BURLEIGH DODDS SERIES IN AGRICULTURAL SCIENCE

Advances in agri-food robotics

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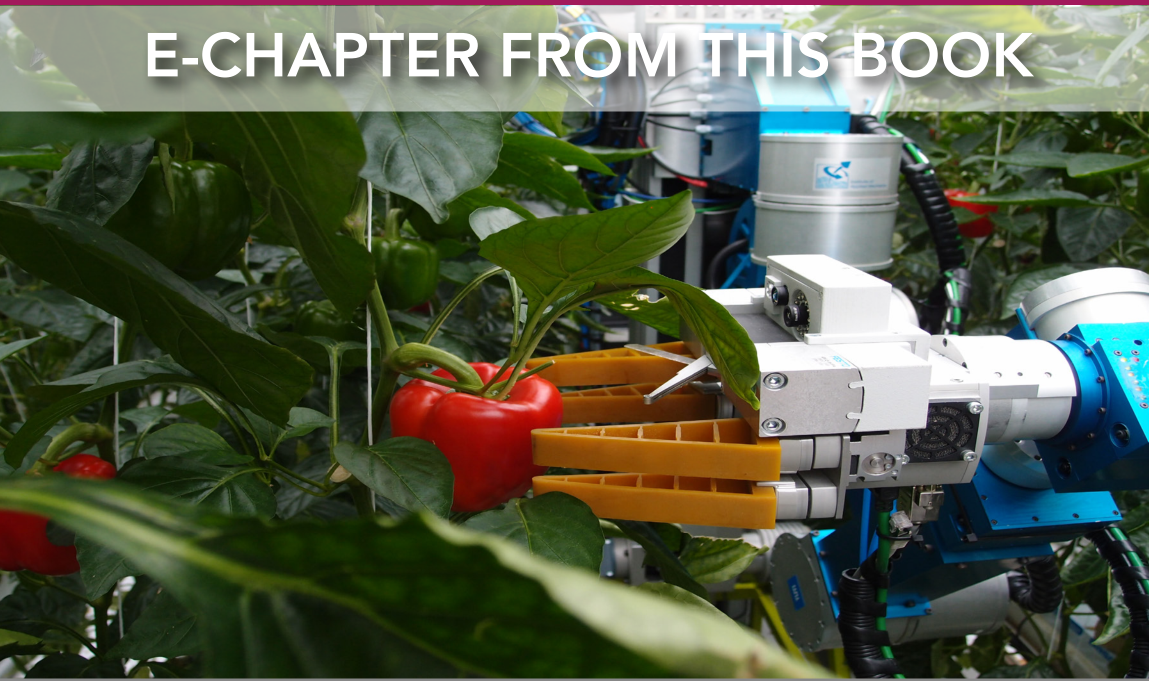
E-CHAPTER FROM THIS BOOK



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Advances in connectivity and distributed intelligence in agricultural robotics

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1 Introduction

Robots can be used in several types of farms to assist or replace human work in heavy, dangerous, dull or high accuracy needing tasks, or when the availability of labour is limited (Basri et al., 2021). Automatic milking systems (AMS), also called milking robots, are widely used service robots in livestock farming, together with increasingly common feeding and cleaning robots (John et al., 2016; Stülpner et al., 2014). In horticulture, several different approaches for harvesting robots in greenhouses have been introduced (Bachche, 2015), and farm implementations are gradually gaining ground (e.g. Ridder (no date)). Weeding and pest control robots have been developed for orchards and vineyards (Horizon The EU Research and Innovation Magazine (no date)).

http://dx.doi.org/10.19103/AS.2023.0124.14

Chapter taken from: van Henten, E. and Edan, Y. (ed.), *Advances in agri-food robotics*,
Burleigh Dodds Science Publishing, Cambridge, UK, 2023, (ISBN: 978 1 80146 277 8; www.bdspublishing.com)

Diverse pot- and bin-handling robots for both greenhouses and orchards have been designed to assist in heavy and monotonic tasks (Ye et al., 2018). Also in arable farming, several commercial field robots have been introduced and are available in markets: drones for remote sensing and ground robots capable of harrowing, weeding, fertilising and seeding (e.g. AgroIntelli (no date); FarmDroid (no date)). However, the adoption of robotic systems in use has been slow in arable farming.

Meaningful use of robots in farms requires smart, user-friendly and the circumstance-adaptive applications. This is difficult to achieve since farms are demanding worksite environments for autonomous machines. Farm operations link with several farm tasks, heterogeneous machinery and decision support systems and people and animals (Fountas et al., 2015; Köksal and Tekinerdogan, 2019). Agricultural robots need to be well connected with other actors in the farm operations they execute as well as with supporting services (Berenstein and Edan, 2017; Vasconez et al., 2019; Anagnostis et al., 2021). Robots also need to mediate data from their operations for further use in food systems since today's data-driven food systems require data or data-based information from agriculture about its production processes, i.e. field operations and production environments to function efficiently and safely, and to improve sustainability in a documented manner (Miranda et al., 2019; Corallo et al., 2018).

For better adoption, especially smallholders benefit from robotic systems that provide well-tailored, easy-to-use system entities. Smallholders have limited economic capacity to employ workers, especially when the labour is needed only seasonally. Usually, the farmer himself executes the main part of farm tasks and takes care of farm management and businesses in parallel. To be useful working partners, the robots, as any automation system, need to be well connected to other farm systems and to the robot's maintenance systems, and the provision of the robot's services needs to fit well to often individual farm circumstances and farmer's preferences (Pesonen et al., 2008).

In this sense, operation environments in arable farming set the most challenging flexibility and configurability demands for robot systems. Arable farms vary in crop selection, production strategies and methods, farm size and technological infrastructure thereof. Arable fields concern large land areas in diverse topographic and (micro)climate environments (The World Bank (no date)). Thus, the operational environments in arable farming cannot be standardised in a way it is possible in indoor animal production or greenhouses. Farm fields locate often in rural areas and in the distance from a farm's physical operation centre, which challenges functions for monitoring, control and logistics of robot systems. There is no electricity network available in the fields, and since arable fields are operated with moving machines, the needed communication requires always wireless connections. Arable farming worksites are open environments that expose robots to varying weather conditions;

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moving obstacles like people, animals and other machines; and suddenly changing working partners due to which connections to supporting services are essential (Steen et al., 2012; Kaloxylos et al., 2012; Goap et al., 2018). The ability to carry out rapid reactions and proportionate changes in plans challenges not only the connections to supporting network of services and other machines but also the intelligence of robot systems. Thus, this chapter focusses mainly on arable farming and issues encountered there.

The increased challenge is faced by the robot entrepreneur who provides RaaS for several farms. This means that the RaaS system must connect with the various machines of the customer, data sources and Farm Management Information Systems (FMIS). This usually means that the Robot entrepreneur's Management Information System (RMIS) must be able to connect with 'things' and services provided by different brands. Figure 1 illustrates the problem field of such a complex challenge. The complexity is increased when the RaaS system consists of multiple robots operating as a fleet in the same farm operation.

The RaaS system needs to connect with other systems to communicate in several operational levels of farming systems, i.e.:

- farm tasks, which include from a farm or field viewpoint what task should be done, where and when;
- fleet tasks, which indicate the allocation of farm tasks to different robots;
- robot tasks, which contain waypoints for navigation, mission parameters and main actions; and
- detailed robot tasks containing detailed instructions for the robot's actuators.

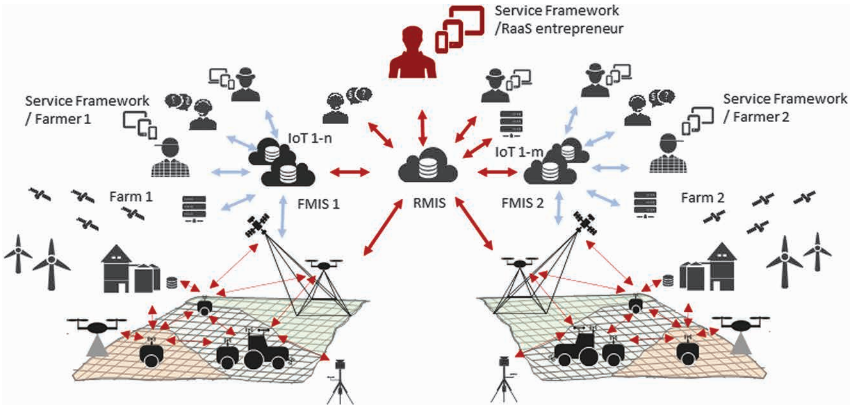

Figure 1 An illustration of a complex connectivity environment of robot systems from the viewpoint of RaaS (Robot as a Service) provider. The RaaS entrepreneur's Robot Management Information System (RMIS) must be able to communicate with several customers' Farm Management Information Systems (FMIS), Internet of Things systems and directly with robots and other machines and sensor systems in customers' fields. Data connections are depicted with arrows. Robot entrepreneur and farmers have grouped their individual sets of services as Service Frameworks.

From farmers' and robot entrepreneurs' points of view, there is a need to use and control the systems that are needed in everyday work. Internet of Things (IoT) and further the concept of Internet of Robotic Things (IoRT) (Ray, 2016) bring possibilities to include a growing number of services to farms' and entrepreneurs' toolboxes. To maintain awareness of ongoing operations and forecasts and adjust plans accordingly, there is a need for a Service Framework that offers a single access point to diverse user interfaces (UI) of the systems in use (Fig. 1).

The connectivity and intelligence of robot systems contribute to efficient, reliable and safe operation. Efficient and reliable operation requires that the robot system operates correctly even in suddenly changing operating circumstances and environments. The robot system can recover fast from disturbances, with minimal manual interference by the robot operator. Remote monitoring and notifications of deviations from plans create trust in the system. Robots must be able to operate safely as a part of various collaborating machine fleets and workforce. The functionalities must support the overall easiness to adopt and use of robot systems and economic viability of use.

The desired functionalities demand advanced connectivity of robots within a robotic system and with their support systems like robot IoT platform, FMIS, RMIS and possibly other supporting (AI) systems and data sources. The networked connections are essential to enable timely and correct autonomous decision-making through advanced distributed intelligence. Dyke Parunak (1994) explains that a system utilising distributed intelligence is a multi-agent system where 'the autonomous agent approach replaces a centralized database and control computer with a network of agents, each endowed with a local view of its environment and the ability and authority to respond locally to that environment. The overall system performance is not globally planned, but emerges through the dynamic interaction of the agents in real-time'. In agricultural environments, also the edge computing paradigm (i.e. Bierzynski et al., 2021) i.e. the sharing of the computational load among different network nodes as well as distributed problem-solving are relevant aspects of distributed intelligence.

The following sections deepen the views on how key challenges are addressed in agricultural systems. The system parts handled in this chapter are shown in Fig. 3. The system architecture is described in Section 2. The challenges of communication and interfacing methods of robots and their support systems are dealt with in Sections 3 and 4. Timely analytics and decision-making are discussed in Sections 5 and 6. Access to various farm- and business-specific data sources and services is handled in Sections 7 and 8. Section 9 gives a practical example of solving.

2 Robotic system architecture

Along with the Industry 4.0 era, robots are increasingly part of connected machinery or service systems in industrial production environments. It requires the ability of robots to function in meaningful ways, to integrate into diverse production chains and to operate efficiently and safely in demanding conditions. IoT has been one of the main technological concepts of Industry 4.0. As Ray (2016) abstracts, IoT allows a massive number of uniquely addressable 'things' to communicate with each other and to transfer data using existing internet or compatible network protocols. The concept of Cloud Robotics increases robots' processing power and data needs, i.e. by utilising distributed computing and data sources and BigData analysis (Ray, 2016). The concept of the IoRT combines these two concepts, providing means to support, control and monitor activities at deployment sites like agricultural fields (Khalid, 2021; Villa et al., 2021).

The architecture of IoRT consists of several layers, including typical hardware, network connectivity, internet connectivity, infrastructure for the robotic platform and cloud platform support, and application layers (Ray, 2016; Batth et al., 2018).

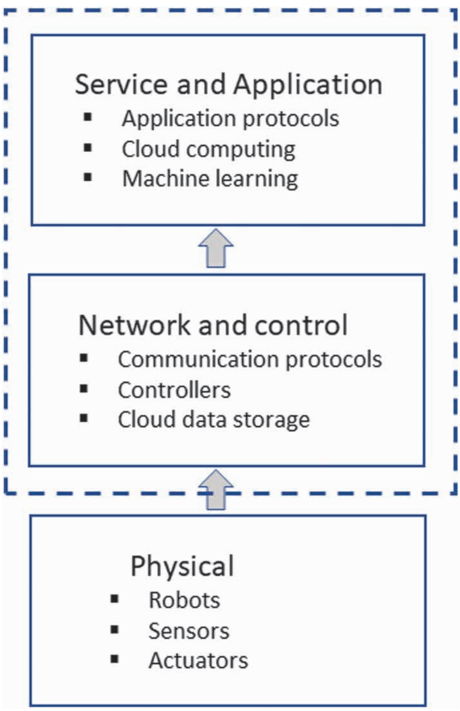

Figure 2 Internet of Robotic Things architecture overview after Villa et al. (2021). The dashed line depicts the focus of this chapter.

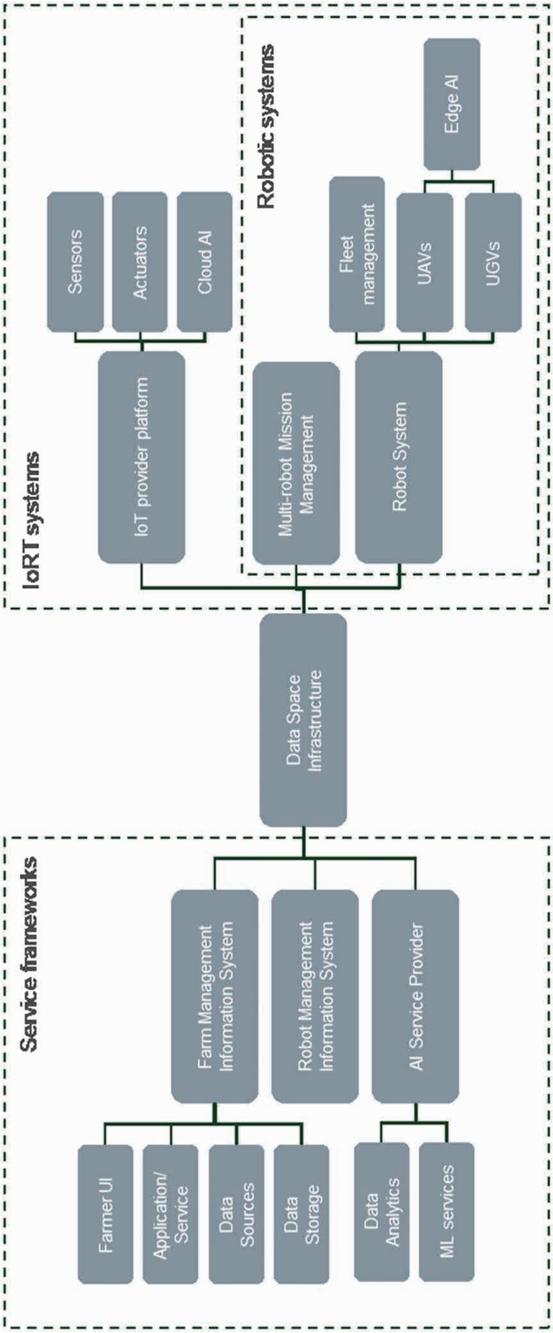

Figure 3 Advanced robotic system architecture based on connectivity and collaborative intelligence as discussed in this chapter.

The layers enable composability of the system, context awareness in operations, virtualised diversification, interoperability, dynamic and self-adaptive operations, geo-distribution of data and data processing, and ubiquitous network access. Villa et al. (2021) described the IoRT architecture overview by three main layers (Fig. 2): (1) physical layer including robots, sensors and actuators; (2) network and control layer including communication protocols, controllers and cloud data storage; and (3) service and application layer including application protocols, cloud computing and machine learning (ML).

To meet the challenges presented in Section 1, the concept of IoRT is evolving to support networked co-operation models between business entities and their heterogeneous systems (FMIS, RMIS and AI Service), as indicated in Fig. 3, in which the architecture includes distributed AI, data sovereignty and data ownership respecting data space infrastructure for agile data connections, multi-robot systems (MRS) management and service compositions as service frameworks.

3 Communication networks

In IoRT, robots are extended with functionalities in the cloud. By definition, it involves the need to be connected to the Internet and certainly, the Internet is the most important communication network of robots and the agriculture domain, too. In the case of agricultural robots, the main challenges related to the Internet have been the unpredictable delays of the network and the 'last mile connection' that needs to be wireless when agricultural robots perform their actions in fields. Recently, for example, the need to transmit large image files or video and the need to use external third-party services is creating new challenges with respect to transfer capacity, privacy and safety (Guo et al., 2020; Kaknjo et al., 2018).

Originally, consumer electronics have been the main driving force in the development of communication networks, especially cellular networks, i.e. mobile phone networks. However, in recent times, the requirements for the development of cellular networks have come from applications other than consumer applications. Industrial applications such as robotics may be more demanding than consumer applications in terms of low latency, high bandwidth, low power consumption or secure connection (i.e. Backman et al., 2019). The concept of cellular networks was developed by Bell Laboratories in 1947 (Asif, 2018). However, the first generation (1G) of commercial cellular networks was not introduced until the 1980s. The 1G networks were analogue systems and are no longer operational. However, the second-generation (2G) digital networks, which were introduced in 1990s, are still operational. Before the introduction of 2G networks, the European Telecommunications Standards Institute (ETSI) was founded in 1988 (ETSI, 2022). The Global System for Mobile

Communications standard, which is the basis for 2G networks, was the first of the standards developed and published by ETSI. To provide worldwide coverage of technology, seven telecommunications standard development organisations (ARIB, ATIS, CCSA, ETSI, TSDSI, TTA and TTC) have agreed to co-operate in Third Generation Partnership Project (3GPP, 2022). The first 3G networks were introduced in 2001 and the successor 4G in 2009. The latest generation, 5G networks, was launched in 2019 (Tang et al., 2021). All these technologies are operational at the same time. 4G was the first mobile broadband technology to enable 100 Mbps or higher data rate. The 5G systems are expected to provide a 20 Gbps peak data range and enable mission-critical applications that require ultra-high reliability and low latency (Asif, 2018).

In cellular networks, the data is transferred to public networks through the internet. In some applications, such as remote operation solutions or robot collaboration, this might be a problem if low latency, reliability and security are needed. Virtual Private Networks and other similar technologies are possible to use, but still the data is essentially transferred together with all other traffic that uses the same networks. In the future, 5G technology can be also used to construct wide-area private networks (Ericsson, 2019), but for short-range (<100 m) wireless communication, there are also other technologies developed. The Wireless LAN (WLAN) technologies are based on the IEEE 802.11 standards which contain several different protocols (IEEE 802.11). With WLAN technology, it is possible to build local closed private networks for specific use.

In agriculture, Agricultural Industry Electronics Foundation (AEF) is the organisation that develops guidelines for new communication technology standards (AEF, no date) and initiates the standardisation process in ISO. For standardisation of wireless communication between tractors and other entities, a dedicated workgroup in AEF exists. AEF has identified the use cases where wireless communication is needed and the requirements that those use cases set (AEF, 2022a). However, technological choices are still open, but the developments of road vehicles are followed. In the automotive industry, Vehicle-to-Everything (V2X) communication technologies have been developed for communication between a vehicle and other entities. The original V2X technologies were based on WLAN technologies (IEEE 802.11p-2010), but more recent development C-V2X has used cellular technologies and is expected to use 5G networks (3GPP, no date; Christopoulou et al., 2023). C-V2X technologies are interesting to employ also in agriculture since C-V2X is able to directly connect individual vehicles within the same area and also enables the development of cooperative intelligent systems using conventional mobile network (GSMA, no date; HKT, 2020), and the first use cases for agricultural machinery have been introduced by commercial actors (Autotalks, no date).

Highly accurate real-time positioning is an essential part of robotic operations. The backbone of the global level positioning is the GNSS (Global Navigation Satellite System). Single GNSS positioning is inaccurate. High-accuracy GNSS systems (Ogaja, 2022) such as real-time kinematics GNSS require communication between the satellite receiver and service-providing parameters needed to determine precise coordinates for the position. Methodologies such as PPP (precise point positioning) that require not only a single GNSS but also precise measurements of the GNSS satellites' orbits from external sources are also applied in robotics and autonomous navigation. Typical communication networks with networked transport of RTCM via internet protocol (Lenz, 2004) or separate radio links are used with the accurate GNSS. Solutions such as satellite-based augmentation system do not need two-way communication. Generally, GNSS-positioning technologies are becoming smaller, cheaper and more accurate. However, high-precision positioning relying on smartphone devices is still challenging (Zangenehnejad and Gao, 2021) but is under constant development. The current challenges include multipath errors due to polarising antennas, frequent cycle slip (signal interruption) and missing signal phase observations, and lack of phase center offset and variation information (Zangenehnejad and Gao, 2021). GNSS vulnerability (Zidan et al., 2020) remains a great challenge.

4 Internet of things to link robots

IoT concept has been widely adopted in almost all kinds of systems, industrial and private. IoT is an important integrating technology also in smart farming (Verdouw et al., 2016). Lezoche et al. (2020) lists that IoT has positive impacts on:

- functionality (sensing, monitoring, controlling);
- economics (operational efficiency);
- environment (enhanced farming methods, resource efficiency);
- social issues (endured certification schemes in food chains, less manual labour);
- business (new business models and collaboration); and
- technology (low-power wireless sensors and machine-to-machine (M2M) connectivity).

In the same review, capital investment costs, especially for smallholders, user acceptance and current lack of technical skills, and technical issues like lack of interoperability and connectivity in rural areas, absence of data processing power, unclear data governance (data ownership), decentralisation, among others are listed as challenges.

In the case of agricultural robots, the IoT concept has two roles. First, it can provide data for the robot, and second, the robot itself can be considered as a thing connected to internet. Today's IoT solutions are typically cloud services that:

1. collect data from sensors and devices;
2. store the data both in databases meant to provide contextual information from some specific place (context brokers) and in time series databases of individual data sources; and
3. provide means to analyse the collected datasets using data analytics and artificial intelligence (AI) services.

The IoT today can be considered as a platform, on which smart applications or cyber-physical systems are built.

The origins of IoT are different and consist of three main concepts. The first concept, the networked things, is to combine small digitalised or computerised physical appliances (i.e. things) into a networked system. M2M communication was the main enabler that allowed communication within the group of machines and devices, and when at least one point (machine or device) of the network was connected to the internet, the other 'things' were connected as well. The second concept was to see the connected thing as a service that could be accessed via a web browser. This approach called the Web of Things creates an application programming interface (API) to the 'things' enabling a user to access or manipulate the 'things' through it. The main difference compared to the first approach is that the 'thing' is not considered as a node in a network but as a service. The third concept was to connect things that do not have digital interfaces to internet. The unique identifiers in the form of codes and tags were used to connect the physical things to data that represented them or to the service that was linked to them. Bar codes, QR codes and Bluetooth beacons transmitting digital identifiers of things to be sensed by Bluetooth devices were the first techniques to associate objects with digital services. Later, for example, image recognition has partly removed the need for specific codes.

The Internet of Things–Architecture Reference Model (IoT-ARM) has been the baseline for the development of IoT platforms (Bauer et al., 2013). IoT-ARM defined the five basic models of IoT system architecture: domain model, information model, functional model, communication model, and trust, security and privacy model. The IoT platforms have largely been developed based on the IoT-ARM. The FIWARE platform (FIWARE no date) is an open-source platform for smart solutions, including smart agriculture. It was based on extending the M2M communication model with virtual models of real-world entities. Its main components are an NGSI protocol that connects system modules together, a Virtual Entity model for managing the data of connected objects, and generic enablers such as a context broker, a time-series database and other functionalities that provide, for example, data analytic and visualisation services for applications. FIWARE has been applied in many agriculture solutions (Rodriguez et al., 2018; Corista et al., 2018). The smart objects for intelligent applications project extended the IoT towards smart spaces, semantic interoperability and LinkedData (LinkedData, no date). The idea of smart spaces was to create an IoT data-sharing environment for limited physical places and to enable the data-centric creation of smart services in it (Kiljander et al., 2014). Semantic interoperability is the ability to share data with unambiguous shared meaning. This is typically achieved by using common ontologies and semantic data models that are models where data elements are linked with the definitions of their meaning. When the links given in ontology models are provided between data elements, we end up with the graph model of data called LinkedData. Since these early solutions, the IoT platforms have evolved to become application domain-specific services that users can connect to with a huge variety of sensors and communication technologies and which provide advanced services for implementing cyber-physical systems (Chen, 2020; Farooq et al., 2020; Ojha et al., 2021; Ray, 2016).

The future IoT has two main roles. First, it provides means to share data of the physical world in the cyber world and enables analysis and optimisation of large-scale systems of systems. Second, it provides means to create advanced situational awareness and physical interaction in more local contexts and thereby allows developing more intelligent and autonomous robotic systems (Ploennigs et al., 2018). Digital twins are software models of real systems that are either targeted to analyse, simulate or extend the physical systems. The main use has been, for example, in maintenance, where the wearing of parts can be analysed using simulation models (Pylianidis et al., 2021). Currently, IoT feeds digital twins with real-world data, but the trend is in expanding the use of digital twins towards the exploration of alternative futures that can be a basis for better decisions today (Verdouw et al., 2021).

5 Distributed intelligence

5.1 Artificial intelligence

The evolution of humankind is permeated by revolutions that transform radically the way of life, relations and the environment. It is impossible to understand current societies, economies or philosophical and political movements without considering the impact of the cognitive, agricultural, scientific and the three industrial revolutions. Currently, the world is at the dawn of the fourth industrial revolution and many experts predict that it will bring disruption and changes of a magnitude never seen before in history (Xu et al., 2018). The convergence in the same temporal window of a great number of advances in fields like computer systems, telecommunications, biotechnology, photonics, nanoelectronics or materials engineering has enabled the development of new technologies with applications in a wide variety of verticals. Relevant examples are IoT, BigData and Blockchain but especially AI.

The basic concepts of AI were proposed in the middle of the last century. In 1943, Warren S. McCulloch and Walter Pitts designed the first computational neural model (Chakraverty et al., 2019). In 1952, Marvin Minsky built the Stochastic Neural Analog Reinforcement Calculator, one of the first implementations of neural networks, which was based on vacuum tubes. Since then, the history of AI has been a roller coaster ride, with several winters but also with golden ages, being the actual moment may be the definite one (Toosi et al., 2021). In order to explain the renewed prominence of AI, multiple factors can be mentioned:

- The advances in hardware systems and the consequent increase in processing power enable complex models and algorithms to be designed and implemented in reasonable times;
- The definite maturity and adoption of IoT, cloud computing or big data. They are basic technologies that make it possible to collect, aggregate and process huge amounts of data, which are needed for training; and
- Finally, it is also important to emphasize the release of tools that abstract the complexity of the underlying mathematical concepts.

At least, the following main areas can be identified within the AI realm (Claire, no date):

- ML comprises tools and techniques that allow systems to learn from data (Zhou, 2021). Supervised and unsupervised learning can be used depending on whether data is labelled or not (Alloghani et al., 2020). The most common forms of implementation are neural networks, deep learning (DL) and generative adversarial networks. Lately, systems based on reinforcement learning are gaining importance. They are based on algorithms that learn how to achieve a certain objective through positive or negative incentives defined by the designer (Wiering and Van Otterlo, 2012).
- Knowledge representation and reasoning is a field that focuses on how to represent information so that a system can solve complex tasks. It covers aspects such as semantic networks, ontologies and knowledge graphs to represent information (Duan et al., 2019), metamodels, fuzzy logic that allows working with uncertainty (Mittal et al., 2020), first-order logic etc.
- Search paradigms try to solve problems in which, starting from an initial state, a certain objective must be reached and to do so a sequence of

actions must be executed (Korf, 1999). Optimisation techniques are used when, in addition to finding the right sequence of actions, costs must be reduced (Mirjalili and Dong, 2020). The simplest examples are algorithms such as Depth-First Search.

- Planning enters those larger scenarios where a blind or even informed search is inefficient. In this context, planning algorithms differ in the amount of information they handle when deciding. Some relevant techniques are Stanford Research Institute Problem Solver framework (Lifschitz, 1987), planning graphs, heuristic search planners (Bonet and Geffner, 2001), inductive logic programming (Riguzzi, 2022) or decision networks.
- Multi-agent systems include concepts such as self-organisation or self-direction and multi-agent learning (Wood and DeLoach, 2000). Multi-agent systems could be framed within a larger field and distributed AI (Peteiro-Barral and Guijarro-Berdiñas, 2013), in which there is also an interesting topic such as swarm computing.
- Natural Language Processing (NLP) is with areas such as machine translation or translation from one language to another, understanding or generation of natural language (Chowdhary, 2020).
- Robotics (Craig, 2005) is where many of these techniques are applied but where we have to take into account additional factors such as physical safety issues (Haddadin, 2015), human-machine or machine–machine interaction (Yang et al., 2021), mechatronic systems (Merzouki et al., 2013), real-time requirements or physical intelligence.
- Computer vision (CV) is including aspects of recognition, identification, detection, motion analysis, scenario and image reconstruction (Forsyth and Ponce, 2011).

During the last years, ML and DL have attracted a lot of attention not only from research groups and companies but also from a more general audience (Sejnowski, 2018). In many cases, to train the models, huge datasets must be used during very long processes that consume a lot of powerful and specialised computation resources (e.g. graphics processing units, tensor processing units or even supercomputers). Thus, the catalogue of services of the main cloud providers following Infrastructure as a Service (IaaS) or Platform as a Service (PaaS) paradigms includes offerings targeting the specific needs of ML processes (Google Cloud, no date) (AWS, no date), (Azure, no date). Software as a Service (SaaS) is also starting to emerge with off-the-shelf components and models for NLP, CV or to boost the training (Hugging Face, no date).

During the industrialisation process of AI and ML technologies, it is essential to guarantee robustness, reliability and accuracy during the complete life cycle. Potential problems may have a strong and negative impact on the performance of the models and the applications or services integrating them. If the models are deployed in a production environment, it is possible that their performance may decline significantly when the input data differs slightly from the training dataset. This difference in data distribution between the training and production scenarios is referred to as 'domain shift' and is a commonly encountered issue in ML (Quinonero-Candela et al., 2008). Unsupervised domain adaptation techniques address the problem of domain shift by transferring knowledge learned from source domains, which have a large number of annotated training examples to target domains that only have unlabelled data. After deployment in production, domain drift may occur multiple times. If these changes are detected, it may be necessary to initiate a new adaptation process. There is also a need for the development and expansion of methods and tools that can monitor the error analysis of neural networks in situ and assess the robustness of neural networks to detect any shift or regression. Machine learning operations (MLOps) is a new paradigm that aims to introduce best practices to deliver efficient, repeatable and reliable end-to-end ML workflows (Alla and Adari, 2021). Tools like Kubeflow (Kubeflow, no date) or MLFlow (MLFlow, no date) are becoming more and more popular in this area.

5.2 Edge computing and distributed artificial Intelligence

While cloud-centric AI solutions are completely dominant in the consumers' applications market (e.g. personal assistants, recommendation systems), industrial or enterprise clients provide a much bigger opportunity, being the agriculture domain one of its clearest exponents. Nevertheless, some barriers must be overcome to achieve the adoption and success of AI:

- Protect data security and privacy since the information may be confidential;
- Satisfy real-time requirements for decision-making and control;
- Provide high accuracy and adaption to evolving data distributions and contexts; and
- Guarantee cost-effectiveness and scalability in scenarios with a massive amount of data sources.

In many cases, AI systems relying on cloud platforms are not able to comply with these requirements due to the need to centralise the information on a single location for the training process and the limitations of the communication protocols and network technologies during the inference phase. To mitigate these problems, edge computing offers important advantages by exploiting the increasingly powerful computing capabilities of resources like IoT devices, gateways, robots, customers' infrastructures, regional data centres, etc. (Bierzynski et al., 2021). At the software level, approaches like Tiny Machine Learning or lightweight neural network architectures enable AI to be executed

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over more limited edge computing resources (Ray, 2021). There are also available approaches that leverage the distributed nature of edge-based systems, being Federated Learning (FL) one of the most well-known (Yang et al., 2021). Using FL, each edge device trains its own version of the model without sharing the raw information with other devices or with a cloud platform. Then, all the partial and local models are combined by a central node resulting in a global model that is distributed to the edge devices for inference. Thus, edge computing offers important advantages for distributed intelligence enhancing both the concept of multi-agent systems and shared computational load. Distributed Artificial Intelligence or Decentralised Artificial Intelligence (DAI) aims to leverage independent and autonomous computational resources to learn, plan or make decisions (Huhns, 2012). The availability of multiple resources enables the speed-up of processes through paradigms like Parallel Programming or Distributed Training (Verbraeken et al., 2020). Multi-agent systems (MAS) have emerged also as a technology to solve problems that cannot be addressed properly by a single individual agent, having vast applicability in the control of robotics systems (Van der Hoek and Wooldridge, 2008). Multi-agent deep reinforcement learning (MARL) is being recently been proposed to implement scalable solutions in environments with partial knowledge or a high level of uncertainty (Oroojlooy and Hajinezhad, 2022).

5.3 Smart agriculture solutions and applications

A great diversity of services can be implemented powered by digitalisation and AI, contributing to addressing some of the challenges that currently limit the sustainability of food systems. Relevant examples and opportunities are being explored in farming, post-harvest operations, processing, logistics and consumer support, covering the complete farm-to-fork value chain (Marvin et al., 2022). The interplay with aerial and ground robots is also vast: on one hand, they require different types of ML models and AI algorithms for object recognition, people detection, localisation, navigation, decision-making and actuation. One example is the work released by Facebook Research with DETIC (Zhou et al., 2022), a detector that is able to identify more than 20 000 classes off-the-shelf and that can be used to analyse or process images and video streams for different tasks in which robots are involved. On the other hand, robotics systems collect high-quality and heterogeneous information from crops thanks to onboard cameras and sensors that can feed the different phases of MLOps pipelines. In precision agriculture applications, images captured by drones can be combined with satellite information to assess the crops' growth and health through the calculation of relevant indexes like NDVI (Normalised Difference Vegetation Index) (Harsh et al., 2021). Drones and ground robots with onboard cameras can be used to detect in real-time the early presence of pests and diseases, applying appropriate treatments with high accuracy, which leads to important savings in terms of costs and environmental pollution (Iost Filho et al., 2020). They can also perform a high number of actuations (e.g. soil sampling, weeding, harvesting) in an automatised way, improving the labour conditions of farmers and the sustainability of their businesses (Krishnan et al., 2020).

6 Mission control platforms

6.1 Need for mission control

Robotic systems and autonomous vehicles have become powerful instruments that complement and extend the capabilities of traditional agricultural machinery. They incorporate a variety of onboard sensors and cameras to obtain high-quality information and to perceive the environment. The integration of advanced embedded systems and connectivity, as explained in previous sections, allows processing in real-time collected data to apply AI techniques in order to make decisions or to offload part of the heavier algorithms to systems running on cloud platforms. The resulting decisions require controlling different systems (e.g. navigation and actuation) or even interacting with human actors or other devices. In the specific case of agricultural applications, an additional challenge is a need to work in highly dynamic and unstructured environments, characterised by the uncontrolled presence of people, vehicles, machinery or cattle. Even MRS, consisting of different robots with different capabilities need to be introduced to address the complexity and performance requirements (Ju et al., 2022).

The complexity of robotics missions can differ depending on the level of autonomy allowed to the robots and the possibility to dynamically update the plans according to their evolution and to the changes in the context. For instance, in the case of highly autonomous and automated robots, a mission can be seen as a sequence of locations to be visited and a set of actions to be performed, satisfying some high-level goals and constraints, e.g. mission duration and fuel consumption. In the case of simpler robots, the mission control must be closer to the actual robot control system that includes instructions on what is expected from various parts of the robots (ROS, no date; ROS2, no date). MRS can be divided into fleets of homogeneous robots, typically called robot swarms and fleets of heterogeneous robots. Robot swarm mission control typically involves spatial task allocation, formation control and task execution. Scenarios with fleets of multiple heterogeneous robots require an additional level of intelligence in the planning to determine which is part of the mission that must be assigned to each vehicle and how to orchestrate them (Wheare, 2018; Dumka et al., 2018, Rizk et al., 2019).

Mission Control is a high-level user interface for a robot. Mission Control Platforms are used to visualise the data coming from the robot as well as to give new instructions to the robot (Plura et al., 2011). Usually, the instructions are at a high level, i.e. to start or to stop operation, to change the task or to move to a certain point. A robot may have its own dedicated user interface, but a mission control platform is more general software that can be used to command multiple different robots. They can be seen as a very simple way to plan and manage the execution of the mission, relying mostly on human operator skills and knowledge.

In the following sections, we give state-of-the-art examples of agriculture ground robot control systems and open-source drone platforms that are being developed to be applicable to robot and drone fleets.

6.2 Mission control by ISOBUS and extended farm management information systems data interface

The development of the robot tractors started several decades ago (Rondelli et.al., 2022). Today, there are even commercial robot tractor applications available. However, the robot tractors are rarely in use on farms. The reason may be that the current robot control systems do not integrate well to existing farm ICT systems. Usually, those are vendor-specific closed systems. In agricultural technology, it has already been recognised that the standardisation is the key to the widespread adoption of technology. The ISO 11783 standard, market name ISOBUS, is widely accepted communication standard for agricultural machinery. The standard defines many devices that can be used in precision farming. By using the standard, the devices and the implements of different manufacturers are compatible with each other.

ISOBUS Task Controller (TC) is a standardised device that is used to document and control the precision farming operations on the field. It is based on the ISO 11783-10 standard (ISO 11783-10:2015). The data is transferred to the ISOBUS TC using the ISOBUS Task files. Despite the original purpose of the ISOBUS Task file, it can be also used to describe the robot's work on the field (Backman et al., 2022). The driving lines, implement allocations, timing of operations, description of operation etc. can be described in the Task file in a standardised way. Practically, all the information the robot needs can be included in it.

The Task files are designed in the FMIS software. Today, FMIS software is increasingly running in the cloud service, or the cloud service is part of the operation of the software. For this reason, many manufacturers have made their own solutions for transferring data to the ISOBUS TC from the cloud. There are also broker services that allow transferring of ISOBUS Task files to TCs from multiple vendors (DKE-Data GmbH & Co. KG, no date). However, these are not standards, so universal compatibility with products from all different manufacturers is not guaranteed. The universal compatibility is what the ISOBUS systems are wanted to be.

The AEF recognised the problem of incompatibility between different ISOBUS products and in 2017 set up a working group to develop vendor-independent data transfer between FMIS software and the TC. The data transfer method was named Extended FMIS Data Interface (EFDI). The AEF has published a guideline on the definition of EFDI (AEF, 2020b) and the process of ISO standardisation is ongoing (ISO/DIS 5231, 2022).

In the EFDI's development work, AEF did not develop a protocol from scratch. AEF's EFDI working group has selected appropriate existing protocols already in use on the internet and built functionality on top of them. Before the selection, the working group explored the different options and their pros and cons. The data transfer was required to be reliable and scalable to systems of different sizes, and it needed to work even with a slower network connection. Naturally, it was desired to be compatible with the definition of the existing ISOBUS Task file (ISO 11783-10:2015). As a result of the study, the Protobuf (Google, 2022) originally developed by Google was chosen as the data transfer format. The conversion from XML file to Protobuf format and back is straightforward. EFDI also defines more metadata than the original XML file, describing, for example, what should be done with the transferred Task file. The MQTT (Message Queuing Telemetry Transport, ISO/IEC 20922, 2016), which is commonly used in various IoT systems, was chosen as the data transmission. In addition to these, the HTTP protocol (IETF Trust, 2007) was chosen to log in to the system.

Using the EFDI communication, the instructions to the robot can be sent in a standardised way. The operations can be started or stopped, or the operations can be scheduled to be started at a desired time. The execution of the operation can also be monitored through the telemetry protocol that is included in the EFDI communication. The communication channel is also extensible, and it supports sending and receiving arbitrary binary files. In other words, EFDI is a suitable standardised communication channel between the robot and mission control system similar between the robot and FMIS. On the other hand, FMIS systems seem to be developing in the direction of Smart Farm Management Systems (FIWARE, 2018), capable of also managing Mission Control Systems.

6.3 QGroundControl drone control system

Drones are becoming important farm machines due to their advanced easiness of use and models that are affordable also for smallholders (Puri et al., 2017). Autopilot systems are important techniques in view of user-friendliness and safe use. Drones equipped with an autopilot are robots, which require a mission control system (Kangunde et al., 2021). QGroundControl (QGroundControl, no date) is a powerful open-source software for flight control and vehicle setup (Drone Foundation, no date). It allows mission planning for autonomous vehicles and a full configuration of PX4 vehicles or any autopilot using the MAVLink (Micro Air Vehicle Link) protocol.

PX4 is an open-source autopilot for controlling different vehicle types, including aircraft, ground vehicles and underwater vehicles (PX4 Autopilot, no date, a). It is a core part of a drone platform, along with the QGroundControl station and other hardware components, which communicate via MAVLink protocol. MAVLink is a lightweight messaging protocol for communicating with drones and between them (comparable with EFDI protocol). It follows a hybrid publish-subscribe and point-to-point design pattern where data streams are published as topics while configuration subprotocols are point-to-point with retransmission (MAVLink, no date).

QGroundControl is a multi-platform software, it runs on Windows, OS X, Linux platforms, iOS and Android devices. It provides 2D and 3D aerial maps where the user can build the mission, and which allows visualizing the location where the vehicle is during its mission. One of the most interesting features of this software is the telemetric information of the vehicle and multiple sensors that the user can view during the execution of the mission. Another key aspect of QGroundControl is the logging system, which allows downloading of binary log files from vehicles and sensors to check the status and assess specific information.

QGroundControl software provides an internal MAVLink Console to run commands and a MAVLink Inspector, where the user can inspect real-time messages of multiple parameters and create plots from this information. PX4 supports simulations on computers (SITL) and simulations using simulation firmware on a real flight controller board (HITL). Gazebo (Gazebo, no date) is one of the supported simulators for PX4, it provides a powerful 3D environment for testing object avoidance and computer vision (PX4 Autopilot, no date, b). It can be used with both simulation methods, Software in The Loop and Hardware in The Loop (Nguyen and Nguyen 2019; Hentati et al., 2018).

7 Service framework

Farms utilize increasingly digital technologies to run their farming operations and businesses. Data-driven farm management enables farms to create resource-efficient production as well as to connect digitally with other businesses and thus be part of the evolving data economy. Each farm is unique due to its location, ecological environment, size, production line, machinery, skills, business opportunities and history. Thus, the optimal set of farm technology varies from farm to farm. Typically, the machinery, equipment and management systems of a farm consist of several brands. Farms that are digitalising operations and farm management have faced problems with connectivity and data sharing between the available digital systems.

Farm, as well as machine management, in the field needs several data sources to run efficiently (Sorensen et al., 2010, Fountas et al., 2015). Cloud platforms were presented as a generic solution for the data integration problem in the 2000s and also in agriculture (Kaloxylos et al., 2012). The FMIS as a cloud platform was introduced. The FMIS platform provides the API through which diverse other services, applications, data sources and storages can be integrated into one farm management system. In addition to APIs, an FMIS platform includes data storage and analytics layers for decision support and user interface for the end user. The concept gives the farmer a value proposition that he/she and his/her robot systems can get access to all needed digital tools through the familiar FMIS.

The concept has been found challenging from the business point of view when the number of digital solutions that farms could choose from is increasing. In practice, FMIS providers cannot collaborate with all available applications or data providers that the farmers would wish to use. Therefore, Kaloxylos et al. (2012) proposed the concept of Farm Management System (FMS) which is a kind of application framework including one or more FMISs and other additional services for farmers. The FMS could be provided as a package service offered by another provider. Digesting an additional data source or application to FMIS service provision needs effort and business motivation. Thus, it was stated by Pesonen et al. (2014) that instead of gathering farm's digital tools into a single cloud platform the technology should be provided as an interlinked system of systems from which the farmers could choose the needed services and applications and utilize them through a kind of a Service Framework.

The concept of a Service Framework becomes even more important in the context of field robots. Robots require all information in digital format to function fluently and autonomously. This increases the number of data sources and analytics services that robots must be connected to when compared to manned machinery. Robots need to be connected to FMIS (i.e. using EFDI) to perform the field tasks but also to other machines in the area or linked to the task in hand. The robot also needs to connect to the services providing information about the environment like topography, obstacles, weather, soil and plant condition, roads, traffic, storage etc.

When looking at the needed management system from a robot entrepreneur's point of view, who provides RaaS services to several farms, the currently available information management systems are not adequate. The Service Framework for RaaS management is also needed. The Smart Farming Management System concept introduced by FIWARE (FIWARE, 2018) describes comprehensively the needed FMS elements and their connections. The concept

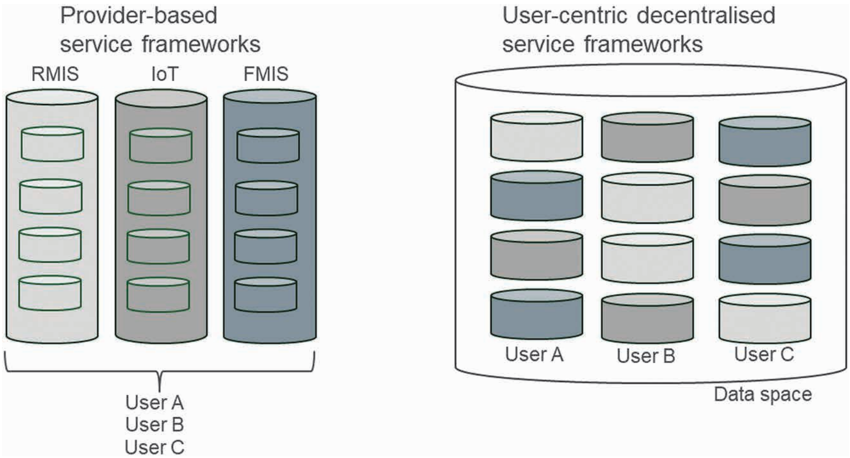

Figure 4 Illustration of a foreseen shift from provider-based service frameworks to user-centric decentralised service frameworks enabled by data space infrastructures and data sovereignty.

could be implemented as loosely coupled independent element clusters from different or selectable providers if data connections were easy to create and data management rights and obligations were clear to all parties. The concept of data space with the idea of data sovereignty provides interesting views for technical solutions (Section 8). Figure 4 illustrates how current provider-based service frameworks, i.e. created around IoT, FMIS or RMIS platforms could change to user-centric decentralised service frameworks, where users can take in only those services that fit their needs and services would be connected. The user of this kind of user-centric service framework could be a farmer as well as a RaaS entrepreneur.

8 Data spaces serving robots

8.1 Data spaces

Agricultural robots are intelligent autonomous devices that both create and consume data. Their role is changing from simple tasks to more complex operations that involve interaction with AI, analytic tasks and even with another robot. Robots are becoming parts of networks that exchange data. They deal with data that is critical to the farmer and valuable to the other actors in the food system. The data is an asset to the data owner, and it is worth the effort to invest in its ownership and governance.

Data space is defined as a decentralised infrastructure for trustworthy data sharing and exchange in data ecosystems based on commonly agreed principles (Nagel and Lycklama, 2021). Data spaces infrastructure tries to create an environment and tools where different companies and entities can share and exchange their data assets without losing control over their data. The aim is to enable both the data economy, where data is considered an asset that is traded as any real-world asset and distributed systems of systems, where data is exchanged automatically between complex digital systems (Curry et al., 2022). The first part relates to buying and selling data assets through data marketplaces (Huang et al., 2021). The main drivers are big data analytics and AI that needs large, high-quality data sets for ML with a level playing field for the participants. The second part is the implementation of cyber-physical systems (Liu et al., 2017) or industry 4.0 concepts (Alcácer and Cruz-Machado, 2019), where physically distributed systems create a single value creation network or complex control or management systems. The data space can even be seen as a distributed alternative to a service framework (Fig. 4). Examples vary from complex logistics chains to smart factories, smart city and smart farming and food production type of systems. The common feature in all of these is that the complete operation requires data from multiple data owners whose ownership must be respected.

8.2 Road towards data spaces

Even though the data spaces are meant for exchanging data between ICT systems running in cloud platforms, their roots are in the networking of systems, in the smartness of collaborative systems, and in the creation of trust between partners. Communication and networking have undergone a transition from networking computers to things and data. This has led to concepts such as IoT and semantic web or Linked Data. IoT has its roots in M2M communications that were extended with digital representations of physical things, which have further evolved into Digital Twins that are models representing physical components and systems (Vermesan and Friess, 2013). The Web of Things turned physical things into digital services providing a more software-oriented approach to real-world interaction. In IoT the main trend has been to develop IoT platforms that collect data and provide integrated and advanced services to process and visualise the data. This has led to the business model of having IoT PaaS, where data are valuable assets that has further led to the data silos and platform lock-ins making data sharing and use more challenging due to business protection reasons.

Networking based on data was started by hypertext and world-wide-web back in 1990s. The next step was to make data machine readable so that data processing could be automated. This and the open data concept-enabled web-based applications and services. The Semantic Web concept is that data elements themselves are linked with each other, and these linkages are embedded into the data. This opened the way to real data networking that means accessing data through its links to other data. Currently related technologies such as XML (extensible markup language), OWL (Web Ontology Language), RDF (Resource Description Framework), SPARQL (Simple Protocol and RDF Query Language) and JSON-LD (JavaScript Object Notation for Linked Data) are widely used in most of the ICT systems (Semantic Web, no data).

Automatic and autonomous devices and robots have been present in visions for ages. Advances in AI,ML and big data analytics have started to make them a reality. Object identification, data fusion and context modelling have been solutions that have enabled systems from autonomous driving and complex cyber-physical systems. Technology is also taking steps towards intelligent fleets of robots or smart places that involve sharing of situational awareness between systems. The data space concept provides means to combine these advanced technologies that need advanced competencies both in development and maintenance into complete systems.

Trust is a critical aspect in the data spaces (TRUSTS, no date). A specific characteristic of the data asset is that it can be easily copied and distributed making the ownership hard to supervise. The creation of trust needs both technical means to share and control the data and its use, and a legal framework that provides policies, rules and regulations for being part of the ecosystem and creating consequences in case of misbehaving. Technical means have focused on interoperability and encryption, while legal frameworks have been based on identity management and smart contracts. Bitcoin and blockchains initiated the development of distributed ledger technology (DLT) that has proven to be a powerful tool for developing transparent and trustworthy systems (Backman et al., 2017; Hummel et al., 2021).

8.3 Recent developments enabling data spaces

During the last decades, we have seen the rise of platforms that have made the owners very powerful and dominant. The security of solutions and reliability of platform providers has raised concerns that have limited digitalisation. Companies have become concerned about their ownership and control of the data. The wishes for more restricted and trustworthy internet and data infrastructure are now recognised as a necessity. Data spaces as described in EU Data Strategy are seen as an alternative to creating an environment for a data economy with more fairness and equality for the players (Anon, 2020; Anon, 2022).

The International Data Spaces Association (IDSA) was initially an industrial data-sharing initiative with a target to create a Linked Data solution that could be used by companies in sharing their confidential data. It was renamed changed as a data space initiative in 2017 and a reference architecture for data spaces was created (Otto et al., no date). The main idea of the IDSA architecture is that all users' identities are validated and that all the activities through the data space occur via open source and transparent components that have been accepted by IDSA. The data sharing includes smart contracts between partners, where usage policies are agreed. The data transfers take place through IDSA Connectors and point-to-point communication. All the traffic is encrypted using X.509 certificates. The data is not transferred to any centralised storage and the data owner has full control over its data. The IDSA architecture defines a component called Metadata Broker for publishing the metadata for the data each partner is making available in the data space. The Broker allows the data users to search available and published data assets but accessing to data must be agreed upon with the data owner.

- GAIA-X is another example of a data space and started as a German–French initiative in 2019, but it has expanded to a global initiative. The aim was to create a federation layer between the physical cloud infrastructures and the use of data (Gaia-X Architecture Document 21.12 Release, no date). The main idea of GAIA-X was to expose the physical infrastructure properties to the users so that users would know in detail where and by whom their data is stored or processed. In some cases, the trade secrets or legislation requires that data must be kept within some specific country, for example. GAIA-X also involves sovereignty preserving data sharing and it also tries to collect companies to set up data spaces in several domains. GAIA-X aims at an open-source, transparent and decentralised implementation. The aim is to create a decentralised autonomous organisation (DAO), where all the operations are defined as software.

Yet another example is the Ocean Protocol which is a crypto ecosystem using the Ethereum blockchain for sharing data. Data tokens are used for sharing URLs of data assets, access control to data services and for different access and usage policies. The network is implemented as a DAO (Ocean Protocol, no date).

iSHARE and i4Trust are examples of an approach where data spaces are built from a trust perspective. The aim of these is to create a trustworthy environment through a federated legal framework with verifiable identities and agreements. The data exchange takes place through common APIs (iSHARE, no date).

Using the data space concept in data economy or distributed and collaborative systems requires data interoperability and common operating principles. The scope of interoperability can vary from a single use case to a single global data space or to a single digital market as in the EU. The baseline for interoperability is the work that has been done in semantic data modelling and smart contracts, but various initiatives to create for example domain-specific solutions have been proposed. For example, in GAIA-X several domain working groups have been established to create common rules and policies (Tardieu, 2021). The EU has also done significant investments in setting up the data spaces in its Digital Europe programme (Anon, 2021). The purpose of these initiatives is not to create new solutions but to agree together on practical issues that are needed in creating collaboration.

8.4 Data spaces and robots for agriculture tasks

Data spaces are a key enabler for implementing robotic systems in complex and fragmented farming environments meaningfully. Complexity implies that the constellation of utilised tools, e.g. IoT solutions, robot platforms and communication channels, must be tailored individually for each farm operation, varying from farm to farm. The chosen technologies must be able to establish data connections between each other and also to other farm services when operating at different levels of farm management, i.e. farm tasks, fleet tasks, robot tasks and detailed robot tasks. Data spaces with evolving standardisation pave the way for such agile utilisation of digital solutions and data in a secure and trusted manner. The data sovereignty of both farmer and service providers (i.e. RaaS provider) enabled by common data intermediary services, consent management functionalities, service catalogues, metadata operators and user's service framework application make the planning and control of complicated MRS possible in an agile and user-friendly way. While data spaces can be seen as a distributed service framework, users like farmers and RaaS entrepreneurs can define their individual Service Framework capturing all services they need for their activities.

9 Case study: FlexiGroBots concept

As a practical example of advanced connectivity and the use of distributed intelligence in agriculture, a use case based on the research project FlexiGroBots is introduced. The use case focuses on oil seed pest management (Kaivosoja et al., 2022).

Efficient oil seed pest management can be challenging. Invasive insect pests can destroy the whole yield, and yet, the reduction of applied pesticides is encouraged. The use case studies modern possibilities for implementing drones and robotics for pest invasion scouting and for precision pesticide spraying against pollen beetles in rapeseed fields. In this case, a drone is first scouting over the rapeseed field to spot individual pollen beetles in traps and taking images for analysis of the level of invasion: how many pollen beetles per trap and in which parts of the field. The drone is operated using QGroundControl for autonomous mission planning and control. The communication uses

MAVLink protocol. The QGroundControl to receive spatial data of field maps and locations of traps from FMIS.

The images taken by drone camera are sent to an IoT cloud platform and from there further to FlexiGrobots platform for AI-assisted analysis where ML techniques are utilised to automize pollen beetle identification and counting. The AI solutions in the platform are trained by exploiting local reference data from the trap images, available from the drone-camera system's IoT platform collected to the IoT platform. After processing, the results are sent back to FMIS where they are translated into a spraying task. The spraying task can be performed by a spraying drone, small field robots, a tractor-sprayer or with different combinations of these platforms. When different types of robotic platforms can utilize similar task applications, the platform selection can be done just before the actual spraying. A spraying drone can spray hotspots rapidly without trampling the rapeseed while the tractor-sprayer can spray the entire field sufficiently.

The field operation by spraying drones follows the same task planning and mission control as in the case of scouting drone operation. When spraying takes place by a small field (ground) robot or tractor-sprayer the mission control center communicates with them and FMIS utilising the EFDI data transfer method with Protobuf format and MQTT data transmission. The service framework enables different service providers to join the use case. Such services can be an FMIS, IoT trap service, drone scouting service, service for machine vision or image classification, service for application task generation and spraying services. The data connections between participating services are arranged using data space infrastructure that follows IDS reference architecture.

10 Conclusion

Farms are demanding worksite environments for autonomous machines. The most demanding cases in agriculture where the communication and smartness of the robotic systems are challenged can be found in the context of open fields of arable farming, when MRS execute farm tasks fluently and safely. Along with the Industry 4.0 era, robots are increasingly part of connected machinery or service systems also in agricultural production environments. Robots need to be able to function in meaningful ways and integrate into diverse production chains and operate efficiently and safely in demanding conditions, especially when robots are exploited as a service (RaaS).

The concept of the IoRT defines connected robots as IoT systems which exploit cloud services to increase calculation, data storage and analytics capacities, i.e. Big Data analytics and ML. When applying the IoRT concept in agriculture, the internet is the most important communication network of

Published by Burleigh Dodds Science Publishing Limited, 2023.

robots. The main challenges related to the Internet are the unpredictable delays of the network and the 'last mile connection' that needs to be wireless when agricultural robots perform their actions in fields. For communication between vehicles and other entities, V2X communication technologies have been developed. The original V2X technologies were based on WLAN technologies, but the more recent development C-V2X uses cellular technologies and is expected to use also 5G networks.

In the case of agricultural robots, IoT has two roles: (1) it can provide data for the robot and (2) the robot itself can be considered as a thing connected to the Internet. In the future, IoT provides means to share data in physical world in the cyber world, enabling analysis and optimisation of large-scale systems of systems. It also provides means to create advanced situational awareness about the state of relevant aspects affecting the decision-making, i.e. weather, pest invasion, progress of other units' working processes and physical interaction in local contexts. Currently, IoT feeds the digital twins with real-world data, but the trend is in expanding the use of digital twins towards the exploration of alternative futures that can be a basis for better decisions today.

The data deluge captured by the heterogeneous digital systems that are currently supporting the different processes that are part of food production systems can be exploited through the application of AI techniques to create intelligent applications. ML models can be trained, deployed and productised following MLOps practices and recommendations that guarantee compliance with ethical and trust requirements. The convergence of AI techniques with the powerful capabilities of the new generation of edge computing devices facilitates addressing some of the most relevant challenges in terms of privacy preservation, scalability and real-time control which has traditionally limited the introduction of AI in the agriculture domain.

Mission Control is a high-level user interface for a robot. Mission Control Platforms are used to visualise the data coming from the robot as well as to give new instructions to the robot. Agriculture has a dedicated state-of-the-art communication protocol for ground vehicle mission control called EFDI as part of the ISOBUS standard. For drones, the QGroundControl drone control system with the MAVLink protocol has the same role.

A data space is defined as a decentralised infrastructure for trustworthy data sharing and exchange in data ecosystems based on commonly agreed principles. Data spaces infrastructure tries to create an environment and tools where different companies can share and exchange their data assets without losing their control over their data. Data spaces are a key enabler for implementing robotic systems in complex and fragmented farming environments meaningfully. Complexity implies that the constellation of utilised tools, e.g. IoT solutions, robot platforms and communication channels, must be able to tailor individually per farm operation, varying from farm to farm. While data spaces can be seen as a distributed service framework, users like farmers and RaaS entrepreneurs can define their individual Service Framework capturing all services they need for their activities.

11 Future trends in research

In agricultural robotics, the future will bring in robots that can do more complex and sensitive tasks. The capabilities developed for industrial robots will be brought to agricultural tasks and the capabilities developed for autonomous vehicles will make the field robots more maneuverable. The development of battery technologies and the need to get rid of CO_2 emissions will pave the way to electrification. This will lead to smaller robots and the need for collaborative robotics will increase (Lytridis et al., 2021). Robots will need capabilities to interact and make joint decisions more efficiently (Oliveira et al., 2021). The role and research needs of shared situational awareness of relevant information needed for decision-making among collaborating systems and humans and distributed decision-making will increase. Edge computing and real-time analysis will produce results in more and more real time, while AI and new analysing methods will offer reliability to systems. The developing connectivity makes it possible for the robots to be more purely only sensors and actuators, the computation and intelligence being separated and outsourced as edge or cloud service. This is an interesting future research topic since outsourcing can result in more precise and intelligent robot operations when several external data sources and services are connected in outsourced service to provide dedicated operational functionalities. This will also have an impact on the farming process by enabling the efficient execution of complex farming operations like mixed cropping. Also, user-centric decentralised service frameworks enabled by data space infrastructures provide new ground for ever-smarted robotic systems research.

The dependency of GNSSs on agricultural robotics and drones is critical. Methodologies for optional navigation systems such as local wireless networks and image recognition and analysis will also be future research topics in connectivity.

The research on synthetic data for training AI, especially ML systems, is topical for further research. Nowadays data is used increasingly to build Digital Twins also in agriculture. This opens possibilities to develop these virtual environments into synthetic simulation environments by utilising synthetic datasets in the environment (parallel to real-world data). These environments provide interactive simulation environments for training ML agents, i.e. reinforced learning agents (Nikolenko, 2021). Simulation carried out using

Digital Twins will also take a role in constructing reference data and providing synthetic data for measurement development (Kaivosoja, 2022).

As the degree of automation increases in agriculture, the challenge of how to make robots cost-efficient and user-friendlier will change the current practices. The possible scenario is to move towards a service model, where robots and robot fleets are owned and operated by service companies instead of farmers (Agam, 2022). This sets requirements for robots to adapt to different types of digital environments and systems, which requires research on new self-learning and cognitive capabilities of robots. User-friendliness requires higher abstraction-level user interfaces, where operators do not need to understand the details of how the robots operate. However, to enhance the operator's and end-user's trust in AI, research on explainable AI (XAI) development increasingly is important. XAI aims to explain transparently how AI performs the decision-making processes (Ryo, 2022).

The future of agricultural robotics will be based on the development of the technologies described in this chapter. Connectivity, AI and data will play a key role in developing robot systems to serve farms individually and feasibly and to assist them to comply with the requirements of food value chains, i.e. sustainability, green transitions, farm-to-fork communication and circular design. Sustainable intensification of food production requires that agricultural actors are better aware of production-related possibilities and constraints (environmental, biological, legal, ethical, economic and technical) in several levels of decision-making and information detail than today and are able to exploit the potential. On the other hand, sustainability, ethical aspects, increasing population, productivity requirements and novel production methods like vertical farming are all issues that change the ways robotics will be applied. While intensifying, production environments must foster the well-being of humans and animals. To be able to cope with all requirements, AI assistance will be embedded widely in everyday farming tools and services having diverse levels of autonomy (Duckett et al., 2018). As stated by Asseng and Asche (2019), we have the components needed to build future farms based on robots, but we need to combine the elements to fully utilize the potential. A more holistic approach than today is needed for the digitalisation of the production at farms, capturing all farming processes, as signposted by 'Hands-Free Hectare' and 'Hand-Free Farm' projects (Hands-Free Farm, no date). For example, it is needed to extend the current MRS control approaches to farm or crop mission management that covers all the phases of the crops including monitoring, analysis and various actions that are needed during growth periods. Such solutions could provide means to collect and combine the crop-related data for later phases of food production. The holistic and farm-specific approach would help to define meaningful division of roles between machines and humans while respecting farmers' individual preferences but exploiting still data-based performance optimisation. On that basis, it would be possible to construct such robot systems as an integral part of farms' workforce, where the system has the ability to react in real-time and even to anticipate the collaborators' actions as suggested by Vasconez et al. (2019). Further research on connectivity and intelligence of robot systems will have a key role in the development.

12 Acknowledgements

The chapter was supported by the European Union's Horizon 2020 research and innovation programme under grant agreement No 101017111.

13 Where to look for further information

The following articles provide a good overview on:

- Communication networks by describing technical and policy elements of telecommunication, particularly in the context of 5G: Asif (2018). 5G Mobile Communications: Concepts and Technologies. https://doi.org/10.1201/9780429466342.
- Internet of Robotic Things gives a novel perspective on the IoRT that involves communication among robotic things and humans and highlights the convergence of several technologies and interactions between different taxonomies used in the literature: Vermesan, O., Bahr, R., Ottella, M., Serrano, M., Karlsen, T., Wahlstrøm, T., Sand, H. E., Ashwathnarayan, M. and Gamba, M. T. (2020). Internet of Robotic Things Intelligent Connectivity and Platforms. Frontiers in Robotics and AI https://doi.org/10.3389/frobt.2020.00104
- Multirobot systems are used in agriculture in terms of platforms, control and application. Ju, C., Kim, J., Seol, J. and Il Son, H. I. (2022). A review on multirobot systems in agriculture. Computers and Electronics in Agriculture, 202, 107336, ISSN 0168-1699, https://doi.org/10.1016/j.compag.2022.107336.

The following initiatives and their websites are worth visiting to gain more information about:

- Data space development and standardization: Gaia-X, https://gaia-x.eu/.
- 6G research and development: Flagship 6G, https://www.oulu.fi/6g-flagship/.

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Published by Burleigh Dodds Science Publishing Limited, 2023.