Towards a layered agent-modeling of IoT devices to precision agriculture

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***Abstract*—Precision agriculture employs IoT devices to smartly monitoring plant vegetation and support food production. Precision agriculture is highly required to improve product quality and better suit the requirements of the market. Among the IoT devices, Unmanned Aerial Vehicles (UAVs), can be equipped with many sensors that allow precise assessments of plant stress by flying over the plots. Notwithstanding the great benefits introduced, IoT devices may suffer from some issues. Many devices provide data in different formats on the same task, therefore they need solutions to integrate data and support a more thorough crop monitoring. This paper introduces a multi-tier architecture to deal with IoT-based intelligent monitoring, as well as an implementation of the architecture through multi-agent modeling of the IoT devices for precision agriculture. The introduced model allows data acquisition from various sources (i.e., IoT devices), an ontology-based integration of data provided by the devices and a knowledge integration process to deal with domain-specific applications.**

***Index Terms*—Precision agriculture, IoT, UAV, Multi-Agent Systems, Ontology**

I. Introduction

The spread of IoT technologies provided benefits in many distinct fields, from healthcare to business. In the agriculture field, the use of smart sensors paved the way to precision agriculture, which allows constant monitoring of plant growth and crop quality. Precision agriculture provides a food supply chain that better suits the requirements of the market, it improves process quality, reduces production times and increases incomes. IoT devices help agriculturists to monitor threats and damages to their plots; equipped with actuators, they can also address the detected issues on time, such as specific environmental conditions, or the spread of viruses, which may have quick devastating effects on the crop. Among the various IoT devices, mobile devices, and more specifically, Unmanned Aerial Vehicles (UAVs) have been investigated to collect information on plant stress, environmental conditions [1]. UAVs are low-cost solutions; since they can be equipped with various sensors and easily take plots from the above, they are particularly suited to make precise assessments on vegetation or even take specific actions on selected plants. In UAV-driven path monitoring, recent studies [2] show how stochastic models support path planning in a UAV swarm and avoid collisions; in [3], a routing algorithm allows UAVs to avoid multi-obstacle areas in a plot. Geo-localization issues are faced in [4] determining the UAV position and orientation during its vision-based navigation or in [5] through data muling from acoustic sensor networks.

Although the use of multiple IoT devices offers interesting benefits, they may suffer from various issues that can compromise their efficacy in precision agriculture. Issues are related to data communication (i.e., network stability issues) [6], control [7], acquisition and sharing of information [8]. Keeping a stable network is fundamental to guarantee the collaboration among the devices and quick replies to the human experts. The solutions in the literature focus on improving network stability in wide-range operations [6], swarm control [7], by building Fuzzy Neural Network models; in [8], an agent-based model allows UAV teams to build collective knowledge through Fuzzy Cognitive Maps to support surveillance applications. Vegetation monitoring and assessment are strictly based on indices from spectral data or vegetation measures as well as unsupervised classification techniques for fruit and plant detection, and vegetation monitoring. The approach proposed in [9], for instance, applies spectral clustering to the collected images to detect tomatoes. In [10], sunflower growth is monitored through multi-temporal imaging.

Since IoT data come from heterogeneous sensors and returned in different formats, the need for a homogeneous data reading claims new and challenging methods for data integration. In [11] a Markov-chain-based model is defined to integrate data in a IoT ecosystem; another study [12] designs an ontology-based architecture to support data integration and sharing among enterprises. Data integration is also required at agriculture domain level. Agriculture processes, indeed, consist of multiple phases (i.e., product, techniques, production processes), and knowledge-based solutions [13], [14] have been investigated to address inter-phases data integration. In knowledge-based approaches, ontologies map accurately the precision agriculture domain [13]; Agri_Ont [14] is an ontology coming from domain-specific ontologies, such as IoT devices, precision agriculture, geo-location, and business aspects. Similarly, in [15], the fusion of two ontologies, one modeling food production domain, the other the agriculture processes, provides a rich knowledge base for applications on

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viticulture and winemaking.

Recent studies evidence the importance of unmanned mobile devices in agriculture domain, but it is evident how a cooperative use of them, enhanced by reasoning capabilities represents the new frontiers for a smart precision agriculture [1], [2]. The precise localization of sensing devices and the sensor swarm control need distributed, cooperative approaches, such as the multi-agent systems [16], that can support data integration and, quick and proactive decision replies to the environment solicitations, especially due to the agent-based wrapping of the IoT devices. In [16] a multi-agent system for UAV swarm accomplishes information retrieval and monitoring in known environments affected by catastrophes. The model proposed in this paper, instead, exploits the multi-agent paradigm to support the whole process for plant monitoring, including the data acquisition, data integration and high-level comprehension to assist real-time monitoring.

This work presents a framework design to deal with IoT device-based smart monitoring for precision agriculture. The main contributions are described as follows.

- A multi-tier architecture design for IoT devices to deal with monitoring of environments, including solutions for data acquisition from devices, data integration from heterogeneous sources on the same observed aspects, and a contextualization process to deal with specific applications.
- An agent-based modeling to manage the data acquisition from sensing sources and IoT devices, their integration, and contextualization.
- An implementation of the architecture for the precision agriculture domain: agent-driven data collection from sensors, data integration from plots and plants and finally, application domain-compliant description by semantic support, such as the ontologies, queries on the collected knowledge and fuzzy rules.

II. A GENERAL MULTI-TIER IOT-BASED ARCHITECTURE FOR INTELLIGENT MONITORING

The IoT-based systems are wide-spreading in the various application domains, from the military mission and surveillance to film-making. In a generic domain, a general-purpose architecture design for IoT based systems where the data collection and arrangement are compulsory activities to interpret complex and dynamic environments, and undertake adequate and responsive solutions, could be defined as sketched in Figure 1. It is a multi-tier architecture for IoT-based monitoring, composed of three main steps: the data acquisition from environmental sensing (IoT) devices, the analysis, processing and integration of the collected data; finally at the upper tier, the context-dependent specialization, i.e., the contextualization of the processed data with regard to the goals of the application domain.

The logical architecture modeling of a precision agriculture system is shown in Figure 1. Let us remark that the three-tier modeling describes a representation of a generic IoT-based system, identifying the main functionalities for the

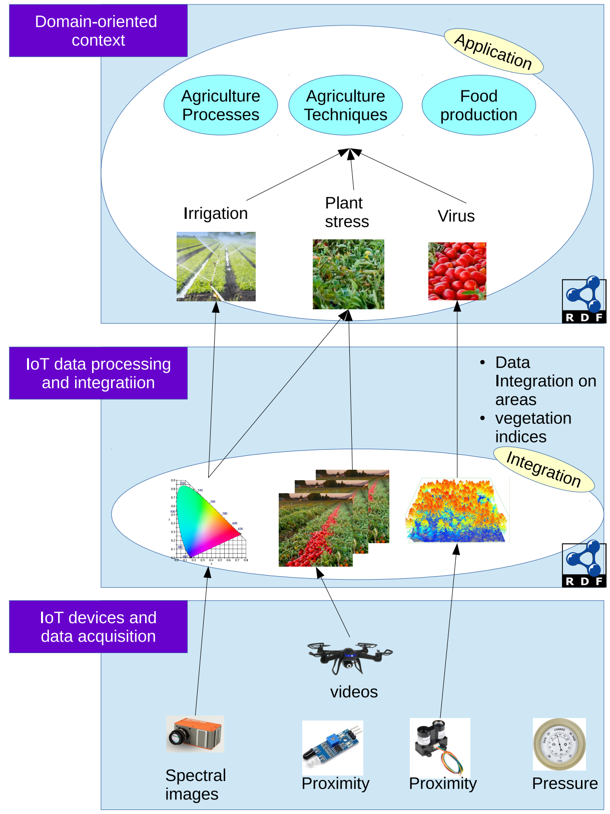


Fig. 1: A logical overview of the multi-tier architecture for precision agriculture illustrates: IoT device data acquisition, IoT data processing and integration, and data contextualization for specific applications.

execution and data flow in a system, aimed at accomplishing surveillance, monitoring and control tasks.

In details, in a precision agriculture system, the lower tier encloses sensing technologies, mostly IoT devices, such as fixed sensors and actuators placed in the plot area, palm UAVs, ground vehicles and sensor-equipped medium-sized UAVs. IoT devices are meant to work in concert: they are designed to monitor the plots, generate warnings in case some plant stress is detected and trigger actuators or humans, accordingly, to take action. In this lower tier, the IoT devices collect data on various areas. At the second tier, the data collected by the IoT devices are integrated. In literature, there are many approaches for data fusion and integration [11], [12]. For example, as in the proposed architecture, data integration is accomplished by defining an ontology for interpreting IoT data and sensing technologies. At the last tier, the integrated data provides a high-level description of tasks and features on the plots inspected, such as weed presence, plant stress, irrigation status. etc. A multi-domain ontology is used to define and collect knowledge on various agriculture phases. This ontology is specialized to describe specific tasks in some domain contexts. Queries on the gathered knowledge enable actions for specific precision agriculture applications (e.g., crop vegetation monitoring, agro-analytics). Next sections focus on the presented architecture, deepening the sketched tiers.

A. IoT devices and data

The architecture comprises several IoT devices, including mobile and fixed sensors. Among them, there are medium-sized UAVs equipped with various sensors, that fly over various plots. Additional fixed sensors are installed on the ground, and small-sized UAVs (e.g., palm drones) targeted at monitoring small areas. The architecture is decentralized and allows the communication among the devices through cloud services.

IoT devices for precision agriculture fall into two main categories:

- *IoT devices at the plot level*: these devices are generally mobile aerial devices, such as UAVs, that fly over the plots and take measurements related to the whole plot to perform plot demarcation, evaluate ground conditions and acquire more refined images than the ones retrieved through satellites.
- *IoT devices at the plant level*: these devices may be fixed sensors (e.g., barometers, gyroscopes, cameras) or small-sized mobile devices (e.g., palm drones) devoted to acquire data about plants.

The IoT devices are equipped with one or more distinct sensors to capture data from the environment. At the same time, data collected from these devices can be divided into four main categories, listed as follows.

- *Environmental data* describes the climate and ground conditions. They are acquired through scalar sensors, such as barometers, magnetometers and satellites that return values representing the wind pressure and direction, the current weather and weather forecast.
- *Proximity data* estimate the proximity among devices, and between the device and features (i.e., plots, plants); if mounted on UAVs and UGVs, they monitor distance, constantly. LIDARs, infrared and ultrasonic sensors, assess feature proximity and perform feature detection.
- *Video and image data* taken in various temporal phases, enable monitoring plant vegetation and crop evolution.
- *Spectral data* are the most significant data acquired, because they allow to define vegetation indices[1]. These indices reveal the presence and relative abundance of pigments, water, and carbon as expressed in the solar-reflected optical spectrum ($400nm$ to $2500nm$). The analysis of object reflectance from the images at different band ranges allows assessing significant parameter values (e.g., chlorophyll concentration, water presence) to assess plant vigor and stress. The broadband and narrow-band greenness are two types of vegetation indices that have been taken into consideration. The former captures spectral reflectance in the band range $[600, 690]\,nm$ to describe foliage cover, chlorophyll concentration, canopy area, and canopy architecture. The latter is much more sensitive, considering spectral reflectance in the red edge of the spectrum (band range $[690, 740]\,nm$). These indices provide great support to precision agriculture allowing identification, analysis and management of site-specific spatio/temporal variations of the soil. Other vegetation indices taken into consideration are Light Use Efficiency, Canopy Nitrogen, Dry or Senescent Carbon, Leaf Pigments and Canopy Water Content. Analyses of spectral images are often based on the spectral clustering to generate clusters of pixels at different wavelengths. The spectral clustering takes into account vicinity of irregular form groups which provides more refined results than classical clustering approaches. When the spectral clustering converges, it provides detection of plot features (e.g., fruit, ground, canopy).

[1]http://www.harrisgeospatial.com/docs/VegetationIndices.html

B. IoT data processing and integration

This tier is in charge of data processing and integration from various sources. Digital and analog values, retrieved from scalar sensors represent measurements explaining a specific feature (e.g., wind pressure, humidity rate, etc.). More enhanced sensor data such as spectral images instead, require to be processed to extract meaningful data from them. To this purpose, spectral clustering can be used to process spectral images and capture objects of interest (e.g., canopy, ground, fruit) through image segmentation. Then, vegetation indices (see Section II-A) on the detected features assess plant stress, water supply status and fruit vegetation.

As stated in Section II-A, the data come from different types of sensors, in different formats. To exploit all the data for monitoring tasks, a data integration is required. For instance, humidity value assessed through a hygrometer and the Vogelmann Red Edge Index (VREI), describing water presence in the same area, need to be integrated in a common format to express plant vigor in that specific area. Data integration can be achieved by using various methodologies, as demonstrated in literature [11], [17], [18]. In [11] a Markov-chain-based model is used to project raw data into a sequence of states to perform multi-modal data integration computation over the states. In [17] a multi-layered network is built to bridge agricultural data collected, edge computing, data transmission and cloud data, and exploits the deep reinforcement learning to support quick decisions (i.e., determine the water supply required). In [18], an intelligent fuzzy inference system is introduced to deal with Variable Rate Irrigation (VRI). The system integrates the knowledge on precision irrigation and zones to generate maps aimed at controlling the central pivot of the irrigation system and, accordingly, govern the pivot to guarantee an appropriate irrigation for the zone. Other solutions to data integration use the ontology modeling [12], defining concepts and relations that describe the specific domain and, at the same time, exploiting an existing ontology that provides usable knowledge. The Semantic Sensor Network Ontology (briefly, SSN) is indeed, a well-known ontology to describe sensors and their measures. It uses in turn the GeoRSS ontology, which models GPS data, to represent knowledge on the areas monitored by the IoT devices. The ontological design allows integrating the vegetation indices and the scalar values on plot features (e.g., wind pressure) in the same area and the objects detected through clustering in those areas. This way, the ontology provides a complete description of IoT data integration on plot features of the same area.

C. Domain-oriented context

The last tier of the architecture, namely *Domain-oriented context*, employs context-based solutions to put the integrated IoT data on areas and plot features in a domain, and supports the accomplishment of specific precision agriculture applications, such as agro-analytics, plot real-time monitoring, crop yield, etc., or specific activities, e.g., irrigation management, seeding, weed management, etc.

Data, integrated at the lower level, need further processing concerning the application context, in order to guarantee common interoperability among highly-varied data. For example, in the irrigation process for growing buckwheat, the ground humidity rate, provided by a hydrometer, and the vegetation index Vogelmann Red Edge Index (VREI), assessed through spectral cameras, need to be related and read in the context of the specific application to fulfill (i.e., the assessment of the possible plant water supply planning). Context-aware data interpretation is often achieved, at a higher level, through the use of well-defined semantic technologies for data (e.g., RDF, OWL, SPARQL and Linked Data) and ontologies (e.g., AGROVOC, Agricultural Ontology Service and AgOnt) [19], [20]. In particular, the architecture uses AGROVOC, which provides a vocabulary on precision agriculture to model knowledge on domain concepts and the data collected. Since each application may involve sub-domains or related domains of precision agriculture, the AGROVOC ontology can not be adequate to describe the reference application domain, completely. Additional domain-specific ontologies [13]–[15] can be used to extend precision agriculture concepts in several application contexts (e.g., agriculture techniques, production evaluation, food chain). In particular, in [13], ontology modeling allows the classification of the information related to a specific context and application. In [14], an ontology architecture (AgriOnt) is defined to bridge various subdomains of precision agriculture. In [15], an ontology network is defined over preexisting ontologies for agricultural production and food processing. To allow the architecture to support the decision on application tasks, Fuzzy Logic has been explored [21]. Vegetation indices and sensor measurements are described by fuzzy sets and related to the application through fuzzy rules. Recalling the previous water supply case, a fuzzy rule allows the detection of water supply required in terms of VREI and hygrometer measurement (i.e., *if VREI is low and hygroMeas is low, then waterSupply is low*). Fuzzy rule-based reasoning provides support for making decision and solve the application task.

III. A Multi-Agent modeling of the architecture

The multi-tier architecture, presented in Section II is a high-level representation of generic activities, that allows collecting and processing data across the tiers to get a comprehensive domain description for further application-based processing. To introduce this architecture applied to the precision agriculture domain, the agent-based modeling is used to solve device heterogeneity, data interoperability and vehicle autonomy issues encountered across the tiers. The multi-agent modeling allows supporting data acquisition and action planning activities for each fixed or mobile device in the environment; collecting tier-based data and processing them to achieve an individual or collective goal; interact to each other when the final goal requires it. It achieves a distributed computing, where each agent can autonomously acquire and process data that are then shared and integrated.

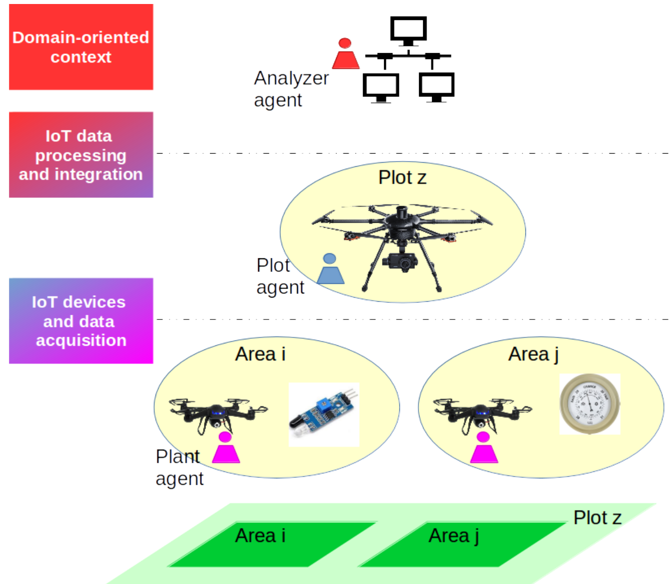
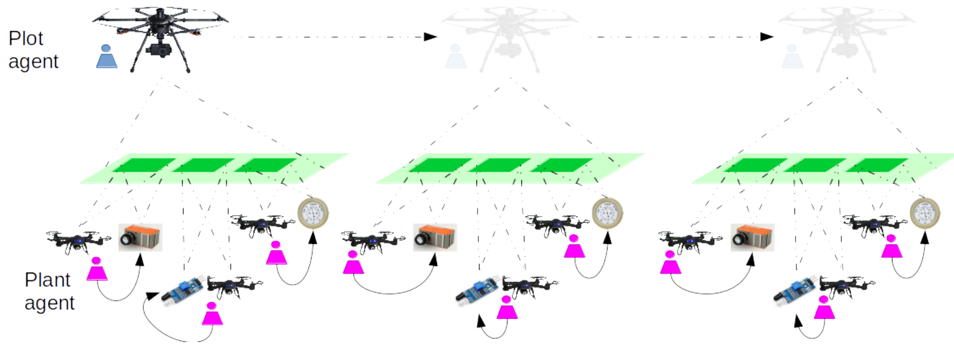


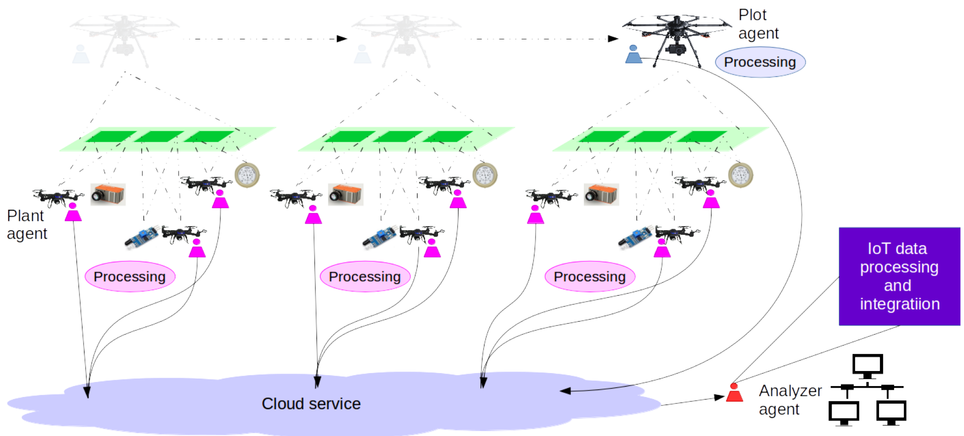
Fig. 2: Multi-agent modeling of IoT devices: plant agents and plot agents, wrap IoT devices placed in sub-areas of plots and devices flying over the plot, respectively. An analyzer agent support data analysis.

The introduced agent-based model defines specific agents in correspondence with the types of devices in the precision agriculture domain. Each agent achieves a wrapping on a specific device, through an interface to interact with the device, exploits its features and services, and monitors the device in action. Three different types of agents are designed in the modeling, devoted to accomplishing different tasks:

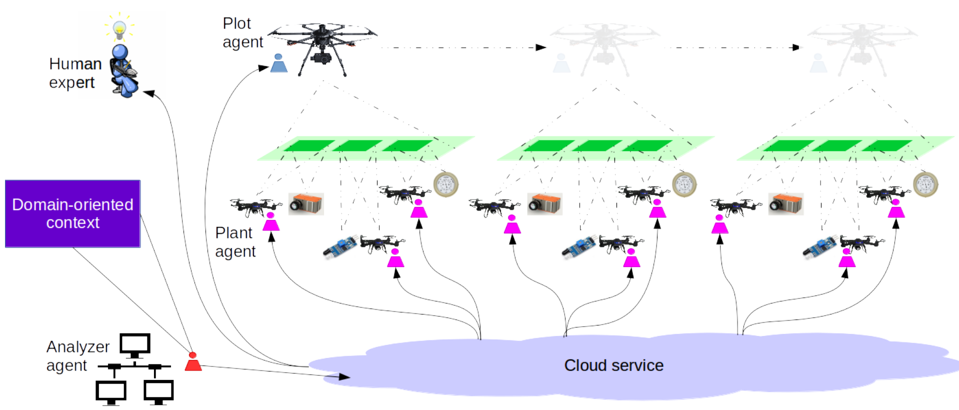
- **Plot agent**: this agent wraps a medium-sized UAV that is assigned with the task of collecting data on entire plots from considerable heights.
- **Plant agent**: this agent is associated with a small-sized drone, such as a little ground robot or a palm drone that has the task to collect data on plants at very close distances from the subject.
- **Analyzer agent**: this agent occupies the highest tier of the architecture. It interacts with the agents of the lower tiers to acquire information about the data collected and stored in the cloud. Then, it can start the appropriate processes



(a)



(b)



(c)

Fig. 3: Multi-agent interaction on (a) data collection, (b) data processing and integration and (c) domain-oriented contextualization.

for data analysis and processing.

The multi-agent modeling is sketched in Figure 2, that shows the description of the different types of agents, in correspondence with the devices at the different architecture tiers. The plot and plant agents monitor the environment; they provide a multi-level view on the crop to serve various tasks. The plot agent collects global views on the demarcated plot and returns a digest description of the plot to support ground condition analysis. The plant agent provides local views on plants: the analysis of plant stress, pesticide handling, water supply handling, etc. The analyzer, at upper tiers, starts analysis and processing activities to produce a complete, comprehensive view on the plots inspected.

A. Agent interaction

The data acquisition phase (lower tier in Figure 1) is described in Figure 3a. The data collection phase may have several collection turns. In a turn, the plot agents visit various plots and collect data from each of them; in the meanwhile, the plant agents collect data from local areas inside a plot. In detail, each plant agent acquires data from a specific small area which it has been assigned with. To perform data acquisition, the plant agent uses the sensors mounted on its wrapped device and also it queries fixed sensors, placed in the recognition area to get local data. In the meantime, the plot agents, that also wrap mobile devices, move following a prefixed path; they can stay in hovering to acquire data through their sensors. These agents indeed collect data captured by drones with embedded cameras, such as videos and spectral images.

Once the plant agents completed a data collection turn (see Figure 3b), they share collected data with plot agents, at the second architecture tier (*IoT data processing and integration*). The plot agents process videos or spectral images (see Section II-B) to calculate vegetation indices and detect features through image classification. They embed techniques such as clustering and Machine Learning to get a preliminary process of data. Anyway, both agents share the data collected and processed them by a cloud service.

The analyzer agent interacts with the agents at the lower tier; it is in charge of starting data analysis and processing activities, through cloud computing (see Figure 3b). Data gathered in a turn, include the sensor data about the areas (the plant agent data), as well as the whole plot (the plot agent data) over time, and the GPS data about the area or plot. At this stage, the analyzer acquires processed data from cloud; these data are semantically described by known and ad-hoc defined ontologies, in order to define data from sensors (e.g., by means of SSN Ontology), area position (e.g., GeoRSS), to get a synthetic view on the same areas and plot coming from distinct devices.

The last architecture tier (*Domain-oriented context*) concerns an ontology-based contextualization on domain applications. To perform this task, additional, high-level ontologies modeling the domain of interest are introduced. Then, according to the type of devices, application goal, time of measurement, position and identity of the monitored crop, the analyzer agent works with the domain ontologies to associate a semantics to the integrated data. At this tier, the achieved goals are domain-oriented, such as the analysis of the vegetation phases, plant stress and plot condition to serve the application. The analyzer agent, acting as the ground station, ”interprets” data from cloud computing to alert human experts or plant and plot agents to make a decision/action. Actions are assigned to agents according to the type of device they wrapped, for instance, UAVs are in charge of spraying and irrigation, while ground vehicles perform seeding and weed management.

The three types of agents, along with their methods and functionalities, are depicted in Figure 4 as a UML class diagram. The agent classes include attributes and methods implementing the agent tasks. The attributes are device features and data, such as *Schedule: double[]* that lists the positions ($x - y$ coordinates) of the areas to monitor, committed to a plot agent. Methods implement specific functions, such as the method *askForVals(dev, type)* that the plant agent calls to get data of specified type (*type*) from nearby fixed sensors (*dev*) in the same area.

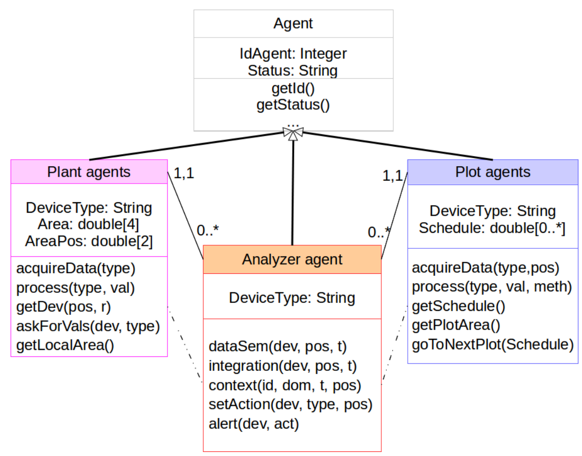


Fig. 4: UML class diagram of the agent model.

IV. Ontology model

Ontologies allow enriching semantically several heterogeneous data from different sensors, devices, using different technologies and formats. They accomplish the *IoT data processing and integration* (middle tier in Figure 1) and *Domain-oriented context* (upper tier in Figure 1). SSN Ontology has been widely used to represent knowledge on sensors and their measurements. This ontology supports the fusion of data from heterogeneous sensors. Our approach employs SSN to represent each IoT device, including UAVs, UGVs, barometers, spectral images, etc., in the environment along with the data they collected. Positions about the IoT devices and the monitored areas are defined by GeoRSS ontology which models geo-location information by representing coordinates of geometrical points and areas.

The integration of the two ontologies SSN and GeoRSS provides a semantically-enhanced description of data collected by the agents. The ontology population is indeed composed of

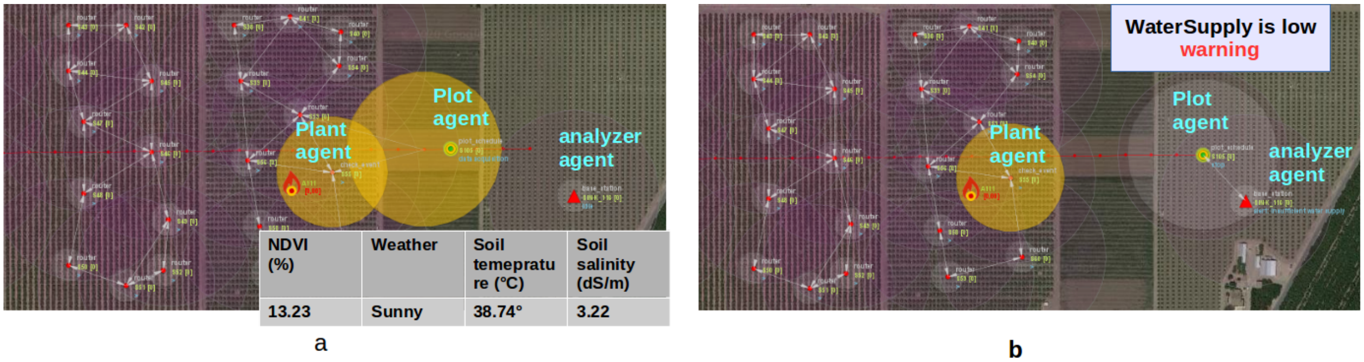


Fig. 5: Simulation images for irrigation management in two phases: (a) data sensing and processing (b) analysis and alerting.

instances of IoT device agents, along with their collected data and GPS data of the plot area, where the agents collected the data.

At the *Domain-oriented context* tier, expert-designed domain ontologies are taken into consideration. AGROVOC provides a general dictionary of agriculture concepts that helps to provide a semantics to the data. Therefore, the integration of AGROVOC with SSN and GeoRSS allows us to describe and relate the vegetation indices and sensor scalar values with high-level domain concepts. Additional ontologies can be used along with SSN, GeoRSS, and AGROVOC ontologies to include further specific concepts. For example, the agriculture domain ontology Agriculture Ontology (AO) [13] models knowledge on several aspects (object of labor, means of labor, production process). This ontology integration provides a high-level knowledge description of the data (vegetation indices, sensor values), specific activities carried out on the application domains (e.g., tomato crop yield).

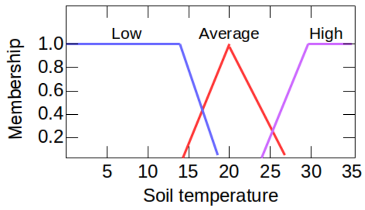
Expert systems acquire knowledge from human experts and allow computers to use it for accomplishing complex decision-making tasks. Those systems may use fuzzy logic that allows them to behave and express like humans do. In precision agriculture, fuzzy-based expert systems give the chance to answer to relevant questions, as well as explain the reasoning process behind decisions, to interact with end users (e.g., farmers) by using a language that can be understood by them (i.e., the natural language). In our approach, the collected knowledge base supported by the ontological modeling can be enriched by fuzzy rules to detect the plant vegetation status (see Section II-C), to support decision in the management of simple activities (i.e., seeding, irrigation management, etc.) and complex applications (e.g., crop yield assessment).

V. An Illustrative Case Study

Let us introduce a simple case study in the potato crop vegetation monitoring, showing the agent-based interaction for the detection of an irrigation issue (e.g., mal-distribution of water). A potato field map with sensors and agents in action is shown in Figure 5 as two consecutive screenshots. The simulation has been carried out by using CupCarbon[2], a simulator for IoT and sensing environments. The red points on the map, in the figure, are the devices wrapped by the plant agents. The green point is a big-sized drone wrapped by a plot agent that flies over several fields. The red triangle on the right of the figures is the analyzer agent in charge of the higher-level tiers. The white lines among the agents represent the communication among them. A snapshot of the data acquisition and processing phase is shown in Figure 5-a, this phase occurs in the lower tiers of the architecture, where the plant agents collect data from sensors in the assigned area. The plot agent moves along its cross-plot path, shown by the dashed red line, and takes spectral images of the visited plots. The data acquired by the plot and plant agents are stored on a cloud and then processed. In details, the plot agent gets values of the vegetation indices on the various plots, for example, in the figure, the yellow circle on the right represents that data in that sensing radius have been detected and collected; while the plant agents get analog sensor data, such as the ground humidity values (shown by the yellow circle on the left). Then, the analyzer agent, solicited by the agents, puts data in an ontology-compliant format (JSON-LD) to easily analyze and process the data. Figure 5-a shows various data, including the vegetation index NDVI, the soil salinity, soil temperature and the weather, about an area provided by the plot and plant agents. Due to large amount of data collected on each plot, in each area, over the time, cloud computing is the strategy to store and process environmental information. The analyzer is able to analyze and interpret the results from cloud process and generate reports on the overall system. Let us remark that data are semantically described by domain ontology, supported by fuzzy rule-based inference that helps analyzer to interpret results. Thus, vegetation indices and humidity values, assessed by the agents on the various plot areas, enrich the potato cultivation domain ontology and support new semantic deductions.

Data interpretation is shown in Figure 5-b: the analyzer processes the sensor data by using expert-defined fuzzy rules. Linguistic variables are associated with the data, for instance, the soil temperature (ϕ) is described by three linguistic variables, defined by three fuzzy sets, shown in Figure 6. Then the analyzer detects an irrigation deficit, because the following

[2]http://cupcarbon.com/



Input variable	Linguistic variables		
	Low	Average	High
Soil temperature	$\Phi < 14$	$14 < \Phi < 27$	$\Phi > 24$

Fig. 6: Fuzzy sets for the input variable soil temperature.

rule has been triggered: *IF ndvi is low AND weather is sunny AND soilTemperature is high AND SoilSalinity is low THEN waterSupply is insufficient*. The rule captures an insufficient water supply due to various aspects, including vegetation (NDVI index), salinity, temperature, etc. At this point, the analyzer sends a warning to the other agents and humans on the current threat, suggesting possible actions to be taken.

VI. Conclusion

The paper introduced a multi-agent model to map a generic multi-tier architecture in the precision agriculture. In details, the contribution of the approach is manifold, listed as follows:

- **A multi-tier architecture for intelligent monitoring.** Three architecture tiers are designed as reusable templates to deal with (a) IoT data acquisition, (b) IoT data processing and integration and (c) a domain-oriented contextualization.
- **A multi-agent implementation of the architecture.** A multi-agent-based interface supports the three architecture tiers: data collection through specialized agents, data integration and contextualization through an analyzer agent to alert humans if some issues occur.
- **Ontology-based IoT data integration.** The integration of several ontologies on sensors and GPS data on plots and areas allows an improved knowledge on the crop, by combining a global view (plot agent view) and a local view (plant agent view) on the plot to better serve different tasks (e.g., irrigation, weed management).
- **Domain-oriented context to support various applications.** Multi-domain ontologies contextualize data to support their interpretation in a specific domain (e.g., tomato monitoring, winemaking, etc.). The use of various domain ontologies allows to support various precision agriculture applications.

References

[1] A. Mukherjee, S. Misra, and N. S. Raghuwanshi, "A survey of unmanned aerial sensing solutions in precision agriculture," *Journal of Network and Computer Applications*, vol. 148, p. 102461, 2019.

[2] I. Mahjri, A. Dhraief, A. Belghith, S. Gannouni, I. Mabrouki, and M. AlAjlan, "Collision risk assessment in flying ad hoc aerial wireless networks," *Journal of Network and Computer Applications*, vol. 124, pp. 1 – 13, 2018.

[3] L. Yunling, X. Zili, L. Na, X. Shuxiang, and Y. Gang, "A path planning algorithm for plant protection uav for avoiding multiple obstruction areas," *IFAC-PapersOnLine*, vol. 51, no. 17, pp. 483 – 488, 2018, 6th IFAC Conference on Bio-Robotics BIOROBOTICS 2018.

[4] J. Zhang, Y. Wu, W. Liu, and X. Chen, "Novel approach to position and orientation estimation in vision-based uav navigation," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 46, no. 2, pp. 687–700, April 2010.

[5] D. Klein, S. Venkateswaran, J. Isaacs, J. Burman, T. Pham, J. Hespanha, and U. Madhow, "Localization with sparse acoustic sensor network using uavs as information-seeking data mules," *ACM Transactions on Sensor Networks (TOSN)*, vol. 9, 05 2013.

[6] G. Danoy, M. R. Brust, and P. Bouvry, "Connectivity stability in autonomous multi-level uav swarms for wide area monitoring," in *Proceedings of the 5th ACM Symposium on Development and Analysis of Intelligent Vehicular Networks and Applications*, ser. DIVANet '15. New York, NY, USA: ACM, 2015, pp. 1–8.

[7] E. Camci, D. R. Kripalani, L. Ma, E. Kayacan, and M. A. Khanesar, "An aerial robot for rice farm quality inspection with type-2 fuzzy neural networks tuned by particle swarm optimization-sliding mode control hybrid algorithm," *Swarm and Evolutionary Computation*, vol. 41, pp. 1 – 8, 2018.

[8] D. Cavaliere and S. Senatore, "Towards an agent-driven scenario awareness in remote sensing environments," *2018 IEEE Symposium Series on Computational Intelligence (SSCI)*, pp. 1982–1989, 2018.

[9] J. Senthilnath, A. Dokania, M. Kandukuri, R. K.N., G. Anand, and S. Omkar, "Detection of tomatoes using spectral-spatial methods in remotely sensed rgb images captured by uav," *Biosystems Engineering*, vol. 146, pp. 16 – 32, 2016, special Issue: Advances in Robotic Agriculture for Crops.

[10] S. Zhang, G. Zhao, K. Lang, B. Su, X. Chen, X. Xi, and H. Zhang, "Integrated satellite, unmanned aerial vehicle (uav) and ground inversion of the spad of winter wheat in the reviving stage," *Sensors*, vol. 19, p. 1485, 03 2019.

[11] S. Cheng, Y. Li, Z. Tian, W. Cheng, and X. Cheng, "A model for integrating heterogeneous sensory data in iot systems," *Computer Networks*, vol. 150, pp. 1 – 14, 2019.

[12] M. Mahmoodpour and A. Lobov, "A knowledge-based approach to the iot-driven data integration of enterprises," *Procedia Manufacturing*, vol. 31, pp. 283 – 289, 2019, research. Experience. Education. 9th Conference on Learning Factories 2019 (CLF 2019), Braunschweig, Germany.

[13] G. Song, M. Wang, X. Ying, R. Yang, and B. Zhang, "Study on precision agriculture knowledge presentation with ontology," *AASRI Procedia*, vol. 3, pp. 732 – 738, 2012, conference on Modelling, Identification and Control.

[14] H. Ngo, N.-A. Le-Khac, and T. Kechadi, *Ontology Based Approach for Precision Agriculture: 12th International Conference, MIWAI 2018, Hanoi, Vietnam, November 18–20, 2018, Proceedings*, 11 2018, pp. 175–186.

[15] A. R. Muljarto, J.-M. Salmon, B. Charnomordic, P. Buche, A. Tireau, and P. Neveu, "A generic ontological network for agri-food experiment integration – application to viticulture and winemaking," *Computers and Electronics in Agriculture*, vol. 140, pp. 433 – 442, 2017.

[16] D. Vallejo, J. Castro-Schez, C. Glez-Morcillo, and J. Albusac, "Multi-agent architecture for information retrieval and intelligent monitoring by uavs in known environments affected by catastrophes," *Engineering Applications of Artificial Intelligence*, vol. 87, p. 103243, 2020.

[17] F. Bu and X. Wang, "A smart agriculture iot system based on deep reinforcement learning," *Future Generation Computer Systems*, vol. 99, pp. 500 – 507, 2019.

[18] W. Mendes, F. Araújo, and S. Er-Raki, *Integrating Remote Sensing Data into Fuzzy Control System for Variable Rate Irrigation Estimates*, 06 2019.

[19] R. Lokers, R. Knapen, S. Janssen, Y. van Randen, and J. Jansen, "Analysis of big data technologies for use in agro-environmental science," *Environmental Modelling & Software*, vol. 84, pp. 494 – 504, 2016.

[20] A. Kamilaris, F. Gao, F. X. Prenafeta-Boldu, and M. I. Ali, "Agri-iot: A semantic framework for internet of things-enabled smart farming applications," in *2016 IEEE 3rd World Forum on Internet of Things (WF-IoT)*, Dec 2016, pp. 442–447.

[21] A. Starkey, H. Hagras, S. Shakya, and G. Owusu, "A multi-objective genetic type-2 fuzzy logic based system for mobile field workforce area optimization," *Information Sciences*, vol. 329, pp. 390 – 411, 2016, special issue on Discovery Science.