly resistant to outages, manipulation, and unnecessary complexity. In the trust economy, the individual – not a third party – will determine what digital information is recorded in a blockchain, and how that information will be used and the users may record:

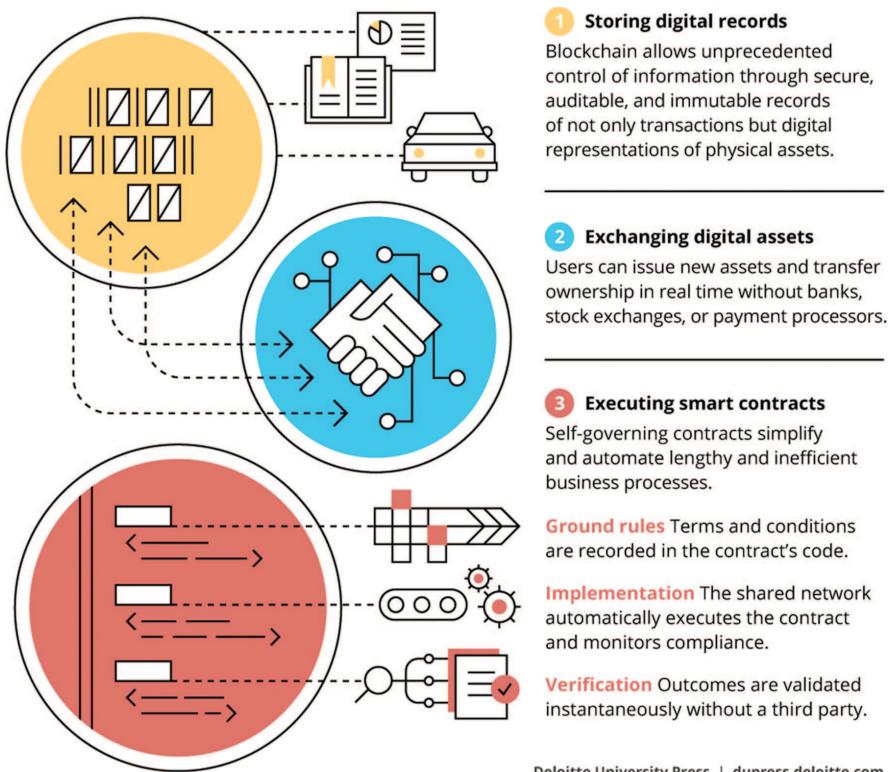


Figure 4.6 Three levels of blockchain [63].

- Digitized renderings of traditional identity documents such as driver's licenses, passports, birth certificates, social security/medicare cards, voter registration, and voting records
- Ownership documents and transactional records for property, vehicles, and other assets of any form
- Financial documents including investments, insurance policies, bank accounts, credit histories, tax filings, and income statements
- Access management codes that provide any identity-restricted location, from website single sign-on to physical buildings, smart vehicles, and ticketed locations such as event venues or airplanes
- A comprehensive view of medical history that includes medical and pharmaceutical records, physician notes, fitness regimens, and medical device usage data

- As a repository of valuable data, blockchain can provide individual users with control over their digital identities. It can potentially offer businesses an effective way to break down information silos and lower data management costs.
- Exchange digital assets without friction: using blockchain, parties can exchange ownership of digital assets in real time and, notably, without banks, stock exchanges, or payment processors – all applications requiring trusted digital reputations. Applying that basic transactional model to P2P transactions, blockchain could potentially become a vehicle for certifying and clearing asset exchanges almost instantaneously.
- Execute smart contracts: not contracts in the legal sense, but modular, repeatable scripts that extend blockchains' utility from simply keeping a record of financial transaction entries to implementing the terms of multiparty agreements automatically. Using consensus protocols, a computer network develops a sequence of actions from a smart contract's code. This sequence of actions is a method by which parties can agree upon contract terms that will be executed automatically, with reduced risk of error or manipulation. With a shared database running a blockchain protocol, the smart contracts auto-execute, and all parties validate the outcome instantaneously – and without the involvement of a third-party intermediary.

The concept can be used for IoRT applications that exchange information and create collaborative networks among of various fleets of IoRT devices. Swarm robotics is such an application with a strong influence from nature and bio-inspired models and known for their adaptability to different environments and tasks. The fleets of robotic swarms characterised by their robustness to failure and scalability, due to the simple and distributed nature of their coordination [22]. One of the main obstacles to the large-scale deployment of robots for commercial applications is security. The security topic was not properly addressed by state-of-the-art research mainly due to the complex and heterogeneous characteristics of robotic swarm systems – robot autonomy, decentralized control, many members, collective emergent behaviour, etc. Technology such as blockchain can provide not only a reliable peer-to-peer communication channel to swarm's agents, but are also a way to overcome potential threats, vulnerabilities, and attacks. In [22] the blockchain encryption scheme is presented and techniques such as public key and digital signature cryptography are considered accepted means of not only making transactions using unsafe and shared channels, but also of proving the identity

of specific agents in a network. A pair of complementary keys, public and private, are created for each agent to provide these capabilities, as presented in Figure 4.7.

Public keys are an agent's main accessible information, are publicly available in the blockchain network, and can be regarded as a special type of account number. Private keys are an agent's secret information, like passwords in traditional systems and are exclusively used to validate an agent's identity and the operations that it may execute. In the case of IoRT and swarm robotics, public key cryptography allows robots to share their public keys with other robots who want to communicate with them. Any robot in the network can send information to specific robot addresses, knowing that only the robot that possesses the matching private key can read the message. Since the public key cannot be used to decrypt messages, there is no risk if it is intercepted by other robot/person. Public key cryptography prevents third-party robots from decrypting such information even if they share the same communication channel. Digital signature cryptography, as presented in Figure 4.7, allows robots to use their own private key to encrypt messages. The other IoRT robots can then decrypt them using the sender's public key. All the robots in the fleet have access to the sender's public key, the contents of the message is not a secret, and since it was encrypted using the sender's private key proves that the message could not have been sent by anyone else, thereby proving its authorship. Public key cryptography ensures that the content of a message, encapsulated in a blockchain transaction, can only be read by the robot owning a specific address, while on the other hand, digital signature cryptography provides entity authentication and data origin authentication between robots or third-party agents [22].

4.3 IoRT Platforms Architecture

The IoT developments in the last few years have generated multiple architectures, standards and IoT platforms and created a highly fragmented IoT landscape creating technological silos and solutions that are not interoperable with other IoT platforms and applications. To overcome the fragmentation of vertically-oriented closed systems, architectures and application areas and move towards open systems and platforms that support multiple applications, new concepts are needed for enhancing the architecture of open IoT platforms by adding a distributed topology and integrating new components for integrating evolving sensing, actuating, energy harvesting, networking and interface technologies.

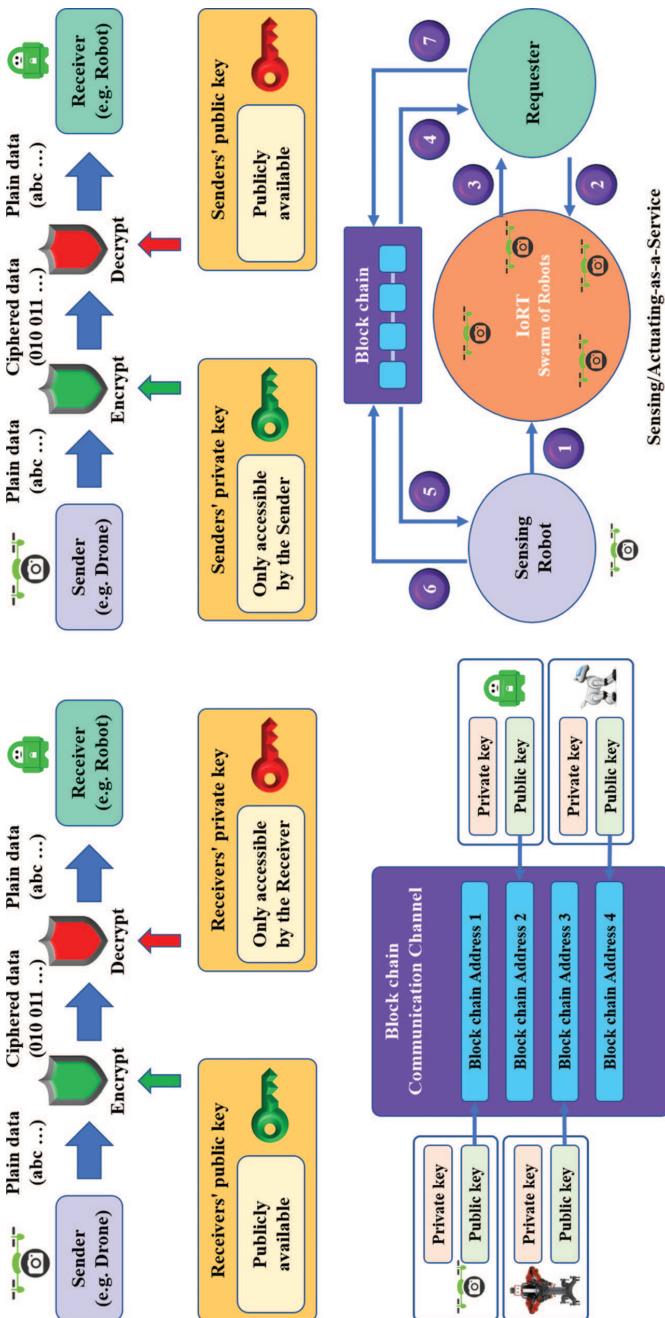


Figure 4.7 Different types of robots share the blockchain communication channel [22].

An IoT Platform can be defined as an intelligent layer that connects the things to the network and abstract applications from the things with the goal to enable the development of services. The IoT platforms achieve several main objectives such as flexibility (being able to deploy things in different contexts), usability (being able to make the user experience easy) and productivity (enabling service creation to improve efficiency, but also enabling new service development). An IoT platform facilitates communication, data flow, device management, and the functionality of applications. The goal is to build IoT applications within an IoT platform framework. The IoT platform allows applications to connect machines, devices, applications, and people to data and control centres. The functionality of IoT platforms covers the digital value chain of an end-to-end IoT system, from sensors/actuators, hardware to connectivity, cloud and applications. IoT platforms' functionalities cover the digital value chain from sensors/actuators, hardware to connectivity, cloud and applications. Hardware connectivity platforms are used for connecting the edge devices and processing the data outside the datacentre (edge computing/fog computing), and program the devices to make decisions on the fly. The key benefits are security, interoperability, scalability and manageability by using advanced data management and analytics from sensor to datacentre. IoT software platforms include the integration of heterogeneous sensors/actuators, various communication protocols abstract all those complexities and present developers with simple APIs to communicate with any sensor over any network. The IoT platforms also assist with data ingestion, storage, and analytics, so developers can focus on building applications and services, which is where the real value lies in IoT. Cloud based IoT platforms are offered by cloud providers to support developers to build IoT solutions on their clouds [5].

The IoT platforms implementations across different industry verticals reveal the use of more than 360 IoT platforms that are using Platform-as-a-Service (PaaS), Infrastructure-as-a-Service (IaaS), Software-as-a-Service (SaaS) deployments. IoT PaaS platforms are built based on event-based architectures and IoT data and provide data analysis capabilities for processing and managing IoT data. IoT-as-a-Service can be built on these different deployments. All the deployments (i.e. SaaS, PaaS and IaaS) have their challenges and security is one important issue that is connected to identity and access management.

Infrastructure as a Service (IaaS) providers and Platform as a Service (PaaS) providers have solutions for IoT developers covering different application areas. PaaS solutions, abstract the underlying network, compute, and

storage infrastructure, have focus on mobile and big data functionality, while moving to abstract edge devices (sensors/actuators) and adding features for data ingestion/processing and analytics services [5].

The IoRT applications require holistic multi-layer, multi-dimensional architectural concepts for open IoT platforms integrating evolving sensing, actuating, energy harvesting, networking and interface technologies. This includes end-to-end security in distributed, heterogeneous, dynamic IoT environments by using integrated components for identification, authentication, data protection and prevention against cyber-attacks at the device and system levels, and can help ensure a consistent approach to IoT standardisation processes.

In this context, the IoT platforms need to integrate new components in the different IoT architecture layers to address the challenges for connectivity and intelligence, actuation and control features, linkage to modular and ad-hoc cloud services, data analytics and open APIs and semantic interoperability across use cases and conflict resolution by addressing object identity management, discovery services, virtualisation of objects, devices and infrastructures and trusted IoT approaches.

The IoRT platforms architectures allow robotic things, local embedded and/or distributed intelligence, and smart networks to interact and exhibit smart behaviour and ultimately create open and sustainable marketplaces for large-scale complex and heterogeneous IoT applications and services. Due to the heterogeneity of the applications, devices and stakeholders IoT platforms generic architectures need to be independent of any specific application domains, which refer to the areas of knowledge or activity applied for one specific economic, commercial, social or administrative scope. The architectural concept builds on the common requirements based on use cases of the IoT and the IoT stakeholders, considering key areas from a requirement perspective combined with representative use cases of the IoT that are abstracted from application domains.

The IoT developments in the last few years have generated multiple architectures, standards and IoT platforms and created a highly fragmented IoT landscape creating technological silos and solutions that are not interoperable with other IoT platforms and applications. In order to overcome the fragmentation of vertically-oriented closed systems, architectures and application areas and move towards open systems and platforms that support multiple applications, there is a need for enhancing the architecture of open IoT platforms by adding a distributed topology and integrating new components for integrating evolving sensing, actuating, energy harvesting,

networking and interface technologies. The key technological shift is to provide tools and methods for implementing components and mechanisms in different architectural layers that operates across multiple IoT architectures, platforms and applications contexts and add functionalities for actuation and smart behaviour. One solution as presented in the layered architecture concept in Figure 4.8 is that the services and applications are running on top of a specific architectural layer and provide higher-level functionalities such as e.g. data filtering and complex event management and processing that allow the services of existing IoT platforms to be integrated. This concept allows solution providers to use, share, reuse the data streams and perform analytics on shared data increasing the value added of IoT applications.

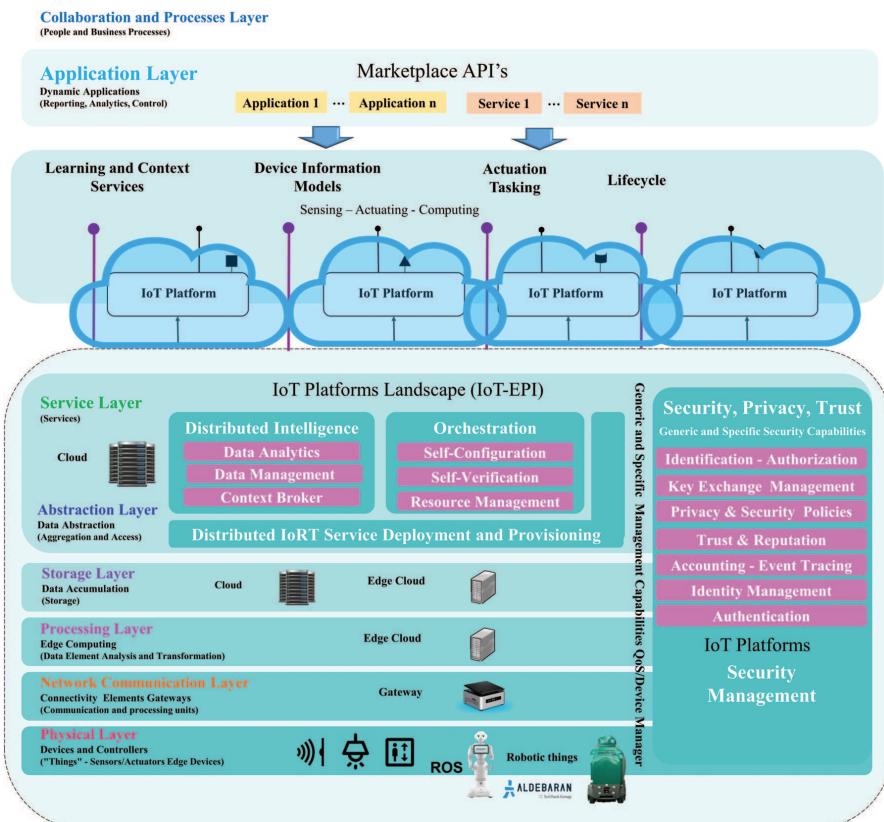


Figure 4.8 IoRT layered architecture.

The IoT applications using this approach integrate data and services among different IoT platforms and between different applications, using shared infrastructure and common standards and reducing the cost for deployment and maintenance. Application developers are able to reuse their applications in different applications, across the IoT ecosystem and greatly reducing development effort and time.

This approach allows to develop a strong IoT ecosystem around the architectural concept providing tools and methods to be used for a number of open IoT platforms that offer solutions across multiple applications and verticals. The ecosystem is built via a combination of tight and loose partnerships between the various industry, and other partners that leads to flexibility in adapting various innovative business models that is demonstrated for heterogeneous systems including autonomous, robotic type of edge devices. The open IoT platforms provided have common or specific features that host various IoT applications and services. The common goal is to capture the benefits from developing easy-to-use IoT platforms that support third party innovation.

The common requirements are classified into proposed categories such as non-functional, application support, service, communication, device (sensing/actuating/mobile/fix), data management, and security, privacy, trust safety protection requirements. The requirements for IoT open platform architectures features are summarised in Table 4.1.

The requirements for IoT open platforms for applications such as IoRT need to ensure an inclusive IoT environment that is accessible to various applications verticals across the industrial sectors and to consumers, end-users, businesses and other autonomous systems. This requires a stable, secure, and trustworthy IoT environment that assure a globally connected, open, and interoperable IoT platforms and environments built upon industry-driven, standards-based that allows the IoRT growth by supporting expanding the applications markets and reducing barriers to deployment.

The IoT open platforms can enable interoperability, infrastructure development and access by fostering the technological, physical and spectrum-related assets needed to support IoRT applications and deployments.

IoRT solutions are emerging and will scale and become more complex as different heterogenous autonomous intelligent devices will be added to the edge and this requires IoT platforms and applications that are open, scalable, extensible, safety and secure.

Table 4.1 IoT open platform architecture requirements

<i>Features</i>	<i>Description</i>
Authentication and authorization	Support multi-layer authentication and authorization
Auto-configuration	Support auto-configuration that allows the IoT system to react to the addition and removal of components such as edge devices and networks.
Autonomous management	Support self-configuring, self-optimizing, self-healing, self-protecting capabilities, for adapting to various application domains, different communication environments, different numbers and types of edge devices.
Compliant components	Support the connection and integration of various heterogeneous set of components performing differing functions based on stakeholders' and applications requirements. Architectural support for discovery and use of components whose characteristics are known and described using standardized semantics and syntaxes.
Cognitive and Artificial Intelligence	Support the cognitive and artificial intelligence components, processes and operations at different IoT architectural layers including end-to-end security.
Privacy and confidentiality	Support for privacy and confidentiality of IoT applications. Possibility to address to scale the solutions and offer context-based implementations.
Content-awareness	Support content-based awareness to enable and facilitate services for path selection and routing of communications, or configuration decisions based on content.
Context-awareness	Support context-based awareness that enable flexible, user-customized and autonomic services based on the related context of IoT components and/or users. The context-based information forms the basis for taking actions in response to the current situation, possibly using sensors and actuators information.
Data analytics	Support for analytics components performed at the different IoT layered architecture, cloud or edge including real-time, batch, predictive, and interactive analytics. The real-time analytics conduct online (on-the-fly) analysis of the streaming data. Batch analytics runs operations on an accumulated set of data. Predictive analytics focusing on making predictions based on various statistical and machine learning techniques. Interactive analytics runs multiple exploratory analysis on both streaming and batch data.

(Continued)

Table 4.1 Continued

<i>Features</i>	<i>Description</i>
Data collection protocols	Support for various types of protocols used for data communication between the components of an open IoT platform that need to be scaled to large number of heterogeneous edge devices. Lightweight communication protocols used to enable low energy use as well as low network bandwidth functionality.
Discovery services	Support discovery services across domains and applications for IoT users, services, capabilities, devices and data from devices to be discovered according to different criteria, such as geographic location information, type of device, etc.
Distributed end-to-end security	Support an end-to-end framework for security with secure components, communications, access control to the system and the management services and data security. Physical, digital, virtual and cyber security aspects need to be considered. Support for blockchain components and distributed implementations.
Heterogeneity	Support heterogeneous devices and networks with different types of edge devices regarding communication technology, computing capabilities, storage capability and mobility, different service providers and different users and support interoperability among different networks and operating systems. Support for universal, global-scale connectivity including legacy system interworking.
Location-awareness	Support for IoT components that interact with the physical world and require awareness of physical location, while the accuracy requirement for location is based upon the application. Components describe their locations, and the associated uncertainty of the locations.
Manageability	Support management capabilities to address aspects such as data management, device management, network management, and interface maintenance and alerts. Availability of lists of edge devices connected to the IoT platform, while tracking the operation status, handle configuration, firmware updates, and provide device level error reporting and error handling.
Modularity	Support components that can be combined in different configurations to form various IoT systems. Standardized interfaces for providing flexibility to implementers in the design of components and IoT systems.
Monetization	Support for monetization of functionalities of robots is crucial as an incentive for ecosystem participation. Examples for such monetization range from micro payments for ordering the help of a service robot

Table 4.1 Continued

<p>at an airport, to ordering a fully customized manufacturing process at an automated plant. Besides the monetization of functionalities and services of robots, the data collected by robots can be monetized as well. For both aspects, functionalities and data, concepts and mechanisms for monetization, such as an ecosystem-wide <i>marketplace</i>, are required.</p>	
Network connectivity	Support connectivity capabilities, which are independent of specific application domains, and integration of heterogeneous communication technologies needs to be supported to allow interoperability between different IoT devices and services. Networked systems may need to deliver specific Quality of Service (QoS), and support time-aware, location-aware, context-aware and content-aware communications
Openness	Support IoT platforms openness, based on standardised, interoperable solutions allowing any edge device, from any IoT platform, to be able to connect and communicate with one another.
Regulation compliance	Support compliance with relevant application domain specific regulations and regional requirements.
Reliability	Support the appropriate level of reliability for communication, service and data management capabilities to meet system requirements. Provide resilience and support the ability to respond to change due to external perturbations, error detection and self-healing.
Risk management	Support operational resilience under normal, abnormal and extreme conditions.
Scalability	Support a large range of applications varying in size, complexity, and workload. Support systems integrating evolving sensing, actuating, energy harvesting, networking, interface technologies, involving a large number of heterogeneous edge devices, applications, users, significant data traffic volumes, frequencies of event reporting etc. Provisions for components that are used in simple applications to be usable in large-scale complex distributed IoT systems.
Shared vocabularies	To be able to build up ecosystems of robots and IoRT platforms, it is crucial to establish shared vocabularies as a basis for interweaving them and enabling collaboration. Thereby, such shared vocabularies are needed wherever data is serialized and transmitted or exchanged.

(Continued)

Table 4.1 Continued

<i>Features</i>	<i>Description</i>
	The types, terms and concepts in the data (e.g., measured data, metadata, authorization data) need to be defined and these definitions should be part of documented vocabularies so that they can be correctly (re)used.
Standardised interfaces	Support standardised interfaces to the platforms components at different architectural layers based on established, interpretable, and unambiguous standards. Standardized web services for accessing sensors/actuators information, sensors observations and actuators actions.
Support for legacy components	Support legacy component integration and migration, while new components and systems are designed considering that present or legacy aspects do not unnecessarily limit future system evolution. Legacy components integrations need to ensure that security and other essential performance and functional requirements are met.
Time-awareness	Support for event management including time synchronicity among the actions of interconnected components by using communication and service capabilities. Time stamp associated to a time measurement from the physical world and combine or associate data from multiple sensors/actuators and data sources.
Timeliness	Support timeliness, in order to provide services within a specified time for addressing a range of functions at different levels within the IoT system.
Unique identification	Support standardised unique identification for each component of the IoT (e.g. edge devices and services) to provide interoperability, support services (i.e. discovery and authentication across heterogeneous networks) and address object identity management.
Usability	Plug and Play capabilities to enable on-the-fly, on-the-air generation, composition or the acquisition of semantic-based configurations for seamless integration and cooperation of interconnected components with applications, and responsiveness to application requirements.
Virtualisation	Virtualisation of edge objects, networks and layers.

4.3.1 IoRT Open Platforms Architectural Concepts

The heterogeneous IoT devices communicate and transmit data to other devices, gateways and to edge or cloud based IoT platforms where the data is analysed and exchanged among applications through systems that take decisions, visualize issues and patterns, steer processes and create new services.

In this, dynamic heterogeneous environment the open platforms architectural concepts play a critical role as there are interactions among intelligent devices across the platforms and application domains.

Figure 4.9 shows the different operations an IoRT open platform should include. The architecture is inspired on the emerging microservices concept, which fosters loose coupling and extendibility.

IoT sensors and actuators post raw or pre-processed data on a distributed event bus, directly or via an IoT gateway. Note that also robots can push sensor observations and actuator statuses. Other services can subscribe to this data, if they are authenticated and authorized. Example services are context creators that semantically enrich the data, IoRT business processes that send actuation tasks to the IoRT platform, and flexible learning services as described in Section 4.2.10.

The IoRT open platform will pick up IoRT tasks from the event bus and perform the necessary reservation and allocation of actuation resources. SLAs and policies govern which tasks can be executed at which time. For example, a robot monitoring task may not be executed in private spaces. All tasks are scheduled by the IoRT platform and translated into concrete actuation plans. These plans may be the result of orchestration mechanisms deciding how multiple things can work together to achieve application objectives and how data should be shared and functions distributed across the system.

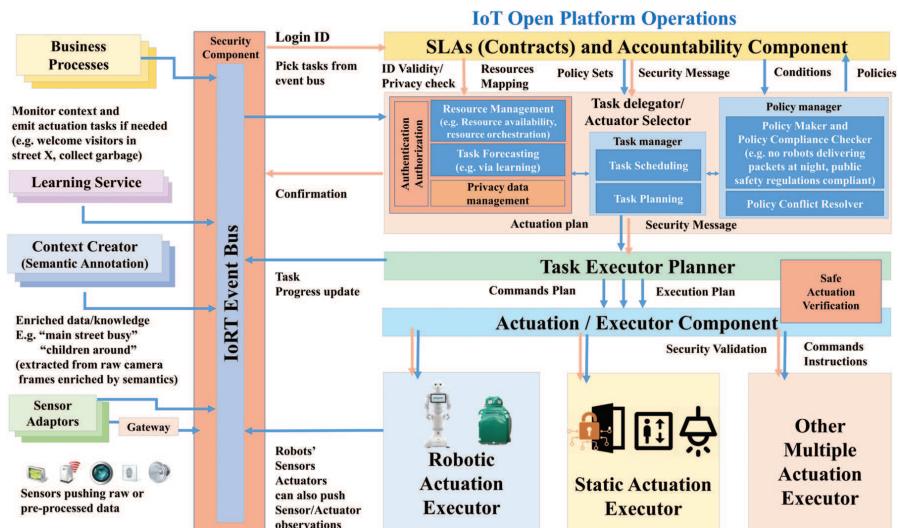


Figure 4.9 A conceptual architecture for the IoRT. Extended from [56].

After the planning stage and validation of policies, the corresponding actuation commands are sent at the appropriate time to the corresponding actuators. Actuators in physical space will perform a final check to see if the requested action is compliant to all safety regulations. This safe actuation verification may be done on the edge, but for robots this is typically implemented as a reactive module on the robot itself.

Task progress is again reported onto the event bus, allowing to adjust plans upon action failures, or to formulate new tasks emerging from the observations made by the robot. The result is a closed and continuous loop.

4.3.2 IoRT Open Platforms Interoperability

Interoperability is one of the topics that has been evolving in the last years with a lot of efforts not only from research communities but industry, the protocols and standards that exist for technical interoperability has been discussed extensively. About semantic interoperability it is common to make use of various IoT standards and platforms that exist today and that can be used for the provisioning of data gathered by smart objects. To enable cross-domain syntactic and semantic interoperability, existing IoT technologies publish open APIs and/or (semantic) data models (e.g., formalized ontologies).

Organisational Interoperability

Advanced Software-Oriented Architecture (SOA) concepts, such as service orchestration and service choreography remains active in IoRT systems, particularly if we are having an increasingly important role in overcoming the ever-increasing complexity of IoRT systems by equipping them with self-configuring, self-healing, self-optimising, and self-protecting properties, etc. (self-*, in short). A service orchestrator acts as a service broker with additional service monitoring capabilities. In cases where previously selected services become unavailable, or their performance drop, or failure occur, the orchestrator may be used again to select alternative services and/or triggering alternative service compositions. IoRT implementations, orchestration will be usually performed on powerful backend, which coordinate and integrate the whole process and its participants via (web-) services and message exchange.

Semantic Interoperability

IoRT requirements in terms of semantic interoperability requires to extend existing ontologies to support the exploitation of robotic elements such as skills, services, shared strategies, and mutual tasks and goals. Further,

engineering aspects should be modelled to allow service orchestration distributed over multiple robotic things, also to enable self-* functionalities. This includes describing mutual, context-dependent configurations for resource sharing, negotiation, and conflict resolution among multiple cross-domain services. Advance the concepts around IoT platforms to enable them to provide access to actuation and smart behaviour of robotic things is a possibility, but also the generation of new vocabularies and formalizations around robotic domains. To do this, we can build up on related work, such as existing actuator ontologies (e.g., IoT lite, or the newly published SOSA ontology by W3C). These ontologies already define terms for actuating device and related concepts. However, those ontologies do not go deeper in the modelling of the interrelations of the actuating device. This contrasts with the term of sensing device in those ontologies, which is linked to various other concepts, as it is the traditional focus.

Syntactic Interoperability

IoRT systems require in term of syntactic interoperability enhance existing open APIs to enable key functionalities needed by robotic things on IoT platforms, such as discovery, actuation, tasking, and lifecycle management.

One form of syntactic interoperability is computational harvesting, i.e. offloading of computational workload. This has been demonstrated in two ways: First, from a resource-constrained device to an edge cloud. There is challenging energy-performance trade-off between on-board computation and the increased communication cost, while considering network latency. Secondly, self-orchestration on edge clouds is related to the opposite direction, i.e. to shift (computational or storage) workloads from the centralized cloud closer to the endpoints (often the sources of data). This allows to reduce latency of control loops, or to mitigate the ingress bandwidth towards centralized servers.

Platform Interoperability

It remains a challenge to support closed-loop systems where sensor information is analysed and used in-situ, and will be necessary investigating de-centralised architectures to overcome the latency and single-point-of-failure problems associated with centralised ones. The associated interaction style, called choreography, is thought to be a more suitable way to enable a seamless integration of so-called smart items or smart objects within general IoT infrastructures. However, rather than on simple devices, e.g. devices with limited configuration options, choreography relies on agent-like IoT

entities, i.e. entities able to execute business logic and decision-making processes, and to interact among each other. A clear disadvantage of such an approach is that, at present, it is very difficult to involve computational constrained devices in the choreography, given their computational, power and network constraints. In addition, choreography opens the question of what protocols should be implemented by the smart entities, as no standards yet exist.

In the context of interoperability is important to mention the work of the newly formed IEEE-RAS Working Group, named Ontologies for Robotics and Automation. The group addresses a core ontology that encompasses a set of terms commonly used in Robotics and Automation along with the methodology adopted.

The work uses ISO/FDIS 8373 standard developed by the ISO/TC184/SC2 Working Group as a reference. The standard defines, in natural language, some generic terms which are common in Robotics and Automation such as robot, robotic device, etc. [30]. Several ontologies have been proposed for several robotics subdomains or applications, e.g., search and rescue, autonomous driving, industrial, medical and personal/service robotics. In the domain of autonomous robots, ontologies have been applied [30]:

- To describe the robot environment. A critical competence for autonomous robots is to be able to create a precise and detailed characterization of the environment as individual robot knowledge or as a central shared repository of the objects in it or the location they are moving;
- For the description and/or reasoning about actions and tasks. Autonomous robots are faced with complex, real-time tasks which might require a large amount of knowledge to be stored and accessed. Ontologies have been applied to the structuring of this knowledge and its different levels of abstraction, to describe task-oriented concepts, as metaknowledge for learning methods and heuristics or to define concepts related to actions, actors and policies to constraint behaviour;
- For the reuse of domain knowledge. Ontologies have been used to define robots as objects by describing its structural, functional and behavioural features or to characterize the domain and subdomains of robotics.

A robot is an agent and agents can form social groups, so robots can also form what we call robot groups. The work in [31] present an upper level ontology called Suggested Upper Merged Ontology (SUMO) that has been

proposed as a starter document by The Standard Upper Ontology Working Group, an IEEE-sanctioned working group of collaborators from the fields of engineering, philosophy and information science. SUMO provides definitions for general-purpose terms and acts as a foundation for more specific domain ontologies. According to SUMO, a group is “a collection of agents”, like a pack of animals, a society or an organization. In this context, a group is an agent, in the sense that it can act on its own. Similarly, to semi-autonomous and non-autonomous robots, the agents that compose the group form their agency. Examples of robot groups are robot teams, such as robot football teams and a team of soldering robots in a factory. This category also encloses what are called complex robots. These are embodied mechanisms formed by many agents attached to each other; e.g., a robotic tank in which the hull and the turret are independent autonomous robots that can coordinate their actions to achieve a common goal. Robots and other devices can form systems. In accordance with ISO, a robotic system is an entity formed by robots (e.g. single robots or groups of robots) and a series of devices intended to help the robots to carry on their tasks (Figure 4.10. Robotic system and its relations with robot and robotic environment [30]). A robotic environment is an environment equipped with a robotic system. Other example of robotic system is an automated home assistant system composed of a helper robot as well as by sensors and actuators to open doors [30].

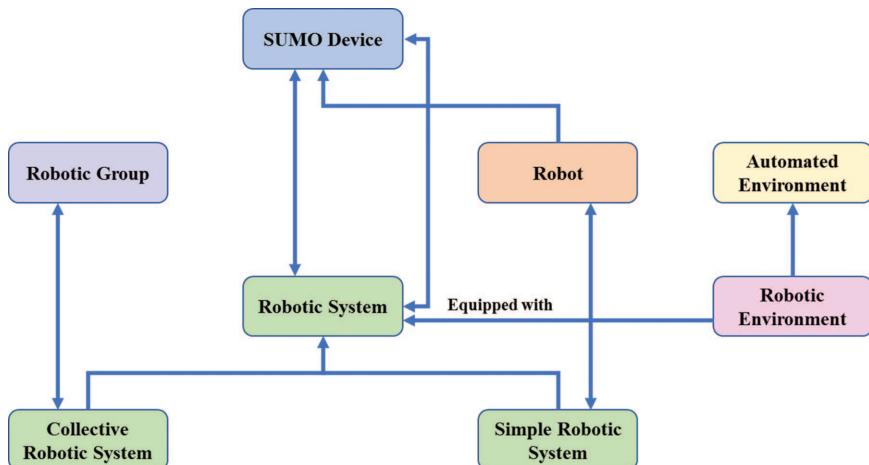


Figure 4.10 Robotic system and its relations with robot and robotic environment [30].

4.3.3 Marketplace for an IoRT Ecosystem

To give incentives for participation and growing of an IoRT ecosystem, mechanisms for monetization of service functions and data are required (Table 4.1). A marketplace needs to be established as a centrepiece of an IoRT ecosystem. Thereby, a marketplace allows the registration and discovery of offerings, i.e., data or functions offered by services. Such services can be standalone components, can be provided by IoRT platforms, or running on a thing or robot itself. The marketplace acts as an exchange point for providers and consumers of offerings. As shown in Figure 4.11, a consumer of offerings is e.g. an application or a service. A provider of an offering is a platform or a service that adds value to an offering of a platform.

According to [62] a marketplace for such ecosystems should provide mechanisms for:

- Registration of offerings, i.e., a provider of an offering can upload a metadata description that is ingested by the marketplace and indexed to support discovery.
- Discovery of offerings, i.e., a consumer utilizes an interface of the marketplace to search for offerings. For registration and discovery, it is crucial to have shared vocabularies for the metadata description of
- Authentication and authorization, i.e., consumer and provider can securely access the marketplace and use role and privilege management (e.g., association with a user group) can be conducted.

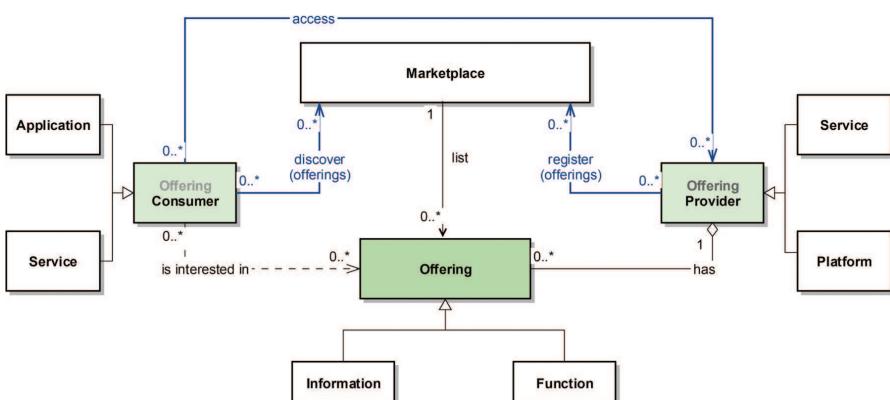


Figure 4.11 Conceptual model of a marketplace for an IoRT ecosystem [61].

- Reputation management, i.e., consumers can rate providers and their offerings; these ratings can be incorporated into search rankings and during discovery.
- Accounting and charging, i.e., the usage of an offering by the consumer is accounted (e.g., API calls are counted) and providers can charge for this usage accordingly. This is a crucial functionality to enable monetization of IoRT offerings and to give incentive for the ecosystem to grow. It is closely related to handling different licenses of data offerings.
- Orchestration, i.e., supporting the design, instantiation, control and sharing of offering compositions. This is not a mandatory functionality of a marketplace; however, it fosters reuse of registered offerings as they will be utilized in multiple workflows. Orchestration can even allow engineering of IoRT applications, e.g., a custom manufacturing process can be modelled as a collaboration of various robotic thing functions.

4.4 IoRT Applications

4.4.1 Introduction

The lessons learnt in researching network robot systems [20], ubiquitous robotics [23] and robotic ecologies [24], is that, although robots are becoming increasingly more autonomous, they are simply more efficient and intrinsically more effective if they are part of ambient intelligence solutions as a natural conditional to have integrated IoT deployed systems with Robotic systems. Patents for robotics and autonomous systems have swelled in the last decade. It is estimated that more than \$67 billion will be spent worldwide in the robotics sector by 2025, compared to only \$11 billion in 2005, reaching the compound annual growth rate (CAGR) of 9% [25]. Besides robots employed in industry and factory automation, service robotics for use in domestic, personal, and healthcare settings is the fastest growing sector. The World Robot Report projecting sales of 333,200 new robots in the period 2016–19 representing a global market more than 23 Billion US dollars. Integrated IoT & Robotics solutions will increasingly represent a significant proportion of this market. The following sections give a brief overview of opportunities in selected application domains.

Research interest in service robotics for assistance and wellbeing has grown during the last few decades, particularly as consequence of demographic changes. Maintaining a healthy lifestyle and trying to achieve a state of well-being helps to improve the life conditions and increase its

durability. Service robotics could focus on early diagnosis and detection of risks, to develop prevention programs. Thus, it is possible to use robots to perform physical activity at home, or planning a proper nutrition program, based on the user's needs. Personal wellbeing management robots can provide services also for people who are alone, or live isolated from families. These robots can both detect physiological parameters and transmit them to the doctor in real time and to interpret the emotional state of the user and accordingly interact. Figure 4.12 illustrate the evolution of robots in different application areas presented as report from Yole Development in 2016 [84].

4.4.2 Predictive and Preventive Maintenance

Machine maintenance for robots and IoT equipment is quite expensive because the dedicated equipment and the necessary to execute that. For instance, maintaining certain equipment may include a “preventive maintenance checklist” which includes small checks that can significantly extend service life. All this information need to be processed by the maintenance robot in real time or at least in the few minutes before the maintenance is

	Flying	Swimming	4+ Legged	2 Legged	4+ Wheeled	2 Wheeled	Arms	Head
Defense								
Industry								
Security								
Medical								
Transport								
Commercial								
Consumer								

Figure 4.12 Robots classification per application areas and mobility evolution [84].

scheduled to assess the best conditions to perform the maintenance. Multiple external factors, such as weather and equipment are considered; for example, heating systems maintenance is often recommended to be performed before the winter time to prevent failures likewise HVAC is better recommended to be performed before the hottest time of the year.

IoRT treats machine failures as part of the device extension and robots' operation, considering that failures as an inherent characteristic that is generated by the natural degradation of mechanical materials or the silicon degradation suffered as consequence of bringing the modification and operation of the devices and systems. The primary goal of maintenance is to reduce or mitigate the consequences of failure of the devices and the systems associated in their operation and or the equipment around them. IoRT not only look at preventing the failure before it occurs but ideally defines planned maintenance schemes and conditions based on maintenance that will help to achieve certain levels of good operation. Robots usually are designed to preserve and restore equipment offering reliability by indicating clearly what are the parts that are required to be replace and likewise identifying those worn components before they fail. Maintenance includes preventive (partial or complete) overhauls at specified periods, as per example, cleaning, lubrication, oil changes, parts replacement, tune ups and adjustments, and so on. In addition, calibration can be also considering part of the maintenance, workers usually record equipment deterioration so they know to replace or repair worn parts before they cause system failure. IoRT should take care of these conditions and even beyond that the ideal IoRT machine maintenance program would prevent any unnecessary and costly repairs.

4.4.3 Autonomous Manufacturing

According to the International Federation of Robotics (IFR), by 2019, more than 1.4 million new industrial robots will be installed in factories around the world [47]. It is projected that the number of industrial robots deployed worldwide will increase to around 2.6 million units by 2019. Broken down per sectors, around 70 percent of industrial robots are currently at work in the automotive, electrical/electronic and metal and machinery industry segments. While the acquisition costs for such robots are continuously decreasing, the costs for programming them for their specific tasks and environments are still very high. For the future, researchers are working on ways to reduce these costs for programming industrial robots, particularly, by making them more and more autonomous through increased intelligence. i.e., the aim is that we

will not specify *how* a robot does something, but we will tell the robot a goal of *what* it should do. Through technologies such as artificial intelligence, the robots will autonomously find a way of how to realize a defined goal.

In this context of increasing autonomy, technologies such as IoT & cloud infrastructure can be used to collect, analyse and visualise real-time production performance indicators, usually to inform existing optimization processes [27], while results from multi-agent systems, and adaptive middleware, can provide advanced suitable coordination and communication protocols to coordinate the operations of multiple robots. Crucial will be in the future the ability of robots to interact and collaborate with human co-workers and ultimately learn from these co-workers on how to conduct a task. Hence, an important topic is to make the co-working of robots and humans in the manufacturing process safer to enable its intensification. Therefore, robots have to be enabled to anticipate human behaviour, while working with them. For instance, Michalos et al., [28] have developed a flexible integration and distributed communication system for data sharing and coordination of autonomous and human-robot collaborative operations, using ontology services to network all possible resources and link them all for higher level coordination by a centralized task planner. Järvenpää et al. [29] have framed production lines as multi-agent systems of heterogeneous devices equipped with self-descriptive capabilities and standardized communication protocols, which they use to negotiate with one another to reduce set-up and changeover times, costs and energy consumption.

4.4.4 Autonomous Logistics, Delivery, e-commerce and Warehouse Automation

The applications in warehouse robotics for IoRT come in response to the rise of e-commerce, where collaborative robots, work alongside human warehouse worker. Logistics firms can use collaborative robots should to ease some of the workforce shortages, and make the work less physically demanding. Delivery using self-driving robots is one typical application for IoRT with fleets of robots, which are designed to operate on pedestrian side and make deliveries within 3–5 kms radius, carrying loads weighing as much as 10 kgs, at speeds of up to 8–10 km/h. The robotic fleets can be monitored remotely and standing by to drive the vehicles remotely if the robots encounter situations are not able to perform in autonomous driving mode.

Amazon has formed a team to investigate how the company might use self-driving technology within its growing logistics network. The team does not intend to design a self-driving vehicle instead it will function as a think tank tasked with helping the e-commerce titan integrate automation into its logistics strategy. The company could use self-driving forklifts, trucks, and other vehicles to expand on its early automation efforts. By further automating logistics, Amazon may be able to cut delivery costs, giving it a key competitive advantage. For example, autonomous forklifts could bring down labor costs in the company's warehouses – the Kiva robots have already cut warehouse operating costs by 20% [46].

4.4.5 Autonomous Home Appliances, and Personal Robots

Personal robots mainly refer to the consumer robotics industry and include solutions to provide services to individuals in personal and household applications.

They are likely to be mass-produced and bought or leased by untrained, or minimally trained people in everyday unstructured environments. The global personal robots market is expected to reach \$34.1 billion by 2022 [74]. Typical applications of personal robots concern domestic appliances, telepresence, entertainment, education, and assistance [75].

Domestic environments represent a major place to integrate new technology; several domestic service robots have been introduced as consumer products for the household chores, with a various portfolio of floor-cleaning robots, lawn-mowing robots, security robots, cat litter box robots, decluttering robots, etc. [76].

Telepresence robotics combines communication technology with robots' perception abilities, thus allowing advanced interaction capabilities of humans with remote environments. It allows people to monitor patients or elderly people at home or in hospitals, to virtually move and inspect through distant environments, to participate in work meetings, etc.

Numerous research studies suggest that robotics integration for educational purposes is an effective teaching method, that allow the development of student higher-order thinking skills such as application, synthesis, and evaluation, as well as teamwork, problem solving, decision making, and scientific investigation. Moreover, robotics employed as educational tool help students develop the knowledge and skills required in order to survive in the ever-changing, interconnected Information society era of the 21st century [77].

Cultural heritages, cinemas and retail environment represent a novel and interesting place to integrate new technology. Public and outdoor environments, as a place for technology, are going to have more and more attentions in the future, mainly because a normal life involve the ability to move and live in social and outdoor environments. The panorama of Service Robotics in social activities is wide: visiting cultural heritage, retail environments, outdoor cleaning robots, shopper assistant robots.

Research interest in service robotics for assistance and wellbeing has grown during the last few decades, particularly as consequence of demographic changes. Maintaining a healthy lifestyle and trying to achieve a state of well-being helps to improve the life conditions and increase its durability. Service robotics could focus on early diagnosis and detection of risks, to develop prevention programs. Thus, it is possible to use robots to perform physical activity at home, or planning a proper nutrition program, based on the user's needs. Personal wellbeing management robots can provide services also for people who are alone, or live isolated from families. These robots are able to both detect physiological parameters and transmit them to the doctor in real time and to interpret the emotional state of the user and accordingly interact.

Personal robots represent a new generation of robots that will safely act and interact in the real world of complex environments, and with relatively limited energy consumption and computational resources.

4.4.6 Healthcare Assistants, Elderly Assistance

The value of the healthcare market is significant and there is a key shortage of support provision on a one to one basis for the ageing population. The 'care deficit' poses a major challenge to ageing societies, especially in the EU and Japan. Since care responsibilities towards dependent adults are unpredictable in both duration and intensity of need, greater flexibility is desirable to allow carers to spread their leave or change their working hours to accommodate their changing needs and those of their dependants.

Autonomous and interactive robots integrated with smart environments for Ambient Assisted Living (AAL) applications have been demonstrated in several research projects [35]. On one hand, the smart environment can act as a service provider for the robot, e.g. feeding it with information about the user's whereabouts and state, by using sensors pervasively embedded in the environment and/or worn by the user. The robot can then provide useful services thanks to its physical presence and mobility capabilities.

On the other hand, the robot provides the user with a user interface that acts as a personalised representative of the services that the intelligent environment offers. This has been shown to increase the user's acceptance of the technology [33] and offer added value with services such as cognitive stimulation, therapy management, social inclusion/connectedness, coaching, fall handling, and memory aid.

Combining IoT with AI and robotic components to deliver practical, modular, autonomous and self-adaptive IoRT systems has thus the potential to complement and improve the effectiveness of existing care practices by providing automated, continuous assessment of users' conditions and support both self-care and assistive services that can be constantly in tune with users' requirements [15]. One example is the use of humanoid robots in the dementia ward of an elderly care home. Using wearables and environmental sensors, behavioural disturbances like shouting and wandering are detected and used as trigger to send a robot to start a personal intervention to temporarily distract the resident. Meanwhile, a nurse or another caregiver is alerted. The type of intervention (e.g. dialogue, music playing) is also based on context information provided by the IoT [57]. This is a clear example of an IoRT system supporting caregivers. Consumers have also a growing interest to maintain the health and wellbeing through personalized coaching. Personal, companion robots with language natural interactions and other social skills can be used to this effect. The health coaching market is estimated to be a 700-million-dollar business in the USA, \$2 billion business worldwide, with an annual growth rate of 18%. IoRT solution have the potential for a large ROI in terms of not only economic factors but also in terms of improving health and well-being of an ageing demographic at a population level. The so-called "silver market" (people aged 55 and older) represent a market of approximately 1500 billion euro per year in EU27, and they spend more on health-related products and household support devices than people on average [36]. This trend is set to become a major lead market for many commercial sectors. Merrill Lynch estimates the value of the Silver Economy at \$7 trillion per year worldwide, which makes it the 3rd largest economy in the world. In the past 20 years, consumer spending among those aged 60 and over rose 50% faster compared to those under 30 (Source: Eurostat). Smart homes and robotic solutions supporting independent living and wellness are among the applications domain that can be empowered by adopting IoRT-driven solution. They are also those that expect to benefit the most from the Silver Economy. If telehealth and telecare were scaled up across Europe to reach 10–20% coverage of the population affected by chronic diseases or old

age, this could generate potential markets for new products and services in the range of €10–20 billion a year [39].

4.4.7 Cleaning Robotic Things, Cleaning and Inspection Appliances

The IoRT application area with potential for further grow is the service robots for inspection, cleaning and maintenance. In these applications drones, can be used in conjunction with sensors mounted on hard to reach places, such as wind turbines or high-voltage transmission lines. Service fleets of robots are used in specific dangerous, monotonous or unreasonable jobs for humans. Examples are pipe inspections and cleaning, sewer system inspection that detects and map damage highly precisely and facade cleaning robots. Other examples include autonomous robotic systems that enable safe and cost-effective underwater cleaning and inspection of bridge substructures.

The robotic things can be used for various cleaning and surface preparation devices i.e. water jetting, power tools for rust and paint removal or vacuum suction systems.

4.4.8 Buildings, Garden, City Maintenance

A robot on city streets for executing hard work under stress conditions for humans is a perfect use case that would improve conditions in the city, likewise for working on times were in a town street there is no possibility to make people work. This results in a condition for the robot where the sensors in the city are the guide pointers for its operation (additional to its own navigation and sensors systems). Initially, the robot would become to be part one more element of the equipment (infrastructure) of the city and when it is right be more a dynamic element for the citizens, for example a garbage collection robot in times of extreme hot or low temperatures can execute cleaning operations on urban areas while during the traffic times can serve as traffic indicator in front of the vehicle indicating better routes for circulation. However, over time the city sensors and robots should have the capacity to learn to correlate “robot blocked street” and “dirty street” thus decision must be taken on what are the priorities for the robot and/or which is his primary role in the city and select with an event “vehicles jammed in a traffic zone”, and adjusts the garbage collection actuation strategy accordingly. Depending on what sensors and actuators are available, the “garbage collection failures” could be correlated with even more indirect events, such as “automatic adjusted roasters only between 10:00AM–11:00AM for example. Note that

this is just an example of two situations in city but at home similar activities can be defined, like gardening the back of the house or clean the front before a delivery of a parcel is expected and not after.

4.4.9 Entertainment and Well-Being

Telepresence robotics combines communication technology with robots' perception abilities, thus allowing advanced interaction capabilities of humans with remote environments. It allows people to monitor patients or elderly people at home or in hospitals, to virtually move and inspect through distant environments, to participate in work meetings, etc.

Cultural heritages, cinemas and retail environment represent a novel and interesting place to integrate new technology. Public and outdoor environments, as a place for technology, are going to have more and more attentions in the future, mainly because a normal life involve the ability to move and live in social and outdoor environments. The panorama of Service Robotics in social activities is wide: visiting cultural heritage, retail environments, outdoor cleaning robots, shopper assistant robots.

4.5 Robotics and IoT Multi Annual Roadmap

The interested reader is referred to the 2020 Robotics Multi Annual Roadmap (MAR) [83] for more details on prime opportunities for robotic technology and to SRIA for IoT technologies [1]. The Robotics Multi Annual Roadmap is a technical guide that identifies expected progress within the Robotic community and provides and analysis of medium to long term research and innovation goals and their expected impact.

The MAR recognises that new automation concepts such as IoT and Cyber-Physical Systems (CPS) have the potential to impact and revolutionise the innovation landscape in many application domains, including:

- Precision farming domain, where improvements in the interoperability and communication both between machines working on the farm and to organisations outside of the farm would allow improvements in the processing of harvested crops, efficient transport and faster time to market.
- Civil domain, where many applications for robotics technology exist within the services provided by national and local government. These range from support for the civil infrastructure, roads, sewers, public

buildings, rivers, rubbish collection etc. to support for law enforcement and the emergency services.

- Environmental monitoring domain, where the ability of robotics technology to provide multi-modal data accurately mapped to terrain data has the potential to accelerate the development and deployment of such systems and enhance those services that rely on this data.
- Inspection, maintenance and cleaning domain, where robots' advantage is in their ability to operate continuously in hazardous, harsh and dirty environments. This include drones, which can be used in conjunction with sensors mounted on hard to reach places, such as wind turbines or high-voltage transmission lines.
- Logistic and transport domains, where robots can provide key services including receiving goods, handling material, e.g. within manufacturing sites (intra-logistics), sorting and storage (warehousing), order picking and packing (distribution centres), aggregation and consolidation of loads, shipping and transportation, e.g. in last mile delivery applications.

4.6 Discussion

As the first ICT revolution (from the personal computer, to the internet, to the smartphone and wearable computers, to Cloud and internet of things) has qualitatively augmented the capability to manage data, the personal robot technology will enable a similar dramatic leap in their capability of acting in the physical world. A crucial role will be played by the integration of robots with Internet of Things and Artificial Intelligence. IoT has features of reconnect with different entities like apps, devices and people interaction, which gives the best solution for many application domains. Combination of Robotics, IoT and Artificial Intelligence results in robots with higher capability to perform more complex tasks, autonomously or cooperating with humans. With IoT platform, multiple robots can get easily interconnected between them and with objects and humans, facilitating the ability to transfer data to them without human to computer or humans to humans interaction. Reasoning capabilities coming from the use of machine learning, also exploiting cloud resources [78], for example, brings beneficial effects in terms of system efficiency and dependability, as well as safety for the user, and adaptive physical and behavioural human-robot interaction/collaboration.

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