Cooperation of unmanned systems for agricultural applications: A theoretical framework

BIOSYSTEMS ENGINEERING XXX (XXXX) XXX

Available online at www.sciencedirect.com

ScienceDirect

journal homepage: www.elsevier.com/locate/issn/15375110

Research Paper

# Cooperation of unmanned systems for agricultural applications: A theoretical framework

*Martina Mammarella* [a], *Lorenzo Comba* [a,b,*], *Alessandro Biglia* [b], *Fabrizio Dabbene* [a], *Paolo Gay* [b]

[a] *Institute of Electronics, Computer and Telecommunication Engineering, National Research Council of Italy, Politecnico di Torino, Corso Duca degli Abruzzi 24, 10129, Torino, Italy*

[b] *Department of Agricultural, Forest and Food Sciences (DiSAFA), Università degli Studi di Torino, Largo Paolo Braccini 2, 10095, Grugliasco, TO, Italy*

ARTICLE INFO

*Article history:*
Received 3 May 2021
Received in revised form
4 November 2021
Accepted 5 November 2021

*Keywords:*
Precision farming
Unmanned vehicles cooperation
Unmanned Aerial Vehicles
Unmanned Ground Vehicles
Control logic
Path and mission planning

Agriculture 4.0 comprises a set of technologies that combines sensors, information systems, enhanced machinery, and informed management with the objective of optimising production by accounting for variabilities and uncertainties within agricultural systems. Autonomous ground and aerial vehicles can lead to favourable improvements in management by performing in-field tasks in a time-effective way. In particular, greater benefits can be achieved by allowing cooperation and collaborative action among unmanned vehicles, both aerial and ground, to perform in-field operations in precise and time-effective ways. In this work, the preliminary and crucial step of analysing and understanding the technical and methodological challenges concerning the main problems involved is performed. An overview of the agricultural scenarios that can benefit from using collaborative machines and the corresponding cooperative schemes typically adopted in this framework are presented. A collection of kinematic and dynamic models for different categories of autonomous aerial and ground vehicles is provided, which represents a crucial step in understanding the vehicles behaviour when full autonomy is desired. Last, a collection of the state-of-the-art technologies for the autonomous guidance of drones is provided, summarising their peculiar characteristics, and highlighting their advantages and shortcomings with a specific focus on the Agriculture 4.0 framework. A companion paper reports the application of some of these techniques in a complete case study in sloped vineyards, applying the proposed multi-phase collaborative scheme introduced here.



* *Corresponding author*. Department of Agricultural, Forest and Food Sciences (DiSAFA), Università degli Studi di Torino, Largo Paolo Braccini 2, 10095, Grugliasco, TO, Italy.
E-mail address: lorenzo.comba@unito.it (L. Comba).

https://doi.org/10.1016/j.biosystemseng.2021.11.008

**Nomenclature**

*Acronyms*

| | |
|---|---|
| ASM | Ackerman steering mechanism |
| CoM | Centre of mass |
| DWA | Dynamic window approach |
| FAO | Food and agriculture organization of the United Nations |
| FW | Fixed-wing |
| GNC | Guidance, navigation and control |
| GSD | Ground sampling distance |
| ICR | Instantaneous centre of rotation |
| ITU | International telecommunication union |
| LOS | Line-of-sight |
| LPV | Linear parameter-varying control |
| LQR | Linear-quadratic regulator |
| LTV | Linear time-varying |
| MPC | Model predictive control |
| NED | North-east-down frame |
| NMPC | Nonlinear model predictive control |
| NN | Neural network |
| PD | Proportional-derivative |
| PID | Proportional-integral-derivative |
| PLOS | Sight-based path following |
| PSO | Particle swarm optimisation |
| PRM | Probabilistic roadmap |
| RPFs | Randomised potential fields |
| RRTs | Rapidly-exploring random trees |
| RW | Rotary-wing |
| SfM | Structure from motion |
| SLAM | Simultaneous localisation and mapping |
| SMC | Sliding mode control |
| UAVs | Unmanned aerial vehicles |
| UGVs | Unmanned ground vehicles |
| UVs | Unmanned vehicles |
| VTOL | Vertical take-off and landing |
| WPs | Waypoints |
| 2WS | Two-wheels steering |
| 4WS | Four-wheels steering |

*Symbols*

| | |
|---|---|
| $d_{ij}$ | Distance from the ICR to the ij-th wheel |
| $F = [F_X\ F_Y\ F_Z]^\top$ | Components of the force acting on the system |
| $F_i$ | Quadcopter i-th rotor vertical force |
| $F_z^B$ | Quadcopter total vertical force in the body frame |
| $g$ | Gravity acceleration |
| $I = [I_{xx}\ I_{yy}\ I_{zz}\ I_r]^\top$ | Quadrotor inertia moments |
| $J = [J_X\ J_Y\ J_Z\ J_{XZ}]^\top$ | Moments of inertia |
| $k_F,\ k_M$ | Quadcopter proportional force and torque constants |
| $L$ | Quadrotor characteristic length |
| $m_{FW}$ | Mass of the FW-UAV |
| $m_{RW}$ | Mass of the RW-UAV |
| $M = [L\ M\ N]^\top$ | Roll, pitch and yaw moments |
| $M_i$ | Quadcopter $i-$th rotor control torque |
| $R$ | Wheel radius |
| $q = [q_s\ q_1\ q_2\ q_3]^\top$ | Quaternion components |
| $V = [u\ v\ w]^\top$ | Longitudinal, lateral and vertical components of the total airspeed |
| $[V_N\ V_E\ V_D]^\top$ | Components of the total airspeed in the North-east-down (NED) frame |
| $v_{ij}$ | Velocity component for the ij-th wheel |
| $x = [x\ y\ h]^\top$ | Position vector in the North-east-down (NED) frame |
| $\delta_{i,o}$ | Steering angle for the inner/outer wheel |
| $\delta_{ij}$ | Steering angle for the ij-th wheel |
| $\delta_m$ | Steering motor angular position |
| $\tau = [\tau_\phi\ \tau_\theta\ \tau_\psi]$ | Quadcopter control torque components in in the body frame |
| $[\phi\ \vartheta\ \psi]^\top$ | Euler angles (roll, pitch and yaw) |
| $\omega = [p\ q\ r]^\top$ | Components of the angular speed |
| $\omega_i$ | Quadcopter i-th rotor angular velocity |
| $\omega_{ij}$ | Angular velocity of the electric motor connected to the wheels |
| $\Omega$ | Angular velocity of the vehicle around the ICR |
| $\Omega_r$ | Quadcopter hover rotational speed |

## 1. Introduction

In recent years, unmanned aerial vehicles (UVs), commonly referred to as drones, have been rapidly growing in popularity for a variety of task. Tactical unmanned systems are now extensively used by the military and various security services, whilst professional unmanned systems are becoming increasingly common in a variety of civilian fields. This expanding use of unmanned systems is not only related to advances in technology but also to the increment in versatility and the reduction in size, risks, and costs that remotely operated systems offer as a result of not having a pilot or operator on board. One of the civilian fields more interested in exploiting drones is surely farming, which is finally undergoing the so-called fourth agricultural revolution by exploiting emerging technologies such as robotics (Rose & Chilvers, 2018) and artificial intelligence (Mazzia, Comba, Khaliq, Chiaberge, & Gay, 2020).

The concept of Agriculture 4.0 consists in the harmonious and interconnected use in agriculture of two different digital technologies: (i) *precision agriculture* for carrying out targeted agronomic interventions, which take into account both farming requirements (Khaliq et al., 2019) and the physical and biochemical features of the land (Morellos et al., 2016); and (ii) *smart farming*, i.e. the digital connection between field activities and all other related processes (Gebbers & Adamchuk, 2010). The Food and Agriculture Organization of the United Nations (FAO) and the International Telecommunication Union (ITU) have identified the use of autonomous unmanned systems as a crucial technology to support and address some of the most pressing challenges in farming in

Please cite this article as: Mammarella, M et al., Cooperation of unmanned systems for agricultural applications: A theoretical framework, *Biosystems Engineering*, https://doi.org/10.1016/j.biosystemseng.2021.11.008

terms of access to actionable real-time quality data and crop monitoring (Sylvester, 2018). Indeed, both unmanned aerial vehicles (UAVs) and unmanned ground vehicles (UGVs) could be favourable complementary tools to conventional farming machines, enhancing operations efficiency as well as human safety and health, thus reducing the environmental impact.

Despite the fact that in the near future, according to the current situation, the market for drone-powered solutions in agriculture will reach $32.4 billion (Mazur, 2016), nowadays the adoption of drones is mainly confined to remote sensing applications, such as crop monitoring (Comba et al., 2019), soil/field analysis (Comba et al., 2021), and irrigation planning (Garrido-Rubio et al., 2020). However, there are many more complex tasks that could be assisted by UVs. In some cases, UVs can even replace conventional machines. These typically involve specific scenarios, as e.g.:

- flat terrains covered by crops with homogeneous canopies (e.g., wheat or paddy fields), where operations need to be performed above crops without interacting with the soil (Kharim, Wayayok, Shariff, Abdullah, & Husin, 2019);
- heavily sloped vineyards or other fields which are not accessible by standard tractors and implements.

Motivated by the above considerations, this paper and its companion provide an overview on the current panorama of agricultural machines cooperation, providing hints on possible cooperative schemes, as well as proposing a collection of technologies and algorithms devoted to the autonomous navigation of drones in the Agriculture 4.0 framework. In the spirit of Agriculture 4.0 principles, the focus is set on solutions which are autonomous, in the sense that the drones do not require a human to drive and control them, but should be able to perform the required operations in an independent and unmanned way. Moreover, this work also devises innovative solutions for extending the use of UAVs in agriculture to scenarios in which they could represent a reliable and valid alternative (or support) to conventional machines, especially whenever the latter are not employable. This manuscript is intended as a form of “user-guide” for researchers and practitioners on the main concepts and technologies currently proposed and exploited for cooperative agricultural vehicles in the framework of autonomous navigation and that can support researchers on three main levels: i) to better understand the concept of collaborative machines, highlighting how the vehicles can collaborate within a complex scenario with respect to the cooperative system architecture and the redistribution of tasks among (either similar or heterogeneous) drones; ii) to have a complete overview of the standard kinematic and dynamic models for the unmanned agricultural vehicles typically exploited in this field, which are critical to analyse, design and implement innovative solutions in the direction of autonomous navigation; and iii) to have a thorough review on the main guidance, navigation and control (GNC) strategies that are currently available in the literature for the fully-autonomous navigation of drones, including examples of agricultural machines that have already been experimenting and validating some of these emerging technologies and algorithms.

Moreover, an unconventional cooperative scheme is proposed. The envisioned architecture involves heterogeneous autonomous vehicles operated within a complex and unstructured scenario such as vineyards on slopped terrains. This solution goes beyond the standard scheme of cooperation by tasks parallelisation, aiming at enhancing productivity, as e.g. proposed in McAllister, Osipychev, Davis, and Chowdhary (2019). Indeed, it is based on a so-called multi-phase approach, where each UV agent has a specific task assigned, whose successful completion is dependent and at the same time instrumental to the tasks of the other agents in order to reach the global result in a precise and time-effective way. In the proposed cooperative framework, different unmanned aerial and ground vehicles are envisioned to perform a combination of remote sensing and in-field operations to properly map the selected area and later provide agrochemicals distribution, also via aerial and ground vehicles. To design and optimise every single step of the proposed framework, a crucial and necessary preliminary step consists in analysing and understanding the technological and methodological challenges of the main problems involved: i) *mission planning*, within the multi-phase cooperative approach; ii) *autonomous navigation*, to allow fully-automated operations by the agents involved; and iii) *in-field operations*, which significantly rely on the preliminary remote sensing mission to allow autonomous navigation within the vine rows thanks to georeferenced, low-complexity maps.

Summarising, in this paper a complete overview of the approaches proposed in the literature which addresses different problems, i.e. machines cooperation, trajectory design, and autonomous guidance, is provided, highlighting their peculiar characteristics, advantages and shortcomings in the Agriculture 4.0 framework. Section 2 focuses on cooperative schemes for agricultural machines and presents a new multi-phase cooperation scheme for the heterogeneous agents involved in agricultural tasks whilst section 3 includes a collection of kinematic and dynamic models for different unmanned vehicles. Section 4 provides a thorough overview of the state-of-the-art algorithms and technologies currently available in the autonomous guidance framework in terms of navigation, guidance and control. The main conclusions and final considerations are provided in section 5, whereas our companion paper (Mammarella, Comba, Biglia, Dabbene, & Gay, 2021) reports a complete case study in sloped vineyards where, following the multi-phase approach preliminarily introduced in this paper, unmanned aerial and ground vehicles are programmed and controlled during their in-field tasks on the basis of a low-complexity vineyard model, constructed starting from a large 3D point cloud obtained during a remote sensing mission performed by a fixed-wing UAV (FW-UAV).

## 2. UV cooperative schemes

The joint use of multiple unmanned vehicles with the objective of fulfilling a complex job was found to be effective in many simulated and practical applications (McAllister et al., 2019). Indeed, they have been shown to provide increased performance with respect to monolithic systems in terms of flexibility, reduction of working time and costs, increased

Please cite this article as: Mammarella, M et al., Cooperation of unmanned systems for agricultural applications: A theoretical framework, *Biosystems Engineering*, https://doi.org/10.1016/j.biosystemseng.2021.11.008

safety, and reduced failure occurrences (Albiero, Pontin Garcia, Umezu, & Leme de Paulo, 2020; Tokekar, Vander Hook, Mulla, & Isler, 2013). In the agricultural framework, there are numerous operations that can profitably be performed by cooperating machines, both fully unmanned or hybrid human-robotic systems. Some examples are represented by crop monitoring (Dusadeerungsikul & Nof, 2019), spraying (Ivić, Andrejčuk, & Družeta, 2019; Xue, Lan, Sun, Chang, & Hoffmann, 2016), weeding (McAllister et al., 2019), ploughing (Albiero et al., 2020), irrigation (González-Briones, Castellanos-Garzón, Mezquita-Martín, Prieto, & Corchado, 2019), seeding (Blender, Buchner, Fernandez, Pichlmaier, & Schlegel, 2016, pp. 6879–6886), and harvesting (Millard, Ravikanna, Groß, & Chesmore, 2019).

As testified by the numerous examples that can be found in both research studies and commercial solutions, when groups of robots are involved in agricultural operations, they can be composed of either homogeneous or heterogeneous agents. In terms of tasks assignment strategies and architectures, systems of cooperative UVs can be defined as:

- *peer to peer* (Fig. 1a): the machines involved are typically similar/identical, and the whole job is split into many parallel tasks, individually performed by each machine. This is the case, e.g., of mechanical weed control by a set of weeder bots (McAllister et al., 2019), or autonomous seeding process made by a group of small robots (Blender et al., 2016). In this case, the task assignment can be either dynamic (Davoodi, Mohammadpour Velni, & Li, 2018), i.e. updated in real-time during operation, or a-priori (Cao et al., 2021), when a field survey is available.
- *master-slave* (Fig. 1b): one or more robotic machines are controlled by a master. This solution can be very effective when a set of different (and/or subsequent) operations have to be performed in the field (Ju & Son, 2019). This is the case, e.g., of grain threshing, collecting and transportation (Kurita, Iida, Suguri, & Masuda, 2012). Another example is represented by tillage operations (Pfaffmann, de Moraes Boos, Tarasinski, & Kegel, 2019), which can be performed by autonomous UGVs (slaves) following a master, such as a combined harvester-thresher. In this case, a specific task is assigned to each player, which has to be properly co-ordinated to accomplish the overall goal.
- *team robots* (Fig. 1c): a joint action of multiple robots is required to fulfil a single task, like in the case of moving large items with a set of small machines (Arab, Shirazi, & Hairi-Yazdi, 2021; Tanner, Kyriakopoulos, & Krikelis, 2001).

Systems of cooperative UVs can be also classified based on the degree of interaction among players and the adopted control strategy. In this case, the following may be identified:

1. *multi-agent systems* (or self-organised systems): computerised systems composed of multiple interacting intelligent agents (Hu, Bhowmick, Jang, Arvin, & Lanzon, 2021). The peculiarity of this cooperative scenario is that the UVs are part of a more complex system, in which other agents (e.g. computers, in-field sensors, human operators, etc.) are also involved. A *centralised* control strategy is typically considered in this case (Arguenon, Bergues-Lagarde, Rosenberger, Bro, & Smari, 2006; Chevalier, Copot, De Keyser, Hernandez, & Ionescu, 2015), but decentralised solutions may also be considered.
2. *swarm robots*: characterised by a set of autonomous machines with simpler control strategies than other categories, and by a high interaction capability among players (Song et al., 2020). A relevant aspect of this strategy is that the desired system behaviour emerges

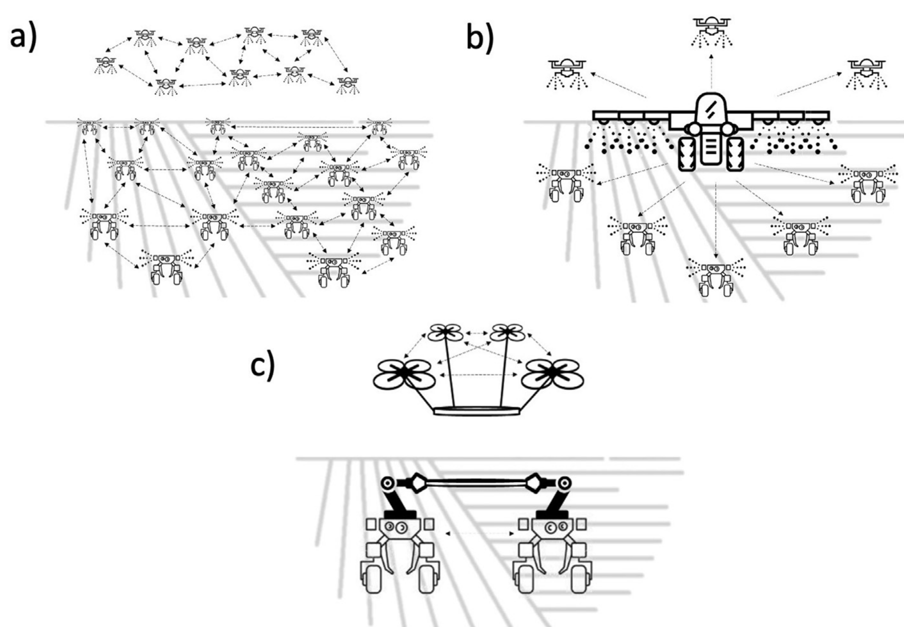


**Fig. 1 – Cooperative architectures: (a) peer-to-peer; (b) master-slave; and (c) team-robots.**

only by considering the whole system, while single machines cannot usually reach the mission target alone (Brambilla, Ferrante, Birattari, & Dorigo, 2013). In addition, swarm robotics have the potential to change the size economies in agriculture, impacting on farm size, structure, and mechanisation (Lowenberg-DeBoer, Behrendt, Godwin, & Frankin, 2019). An example is described in Albiero et al. (2020). where the authors replaced a large tractor with a swarm of small electric robotic machines, that together have the same field capacity. Additional successful industrial applications were recently presented, such as for instance the MARS/Xaver project by Fendt (Blender et al., 2016), the swarm concept by John Deere (Pfaffmann et al., 2019), and the flying autonomous robots for fruit picking by Tevel (Tevel Aerobotics Technologies Ltd, 2021).

A third type of classification can be envisioned by considering whether the cooperation among the robots/agents takes place simultaneously or deferred (e.g. in subsequent phases). The first cooperative scheme, i.e. simultaneous collaboration, represents the most employed operative solution. On the other hand, when agents operate in subsequent phases, they can be assigned completely different missions, sharing strategic information, e.g. regarding the environment in which they are acting, which is essential to the operations success, even if the tasks are not performed simultaneously. This structure can be assimilated within the *shared-world approach* mentioned by Rossi, Bandyopadhyay, Wolf, and Pavone (2018).

In the case of agricultural operations performed by fully-autonomous aerial and ground agricultural vehicles, building a map which report the position, shape and dimensions of the crops becomes crucial, both for obstacle avoidance during navigation and for target localisation (e.g. fruits, canopy, trunk etc.), allowing for the operations of the proper implements. The limited computational resources which typically characterize the currently available low-cost, commercial or experimental, autonomous vehicles as well as the different velocities involved and the complexity of the scenarios envisioned, e.g. vineyards on slopped terrains, discourages on-line simultaneous localisation and mapping (SLAM) procedures. Moreover, as highlighted in Aguiar, dos Santos, Cunha, Sobreira, and Sousa (2020), autonomous mobile robots working in agriculture and forestry are still highly dependent on GNSS-free localisation systems. Robotic localisation and mapping in this framework is still an open issue, even though many solutions have already been proposed. Hence, it is clear that there still are several working lines to be improved. The difficulty of this problem could lead to the creation of new solutions and the development of new concepts to localise and autonomously operate outdoor robots in agriculture.

Within this still-in-evolution framework, an alternative to common cooperative schemes is hereby proposed. When long-cycle crops such as vineyards are considered, it is advantageous to build a simplified geometrical (and georeferenced) model of the crops (referred to as simplified map), identified by using 3D clouds of points acquired during a-priori explorative UAV missions (by LiDAR and/or photogrammetry). Then, this model can be used to plan the tasks to be performed within the crops by the in-field drones, i.e. UAVs and UGVs. In this sense, the classic cooperative approach, in which all the involved agents simultaneously interact and share useful information to properly complete the job, cannot be applied. On the other hand, in a slightly broader sense, the proposed approach is indeed to be considered cooperative, in the sense that the drones that are called to operate in the vineyard rely heavily on both the information about the crops, automatically extrapolated from the data collected during the reconnaissance flight, and the georeferenced maps, generated from the point cloud map for autonomous navigation and precise operations in the field.

Moreover, for the UVs involved in the in-field operations, the system architecture shall be considered cooperative in a stricter sense. In particular, the joint functioning of groups of UAVs and UGVs gives place to a heterogeneous cooperation, as defined in Vu, Raković, Delic, and Ronzhin (2018). Typically, different vehicles in a heterogeneous robot group have the ability to compensate for the each other's weaknesses. Indeed, in the specific case considered, the load that aerial vehicles can carry is limited compared to ground-based vehicles. On the other hand, UGVs often have limited mobility compared to UAVs. Within the proposed scenario, i.e. operation in-field using UVs, such as for spraying agrochemicals while operating in vineyards on a slopped terrain, the heterogeneous system of drones can cooperate in different ways. In the specific case envisioned in this paper, the cooperation among fully-autonomous drones is implemented in the following description:

- UAVs and UGVs are called to operate along vine rows, simultaneously, to properly and efficiently distribute agrochemicals on the crops, by minimising spray drift in order to reduce wasted chemicals and lower costs, via dedicated spraying systems.
- In order to equally distribute the product on the grapevines, the UAV could take care of the upper part of the crop whereas the UGV can cover the lower/lateral parts. In this way, the spraying dispersion can be reduced and drift reduced and improving the uniformity of application.

Hence, according to this solution, the approach can be considered as decentralised since each agent/UV cannot see the local states and local actions of other agents, and has to decide the next local action on its own, according to the definition of decentralised systems/policies in (Xuan & Lesser, 2002). To this regard, it is important to remark that an important ability of decentralised cooperative agents is their ability to communicate.

Indeed, the communication architectures allowing and managing the information exchange between UVs is an important aspect, which has been the subject of different studies. The interested reader is referred to the works of Pitt and Mamdani (2000); Campion, Ranganathan, and Faruque (2018) and Potrino, Serianni, and Palmieri (2019), and references contained therein. In the present work, we decided not to deepen the discussion on communication protocols, since it would distract from the main focus of the paper.

Going into more details, in this work an unconventional cooperative architecture is proposed, in which in-field tasks conducted by two (or fleets of) agents, i.e. an UGV and a rotary wing UAV (RW-UAV), can profitably be planned and controlled by the preparatory mission of a FW-UAV, during which all the needed features of the operative scenario are acquired by the on-board set of sensors and cameras and automatically elaborated in georeferenced, low-complexity maps exploitable in-field by the agents. In particular, the envisioned multi-phase approach is summarised in Fig. 2, where it is possible to observe the two deferred tasks of remote sensing and in-field operations.

The first task consists in flying over the selected area, with the aim of collecting aerial imagery of the target crop via a multispectral camera for mapping purposes. For this task, FW-UAV was selected since it is still the preferred solution in agriculture for remote sensing missions (or similar, e.g. cartography/monitoring) when the area to be covered is quite large and homogeneous (as in the case of the considered vineyard), as also highlighted in Vu et al. (2018). On the other hand, it is important to remark that in the case of small and irregular heterogeneous areas, multi-rotor drones could be preferable due to their improved capability for hovering (see e.g. Kulbacki et al., 2018). In this second cases, the proposed approach can still be extended to the use of RW-UAV, by adapting the mission planning and corresponding requirements to the envisioned vehicle and equipped instrumentation. For the first phase of the proposed approach, a precise knowledge of the crops layout is not required and the mission can be planned by relying only on external cartography. Conversely, the main technical challenges when considering a full-autonomous flight, as in the proposed framework, are represented by the design of ad hoc advanced GNC strategies that can guarantee: i) real-time generation of the desired trajectory, according to the field profile and mission/operative/system requirements (e.g. relative altitude from the terrain, ground sampling distance (GSD), etc.); and ii) proper tracking capabilities in order to follow the desired path while guaranteeing limited (and safe) deviations, despite the presence of external disturbances, e.g. wind gust or turbulence.

The data collected during the remote sensing task is then automatically elaborated to derive the crops layout, starting from the dense 3D point clouds obtained via structure from motion (SfM) techniques, by exploiting the approach first proposed in (Comba, Zaman, et al., 2020). In particular, the obtained point clouds are processed to retrieve a set of relevant information regarding crops, such as planting location and canopy shape, arranged in low complexity and semantically interpreted georeferenced 3D maps, which are crucial for performing tasks within the crops in an autonomous way while guaranteeing collision avoidance. Indeed, in this way the UVs involved in the in-field operations (e.g. spraying) can interact with the crops in a precise and effective ways, exploiting the knowledge of the position and shape of each single crop.

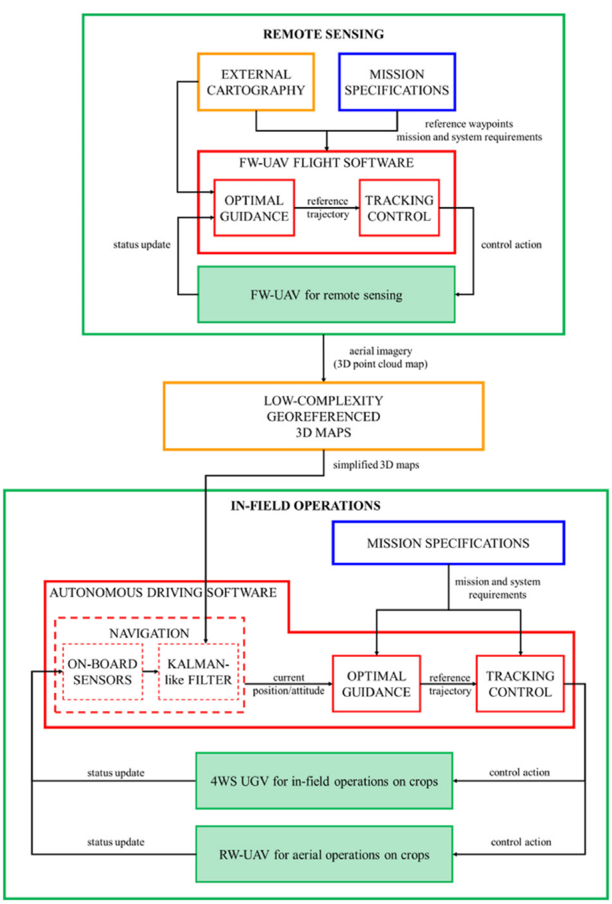


**Fig. 2 – Schematic representation of the proposed multi-phase approach.**

## 3. Drones kinematic and dynamic modelling

This section introduces the basic kinematic and dynamic modelling for the unmanned vehicles that could be involved in the scenarios previously described: i) FW- and RW-UAVs in section 3.1 and section 3.2, respectively; and ii) 2 and 4 wheels steering (WS) UGVs in Section 3.3. The standard models reported below are crucial to design ad-hoc GNC strategies, especially when model-based schemes are envisioned.

### 3.1. *FW-UAV dynamical model*

The nonlinear model considered for UAV dynamics is based on a set of nine equations, written in a body reference frame, as reported in (Etkin & Reid, 1996). Classic assumptions for rigid body and flat non-rotating Earth are made. These assumptions are supported by their application to mini-UAVs,[1] such as those typically used for agricultural applications in Europe. In particular, the total airspeed $V = [u\ v\ w]^\top$ can be decomposed into its longitudinal, lateral and vertical components along the three body axes, respectively, as

$$\dot{u} = \frac{F_X}{m_{FW}} - qw + rv - g\sin\vartheta \qquad (1)$$

[1] The classification of UAVs based on different criteria can be found in the UAS Yearbook. Based on their all-up weight, mini-UAVs are in the 2–25 kg MTOW range.

$$\dot{v} = \frac{F_Y}{m_{FW}} + pw - ru + g\cos\vartheta\sin\phi \tag{2}$$

$$\dot{w} = \frac{F_Z}{m_{FW}} - pv + qu + g\cos\vartheta\cos\phi \tag{3}$$

with $m_{FW}$ being the FW-UAV mass, $[F_X\ F_Y\ F_Z]^\top$ the forces acting on the system, $g$ the gravity acceleration, $\vartheta$ the pitch angle, and $\phi$ the roll angle. The dynamic model related to the temporal evolution of the angular speed components $[p\ q\ r]^\top$ can be written as

$$\dot{p} = \frac{L}{J_x} + \frac{[J_{xz}(\dot{r} + pq) + qr(J_y - J_z)]}{J_x} \tag{4}$$

$$\dot{q} = \frac{M}{J_y} + \frac{[J_{xz}(p^2 - r^2) + pr(J_z - J_x)]}{J_y} \tag{5}$$

$$\dot{r} = \frac{N}{J_z} + \frac{[J_{xz}(\dot{p} - pr) + pq(J_x - J_y)]}{J_z} \tag{6}$$

where $[L\ M\ N]^\top$ are the roll, pitch and yaw moments, respectively, and $J_i$ are the moments of inertia with $i = x, y, z, xz$. Furthermore, the aircraft attitude, expressed in terms of Euler angles $[\phi\ \vartheta\ \psi]^\top$, is defined by the following kinematic equations

$$\dot{\phi} = p + q\sin\phi\tan\vartheta + r\cos\phi\tan\vartheta \tag{7}$$

$$\dot{\vartheta} = q\cos\phi - r\sin\phi \tag{8}$$

$$\dot{\psi} = \frac{q\sin\phi}{\cos\vartheta} + \frac{r\cos\phi}{\cos\vartheta} \tag{9}$$

Last, the position vector $[x\ y\ h]^\top$ is defined in the vehicle-carried vertical reference frame or North-east-down (NED) frame, as

$$V_N = u\cos\vartheta\cos\psi + v(\sin\phi\sin\vartheta\cos\psi - \cos\phi\sin\psi) + w(\cos\phi\sin\vartheta\cos\psi + \sin\phi\sin\psi) \tag{10}$$

$$V_E = u\cos\vartheta\sin\psi + v(\sin\phi\sin\vartheta\sin\psi + \cos\phi\cos\psi) + w(\cos\phi\sin\vartheta\sin\psi - \sin\phi\cos\psi) \tag{11}$$

$$V_D = -u\sin\vartheta v\cos\vartheta\sin\phi + w\cos\phi\cos\vartheta \tag{12}$$

where $[V_N\ V_E\ V_D]^\top$ are the components of the total airspeed along the three axes in the NED frame. This frame is centered on the aircraft centre of gravity. The axis $X_V$ is directed North, the axis $Y_V$ is directed East and the axis $Z_V$ is directed along the local gravity acceleration vector. Starting from the nonlinear model previously introduced, a linearised system of equations in the body axes can be obtained for the design of a linear controller, following the guidelines provided in Casarosa (2004), both for straight-line flights and waypoints (WPs) transitions at non-zero turn rate.

### 3.2. *RW-UAV kinematic and dynamic models*

To describe the kinematics and dynamics of a quadrotor, it is convenient to identify two main reference frames, as reported in Fig. 3: i) an inertial frame $I = (x_I, y_I, z_I)$ with the z-axis $z_I$ pointing upward[2]; and ii) a moving reference frame $B = (x_B, y_B, z_B)$, attached to the UGV body with oriented axes, in which we consider a so-called "+" *configuration*, with the body axes aligned with the quadrotor's arms. In this configuration, there is a pair of rotors (1 and 3) spinning counter-clockwise whereas the other pair (2 and 4) spins clockwise with the angular speed of the i-th blade denoted as $\omega_i$ with $i \in N_1^4$.

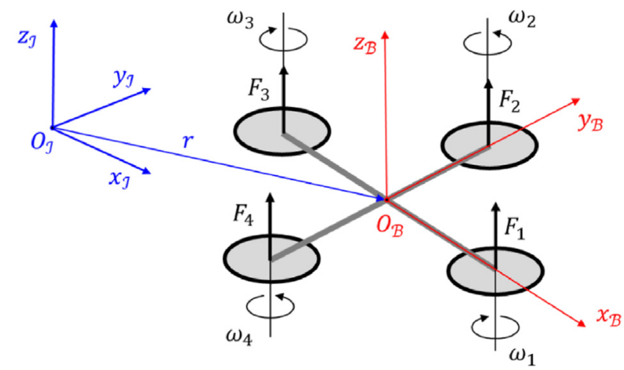


**Fig. 3 – Quadrotor dynamics reference frames: Inertial frame (blue) and Body frame (red). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)**

Each rotor is able to generate a vertical force $F_i$ and a moment $M_i$ according to the laws

$$F_i = k_F\omega_i^2 \text{ and } M_i = k_M\omega_i^2 \tag{13}$$

where the proportional constants $k_F$ and $k_M$ can be determined by experimentation with the fixed rotors or by matching the performance of a simulation to the performance of the real system (Capello, Quagliotti, & Tempo, 2013). According to these assumptions, the models that describe the kinematics and dynamics of the quadrotor can be defined with respect to the inertial and body frames as reported in (Kim, Gadsden, & Wilkerson, 2020), and detailed below.

As in Sabatino (2015), by defining the UAV angular velocity in the body frame as $\omega_B = [p, q, r]^\top$, the quadrotor kinematic equations are the same ones provided for the FW-UAV (7–9). Because of the singularity given by $\theta = \pi/2$, it is possible to describe the UAV kinematics with respect to the quaternion basis, which is able to encode any rotation in a 3D coordinate system, without suffering singularity issues. Technically, a quaternion is a four-element vector $q = [q_s, q_1, q_2, q_3]^\top$ composed by a scalar element $q_s$ and three vectorial components $q_1, q_2, q_3$. Hence, the kinematics of quadrotor can be expressed in quaternion terms as[3]

[2] Another possibility would be to consider a NED frame attached to the UAV instead of the inertial frame, with the z-axis pointing downward.

[3] To recover Euler angles $(\phi, \theta, \psi)$ from the quaternion q, it is possible to use the following formulation $\phi = atam\left(\frac{2(q_sq_1+q_2q_3)}{1-2(q_1^2+q_2^2)}\right)$, $\theta = a\sin(2(q_sq_2 - q_1q_3)), \psi = atam\left(\frac{2(q_sq_3+q_1q_2)}{1-2(q_2^2+q_3^2)}\right)$.

$$\dot{q} = \begin{bmatrix} \dot{q}_s \\ \dot{q}_1 \\ \dot{q}_2 \\ \dot{q}_3 \end{bmatrix} = \begin{bmatrix} -q_1 & -q_2 & -q_3 \\ q_s & -q_3 & q_2 \\ q_3 & q_s & -q_1 \\ -q_2 & q_1 & q_s \end{bmatrix} \begin{bmatrix} p \\ q \\ r \end{bmatrix}.^3 \tag{14}$$

Then, similar to the FW-UAV, the Euler equations are used to describe the quadrotor rotational dynamics. In this case, the moments generated by the rotors are defined in the body frame by three torques $(\tau_\phi, \tau_\theta, \tau_\psi)$ and the contribution of the rotating blades is defined by the rotor moment of inertia $I_r$ and the hover rotational speed $\Omega_r$. Thus, neglecting the aerodynamics effects, the rotational dynamic model is given by:

$$\begin{cases} \dot{p} = \dfrac{\tau_\phi}{I_{xx}} + \dfrac{I_{yy} - I_{zz}}{I_{xx}} qr - \dfrac{I_r}{I_{xx}} q\Omega_r \\ \dot{q} = \dfrac{\tau_\theta}{I_{yy}} + \dfrac{I_{zz} - I_{xx}}{I_{yy}} pr + \dfrac{I_r}{I_{yy}} p\Omega_r \\ \dot{r} = \dfrac{\tau_\psi}{I_{zz}} + \dfrac{I_{xx} - I_{yy}}{I_{zz}} pq \end{cases} \tag{15}$$

On the other hand, to model the translational dynamics, Newton's equations are used (Powers, Mellinger, & Kumar, 2015), expressed in the inertial frame as:

$$\begin{cases} \ddot{x}_I = (\cos\phi\sin\theta\cos\psi + \sin\phi\sin\psi)\dfrac{F_z^B}{m_{RW}} \\ \ddot{y}_I = (\cos\phi\sin\theta\sin\psi - \sin\phi\cos\psi)\dfrac{F_z^B}{m_{RW}} \\ \ddot{z}_I = (\cos\phi\cos\theta)\dfrac{F_z^B}{m_{RW}} - g \end{cases} \tag{16}$$

where $m_{RW}$ is the mass of the RW-UAV, $g$ is the gravity acceleration, and $F_z^B$ is the vertical control force, generated by the rotors, defined in the body frame. Now, it is possible to relate the control inputs, i.e. $F_z^B$, $\tau_\phi, \tau_\theta, \tau_\psi$, to the quadrotor's geometry, the rotors angular velocities $\omega_i$, and the generated thrust $F_i$, knowing that:

i. the *thrust* command given by $F_z^B$ corresponds to the sum of the thrust contributions $F_i$ generated by each rotor, i.e.

$$F_z^B = \sum_{i=1}^{4} F_i = \sum_{i=1}^{4} k_F \omega_i^2 \tag{17}$$

Then, the simple vertical motion is obtained *equally* varying the angular velocity of the rotors, which generates an equal variation of thrust from each blade;

ii. the *rolling torque* $\tau_\phi$ is produced by a different angular velocity variation of the rotors 2 and 4 such that:

$$\tau_\phi = L(F_2 - F_4) = k_F L(\omega_2^2 - \omega_4^2) \tag{18}$$

where $L$ is the quadrotor's characteristic length, i.e. the distance between any rotor and the centre of the drone;

iii. analogously, the *pitching torque* $\tau_\theta$ is produced by a different angular velocity variation of the rotors 1 and 3 such that:

$$\tau_\theta = L(F_3 - F_1) = k_F L(\omega_3^2 - \omega_1^2) \tag{19}$$

iv. the *yawing torque* $\tau_\psi$ derives from the drag generated by the propellers on the quadrotor itself, with a torque direction opposite to the one of the rotors' motion such that:

$$\tau_\psi = \frac{k_M}{k_F}(F_1 - F_2 + F_3 - F_4) = k_M(\omega_1^2 - \omega_2^2 + \omega_3^2 - \omega_4^2) \tag{20}$$

Summarising, the forces and torques on the quadrotor can be written in matrix form as:

$$\begin{bmatrix} F_z^B \\ \tau_\phi \\ \tau_\theta \\ \tau_\psi \end{bmatrix} = \begin{bmatrix} k_F & k_F & k_F & k_F \\ 0 & k_F L & 0 & -k_F L \\ -k_F L & 0 & k_F L & 0 \\ k_M & -k_M & k_M & -k_M \end{bmatrix} \begin{bmatrix} \omega_1^2 \\ \omega_2^2 \\ \omega_3^2 \\ \omega_4^2 \end{bmatrix} = M \begin{bmatrix} \omega_1^2 \\ \omega_2^2 \\ \omega_3^2 \\ \omega_4^2 \end{bmatrix} \tag{21}$$

from which it is possible to recover the actual rotor commands in terms of $\omega_i$ by inverting matrix. $M$.

### 3.3. *UGV kinematic model*

Since a 4WS configuration is considered highly preferable for the envisioned scenarios, it is reasonable to assume that each wheel has its own Ackerman steering mechanism (ASM).[4] Such geometrical structuring implies that the rotation axis of all wheels be arranged as the radii of circles with a common centre point called instantaneous centre of rotation (ICR), as represented in Fig. 4 for the case of two (left) and four (right) wheel steering mechanisms.

For the kinematic description of this type of UGV, the starting point is represented by the 2WS model. So, let us assume to apply a virtual wheel on the centre of the (front) steering axis and define the corresponding steering angle as $\delta$ (see Fig. 4a). Then, for a generic turn, it is possible to recover the steering angles for the inner ($\delta_i$) and the outer ($\delta_o$) wheels as

$$\delta_i = \arctan\frac{2L\sin\delta}{2L\cos\delta - T\sin\delta}, \quad \delta_o = \arctan\frac{2L\sin\delta}{2L\cos\delta + T\sin\delta} \tag{22}$$

Then, to obtain the kinematic model for a 4WS UGV, non-holonomic constraints need to be introduced, as described in (De Luca & Oriolo, 1995) and reported hereafter:

$$\begin{cases} v_{Fj}\cos\delta_{Fl} - v_{Rj}\cos\delta_{Rj} = 0 \\ v_{il}\sin\delta_{Fl} - v_{ir}\cos\delta_{ir} = 0 \end{cases}, \ i = F, R, \ j = l, r \tag{23}$$

An interesting interpretation of these constraints can be promoted: the angular velocity of the vehicle $\Omega$ around the ICR shall be the same for each wheel, i.e. $\frac{v_{ij}}{d_{ij}} = \Omega$ , where $d_{ij}$ is the distance from the ICR to the $ij$-$th^{\cdot}$ wheel (see Fig. 4b).

To obtain a reliable kinematic model, the velocity terms are firstly decomposed into their body-frame components as:

[4] An Ackerman steering mechanism is a geometric arrangement of linkages in the steering of a vehicle, designed to turn the inner and outer wheels of the steering axis at appropriate angles.

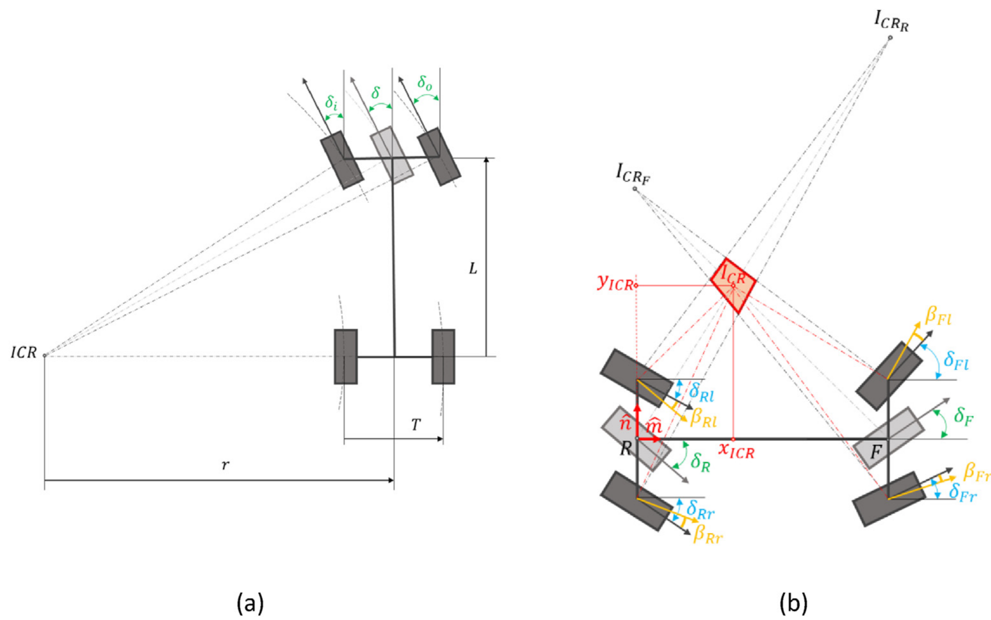

Fig. 4 — ASM geometry for a two-wheels steering (a) and a four-wheels steering (b) arrangements.

$$\begin{cases} v_{ij_x} &= v_{ij}\cos\delta_{ij} \\ v_{ij_y} &= v_{ij}\sin\delta_{ij} \end{cases} \tag{24}$$

Then, their mean values with respect to the left/right and front/rear wheels are computed:

$$\begin{cases} \overline{v_{l_x}} = \dfrac{v_{Fl_x} + v_{Rl_x}}{2} \\ \overline{v_{r_x}} = \dfrac{v_{Fr_x} + v_{Rr_x}}{2} \\ \overline{v_{F_y}} = \dfrac{v_{Fl_y} + v_{Fr_y}}{2} \\ \overline{v_{R_y}} = \dfrac{v_{Rl_y} + v_{Rr_y}}{2} \end{cases} \tag{25}$$

Last, the mean motion of the vehicle's CoM is recovered as:

$$\begin{cases} \dot{x} &= \dfrac{\overline{v_{l_x}} + \overline{v_{r_x}}}{2} \\ \dot{y} &= \dfrac{\overline{v_{F_y}} + \overline{v_{R_y}}}{2} \\ \dot{\theta} &= \dfrac{\overline{v_{F_y}} - \overline{v_{R_y}}}{L} \end{cases} \tag{26}$$

To conclude this subsection, first the model related to the electric motors mounted on the steering axes and then to those mounted on the wheels are briefly recalled. Regarding the steering motors, each one is constrained to drive from its initial position $\delta_{m0}$ at time $t_0$ to the desired angular position $\delta_{des}$ at time $t_f$ according to the relationship:

$$\delta_m(t) = \delta_{m0} + \dot{\delta}_m \cdot (t - t_0) + \frac{1}{2}\ddot{\delta}_m \cdot (t - t_0)^2 \tag{27}$$

until the maximum speed $\dot{\delta}_{max}$ is reached at $t = t_1$. Then, the acceleration remains null for $t \in [t_1, t_2]$ before becoming negative until $\dot{\delta}$ goes to zero and $\delta_m = \delta_{des}$ at $t = t_f$.

However, for the wheel electric motors, each one has to run at a constant angular velocity $\omega_{ij}$ unless different commands are provided by a dedicated controller in terms of desired velocity $\omega_{ij_{des}}$. Hence, the wheel motor behaviour can be described as follows

$$\omega_{ij}(t) = \begin{cases} \omega_{ij}(t_0) + \dot{\omega}_{ij} \cdot (t - t_0) & \text{if } \omega_{ij}(t_0) < \omega_{ij_{des}}(t) \\ \omega_{ij}(t_0) & \text{if } \omega_{ij}(t_0) = \omega_{ij_{des}}(t) \\ \omega_{ij}(t_0) - \dot{\omega}_{ij} \cdot (t - t_0) & \text{if } \omega_{ij}(t_0) > \omega_{ij_{des}}(t) \end{cases} \tag{28}$$

from which it is possible to obtain the linear velocity for the ij-th wheel as $v_{ij} = \omega_{ij}R$, with $R$ being the wheel radius.

## 4. GNC strategies for drones in agricultural applications

The guidance, navigation, and control functions are vital to all forms of (not only autonomous) vehicles, even if they are mostly referred to aerospace systems. Despite the acronym, the actual GNC loop sees the three functionalities performed in a different order sequence. First, the navigation sensors allow the determination, at a given time, of the vehicle's location, velocity and attitude with respect to a given reference frame. This data is typically filtered to obtain a refined state vector. Then, guidance refers to the determination of the desired path (i.e. the trajectory) given the current vehicle location and the desired one, providing also the ideal velocity, acceleration and attitude profile for following that path. Last, control provides the required force and torque sequences, needed to allow the vehicle to follow the desired trajectory while maintaining stability.

Despite the fact that an increasing number of commercial vehicles is available on the market, some of them being designed ad-hoc to operate in specific agricultural scenarios, there still are gaps that need to be addressed to improve vehicles performance when oriented towards full *autonomous navigation*. One example is represented by the negative effects on UAV stability due to wind gust or turbulence, which can disturb remote sensing tasks by additional uncontrolled movements of the drone, leading to inaccurate measurements. Also for aerial drones operating within the crops (e.g. for spraying or pruning), it is crucial to guarantee robustness not only against external disturbances but also against the so-called model uncertainties, which could be related to: i) unmodelled dynamics (for experimental/research vehicles); ii) relevant variations of physical parameters, e.g. centre of mass or inertia (due e.g. to biopesticides release); iii) sensor measurements uncertainties, due to their intrinsic noise errors; and iv) unknown model uncertainties introduced by the manufacturing process. Another crucial aspect, when dealing with autonomous vehicles, is related to safety issues, i.e. to guarantee that the vehicles remain ‘‘close’’ to the planned/desired trajectory within a tolerance range defined by the mission requirements while ensuring collision avoidance.

Considering all the aforementioned issues which could arise when selecting completely autonomous vehicles (i.e. no human in the loop), it becomes crucial to consider the possibility of operating on the GNC functionalities of the (even commercial) aerial/ground vehicles in order to introduce advanced GNC features tailored for autonomous navigation and optimised for the selected job/task. Hence, in the following sections, a vast literature review of the state-of-the-art GNC technologies and algorithms for autonomous drone navigation in the Agriculture 4.0 framework is provided.

### 4.1. *Simplified maps for in-field navigation*

To implement fully autonomous navigation and operations within complex, irregular and unstructured scenarios, in addition to the crop status monitoring tasks (Kerkech, Hafiane, & Canals, 2020; Comba, Biglia, et al., 2020), which have been already object of thorough studies, the accurate spatial description of the environment in which the drones are going to operate (e.g. inter-row width and crop canopy position and shape to avoid damage) are mandatory to properly accomplish given tasks. This information are essential inputs of path planning and navigation algorithms, which should be specifically developed and tuned to be compatible with the agricultural scenario requirements. In this context, enhanced performance can be achieved by 3D path planning, which exploit 3D models of the environment (Jin & Tang, 2011; Gao, Xiao, & Jia, 2020). These representations (see e.g. Fig. 5), which can be in the form of triangulated mesh or point clouds (a set of points in an arbitrary reference frame which represents the surface of given objects), can be generated using 3D sensors (such as LiDAR or depth cameras) or by photogrammetry (Chakraborty, Khot, Sankaran, & Jacoby, 2019; Escolà et al., 2017). Since this kind of dataset are usually generated by integrating a set of multiple raw aerial images, proper geometric processing and radiometric calibration are essential to obtain reliable orthomosaics or point clouds (Aasen, Honkavaara, Lucieer, & Zarco-Tejada, 2018). However, these kinds of datasets are usually huge if acquired with the request degree of detail (e.g. more than 1 Gb for modelling about 1 ha). To be exploited for path planning and navigation purposes, they have to be properly processed in order to extract valuable information (e.g. crop and obstacle locations, parcel boundaries and headlands, inter-row path layout etc.) (Comba, Zaman, et al., 2020). In addition, to enable a rapid communication and data exchange between in-field actors, the drawback of these models related to their complexity and computational demand for the real-time exploitation, must be addressed. The process of “simplifying” maps is thus twofold: firstly, to detect relevant elements and obstacles in the scenario; secondly, to allow the adoption of cost-effective devices for real time application. In agriculture, a crucial constraint which should be fulfilled by any innovative solution is the economic feasibility and, thus, a well assessed approach is to simplify mechanical systems and hardware requirements, and thus enhance algorithms and data processing techniques, without compromising overall performance.

For this reason, when considering cooperating machines and scenarios including drones, unsupervised methods to semantically interpret the models and to perform data reduction are key elements in the presented framework. To this aim, an innovative point cloud processing pipeline, which automatically detects parcels and vine rows locations, was proposed in (Comba, Biglia, Ricauda Aimonino, & Gay, 2018) and later extended in (Comba, Zaman, et al., 2020) to generate low complexity 3D mesh vine row models. The aforementioned algorithms were specifically conceived to automatically process the point clouds of the vineyards. The output of this processing flow is generated by a reduced set of elements which still properly describe the spatial layout and the shape of the vines, allowing a drastic reduction of the amount of data required without losing relevant crop shape information. During the first phase of the pipeline, the parcel boundaries together with a set of vine row information (e.g. the local vine rows orientation and the inter-rows spacing) are detected. This process can be divided into three mains steps: i) precise local terrain surface and height evaluation of each point of the cloud; ii) point cloud scouting and scoring procedure on the basis of a vineyard likelihood measure; and iii) detection of vineyard areas and local features evaluation. More details can be found in Comba et al. (2018). Thus, once the model has been semantically interpreted, by detecting the portion of the model representing the vines canopies, its complexity can be reduced by a methodology based on a combination of convex hull filtration and minimum area c-gon design (Comba, Zaman, et al., 2020). This process was specifically conceived to produce a light mesh model, without losing relevant crop shape information, for path planning and navigation purposes of UGVs and UAVs.

### 4.2. *Optimal guidance algorithms for UVs*

To ensure the UV autonomy, it is crucial to guarantee the ability to generate optimal paths according to the current location, mission tasks compliance, as well as the fulfilment of environmental, safety and kinematic/dynamic/mechanic constraints. The criteria for the optimal path are often based on one or more features such as shortest distance, low risk, smoothness, maximum area coverage, and fewer energy requirements considering different application constraints.

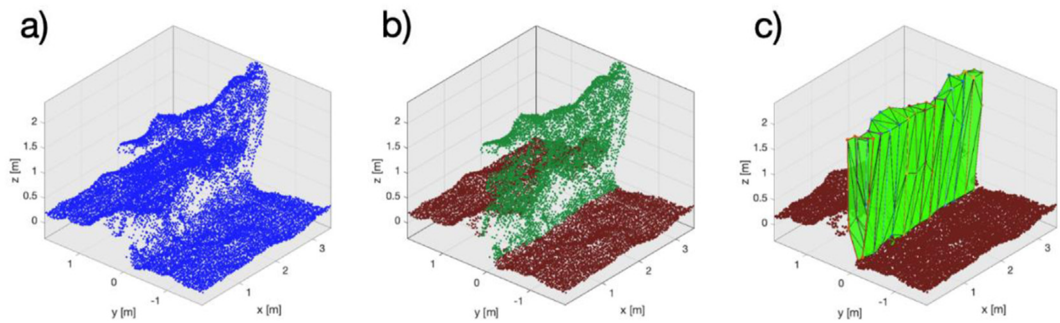


**Fig. 5 — Raw point cloud of a vine row (a), semantically segmented point cloud (b) and low complexity model of the vine canopy (c) (Comba, Zaman, et al., 2020).**

More generally, the motion planning problem can be defined as follows: given a robot with *d* degrees-of-freedom in an environment with *n* obstacles, find a collision-free path connecting the current configuration (*start*) of the robot to the desired one (*goal*). In this section, an overview of the principal algorithms typically exploited for the path planning of autonomous vehicles in the agricultural framework is provided.

### 4.2.1. Guidance strategies for UAVs

Different guidance algorithms can be implemented depending on the mission of the UAV (either fixed or rotary wing) was designed for, as surveyed in Sujit, Saripalli, and Sousa (2014), Rubí, Pérez, and Morcego (2019), and Quan, Han, Zhou, Shen, and Gao (2020). One possibility is to exploit a so-called trajectory smoother that transforms a waypoint-based path (identified either by a mission planner or a trajectory generator algorithm) into a time-stamped kinematically and dynamically feasible trajectory, such as the carrot chasing guidance law proposed in Breivik and Fossen (2005) or the trajectory smoother in Capello, Guglieri, and Quagliotti (2013). This second approach was applied in Mammarella, Capello, and Dabbene (2018) to generate 2D feasible trajectories, starting from assigned waypoints sequences, for different operative missions, such as in precision farming. Indeed, these scenarios are typically characterised by grid patterns for territorial coverage, with variable levels of resolution and image overlap, which are required for an accurate and uniform mapping of the area (crop). Then, the trajectory smoother allowed the generation of a feasible bi-dimensional path that a mini-UAV was following to properly map a (flat) paddy field. By contrast, the well-known line of sight-based path following (PLOS) is a geometric guidance technique that guides the UAV to the following waypoint while steering the vehicle towards the line-of-sight (LOS) (Ambrosino et al., 2009). Another broadly exploited approach is based on direction field theory. The vector field approach is a well-known tool for guidance problems and is based on the construction of a vector field that represents the desired ground track of the aircraft (Meenakshisundaram, Gundappa, & Kanth, 2010). The main drawback of this approach is due to the local minimum point which characterizes the traditional artificial potential field method. Hence, Yingkun (2018) proposed a new vector field-based algorithm for the path planning of the agricultural UAV that is able to include the collision avoidance of different type of obstacles (both static and dynamic) thanks to an improved repulsive force function. A different scheme for path planning in the agricultural framework was proposed by Popović et al. (2017) where the authors proposed an informative path planning approach for active classification using UAVs. Their algorithm used a combination of global viewpoint selection and evolutionary optimisation to refine the planned trajectory in continuous 3D space while satisfying dynamic constraints and it was evaluated for weed detection for precision agriculture.

### 4.2.2. Optimal path planning for UGVs

Path planning in (ground) mobile robotics has been a subject of study for the last decades (Bonadies & Gadsden, 2019). Typically, planning techniques are classified in four groups, as reported in González, Pérez, Milanés, and Nashashibi (2016): i) *graph search-based planners*, i.e. motion planning methods which use graph search schemes to compute paths or trajectories over a discrete representation of the problem (i.e. occupancy maps); ii) *sampling-based planners*, which consist in randomly sampling the configuration space, looking for connectivity inside it and providing suboptimal trajectories; iii) *interpolating curve planners*, often used as path smoothing solutions for a given set of waypoints; and iv) *numerical optimisation planners*, which aim at minimizing a given cost function subject to different constrained variables. The classic approach to path planning, also for agricultural machines, consists in splitting the guidance task into a *global* planning followed by a *local* planning (González et al., 2016). As defined in (Kunchev, Jain, Ivancevic, & Finn, 2006), the global path planner is in charge of generating local goals (i.e. waypoints) towards the final one, whereas the local path planner guarantees the smoothness and affordability of the reference trajectory which interconnects those goals. Since the global path planner controls identification, within a given grid/occupancy map, intermediate WPs between the initial configuration and the desired one, graph searches or sampling-based path planners are typically used for global planning. On the other hand, interpolating curve planners and numerical optimisation approaches are mainly used as local planners. Hereafter, a collection of the main path planning schemes, together with pointers to works that exploited such schemes in the agricultural field for the autonomous generation of trajectories of UGVs, is provided, split into *global* (see section 4.2.2.1) and *local* (see section 4.2.2.2).

4.2.2.1. *Global path planners*. The first class of algorithms used as global planners, i.e. the *graph search-based schemes*, are based on a simple idea: to scan the different configurations/states in the grid and to provide a solution to the path planning problem, selected according to some criteria defined by the specific algorithm. Within this class, the classical Dijkstra algorithm (Madari, Adlinge, & Sharmila, 2019; Wang, Yu, & Yuan, 2011) and its well-known extension, i.e. the A-star algorithm (A*), enable fast node search thanks to the implementation of heuristics logics and the exploitation of a cost function to determine the weights of each node. Within the agricultural framework, Santos et al. (2019) proposed an A* algorithm for safe navigation in a steep slope vineyard, which limits the robot's orientation with respect to its centre of mass. Another scheme is represented by the so-called Dynamic A* search algorithm (or simply D*), which was first proposed by Stentz (1994), and provides optimal solutions for enforcing dynamics in the search task, while avoiding the high computational costs of backtracking. Abrahão, Megda, Guerrero, and Becker (2012) were interested in developing an agricultural mobile robot (i.e. AgriBOT) able to navigate autonomously in a crop, without damaging the plants, and collect data and samples. Hence, they proposed two D*-like algorithms for generating the paths, given initial and goal positions, and compared their performances in terms of the time required to generate the trajectory. On the other hand, stands the family of sampled-based path planners, which operate several strategies for creating samples in free space and for connecting them with collision-free paths in order to provide a solution for path-planning problems. As presented in Khaksar, Sahari, and Hong (2016), three of the more popular sampling-based approaches are:

a. *probabilistic roadmaps* (PRMs) (Kavraki, Švestka, Latombe, & Overmars, 1996): collision-free samples are found in the environment and added to a roadmap graph. Then, the best samples are selected in the graph by minimizing a given cost function and a simple local path planner is used to connect them together.

b. *randomised potential fields* (RPFs) (Barraquand & Latombe, 1991): a graph is built by connecting the local minimums of the potential function defined in the environment. Then, the planner searches this graph for different paths. In the work of Yan et al. (2020), the authors used the RPF algorithm proposed in Hwang and Ahuja (1992) as a global path planner for their AgriRover. Whereas, Shimoda, Kuroda, and Iagnemma (2005) proposed a potential field navigation of high speed unmanned ground vehicles on uneven terrain.

c. *rapidly exploring random trees* (RRTs) (LaValle, 1998): specifically proposed to deal with non-holonomic constraints and high degrees of freedom, this approach builds a tree by randomly choosing a node in the free space and finding the nearest node in the tree (Dong, Zhang, & Ai, 2017). Next, the planner expands this nearest node in the direction of the random node. The improved version of the RRT algorithm, i.e. the so-called *RRT** , first proposed in Karaman and Frazzoli (2011), allows to overcome the limitations of RRT, whose solutions are not asymptotically optimal. Messina, Faedda, Di Pietra, and Lingua (2021) validated the *RRT** algorithm as a (global) path planner for an experimental UGV to be operated on terrains characterised by complex morphology, e.g. in vineyards.

4.2.2.2. *Local path planners*. The path generated by the global planner cannot be directly fed to the control system because of its lack of smoothness, which is vital to guarantee a good control performance. Hence, to obtain a feasible trajectory, the first guidance signal has to be overlapped to the one obtained from a so called *local planner*, which is based on the former and makes it possible to obtain a smoother and more affordable path.

As anticipated earlier, *interpolating curves* and *numerical optimisation planners* are suitable for local path planning, since they provide path smoothing solutions for a given set of waypoints (the former) or optimise a given cost function (the latter) to enforce smoothness to pre-computed trajectories. Within the first category, the most common interpolating methods are based on line and circle curves (Hsieh & Özguner, 2008), clothoid curves (Behringer & Müller, 1998), polynomial curves (McNaughton, Urmson, Dolan, & Lee, 2011), or splines (Berglund, Brodnik, Jonsson, Staffanson, & Söderkvist, 2010). An example of an interpolating curve planner in agriculture is provided in Hameed (2017) where the so-called Dubin (polynomial) curves were used for the coverage path planning of autonomous robotic lawn mowers equipped with GPS. Another interesting possibility is represented by the dynamic-window approach (DWA), which is based on a receding-horizon scheme as described in Fox, Burgard, and Thrun (1997) and Ögren and Leonard (2005). This algorithm is able to generate a smooth and optimised collision-free path for the robot, which is directly derived from the dynamics of the vehicle itself (Zhang et al., 2019). In the agricultural framework, the DWA approach was implemented in Guan, Tean, Oh, and Lee (2019) on a caterpillar-tracked vehicle, characterised by high traction and mobility, to generate a smooth path for the robot, even in rough terrains, satisfying the demand for outdoor agricultural usages.

### 4.3. *Tracking control algorithms for UVs*

Once the reference trajectory has been defined, either offline or online, it needs to be fed to the control block, which is in charge of tracking the desired path while eventually fulfilling operational, mechanical, and safety constraints. Analogously to the path planning framework, several different control schemes have been proposed, tested and experimentally validated in the literature, also for agricultural machines. In the following sections, an overview of the main control strategies for UAVs/UGVs trajectory tracking is reported and examples of agricultural applications are provided with the appropriate references.

#### 4.3.1. *Control strategies for UAVs*

The survey of Nguyen et al. (2020) provides a classification of control algorithms for UAVs, which is based on being either *linear* or *nonlinear* methods. Within the first category, i.e. linear controllers, one finds: i) the classical proportional-integral-derivative (PID) controller, in which the control action is determined according to the deviation between the set value and the real value, trying to reduce the PID errors to zero; ii) the linear-quadratic-regulator (LQR) method, where the control input is selected to minimise a given quadratic cost function; and iii) the well-known $H_\infty$ optimal control scheme, which represents an effective method to deal with issues of uncertain parameters and external disturbances encountered in UAV flight processes.

Sufendi, Trilaksono, Nasution, and Purwanto (2013) used a PID controller for FW-UAVs, tuned according to the Ziegler-Nichols method and later implemented and validated on a ArduPilot mega hardware. Also, a robust PID scheme was proposed in Capello, Sartori, Guglieri, and Quagliotti (2012) where the root locus method was combined with loop shaping techniques to guarantee compliance with robustness requirements. In Ulus and Ikbal (2019), an optimum PID controller was designed for a fixed-wing aircraft used for agricultural applications such as crop monitoring, spraying, etc. For quadrotors, in the work of Bouabdallah, Murrieri, and Siegwart (2004), the authors applied a classic PID to control the vertical take-off and landing (VTOL) of an autonomous robot for indoor flights. More recently, advanced PID schemes have been proposed to improve robustness (Miranda-Colorado & Aguilar, 2020) and adaptability to uncertainty and to specific scenario demands for RW-UAVs (e.g., not only hovering but also route tracking as in Noordin, Mohd Basri, Mohamed, and Mat Lazim (2021) and Sunay, Altan, Belge, and Hacioglu (2020)). An altitude PID-based control system for a quadrotor is proposed in Zhao, Li, Hu, and Pei (2016) to achieve a high degree of control and have it meet the accuracy requirements in the autonomous agricultural plant protection flight. Some examples of LQR control applied to FW-UAV were reported in Anjali, Vivek, and Nandagopal (2016), where it is shown that the LQR approach provides better results compared to a PID in terms of disturbance rejection, and in Bagheri, Jafarov, Freidovich, and Sepehri (2016), where the LQR algorithm is combined with a PID to provide robust stability and step reference tracking for the nonlinear dynamics of mini-UAVs. An LQR controller was proposed in Shamshiri et al. (2018) to control the velocity and the pitch rate of a fixed-wing drone for remote sensing research applications in the precision agriculture of oil palm plantations. For quadrotors, Joelianto, Christian, and Samsi (2020) exploited a combination of PIDs and LQRs to control a swarm of six quadrotors as agents for flocking while tracking a swarm trajectory. Remaining in the linear controllers category, the $H_\infty$ optimal control represents an effective method to deal with issues of uncertain parameters and external disturbances encountered in the UAVs flight process. The effectiveness of this approach, applied to the trajectory tracking of FW-UAVs and quadrotors, was demonstrated, for example, in López, Dormido, Dormido, and Gómez (2015) and Chen and Huzmezan (2003). Despite the fact that the $H_\infty$ features comply with the control requirements of UAVs in agriculture, no example can be found in literature.

To overcome some of the shortcomings of linear controllers, a variety of nonlinear ones have been developed and applied to UAVs. Among these, feedback linearisation, backstepping, sliding mode control (SMC), and adaptive control have received much of the attention. Feedback linearisation is a powerful control algorithm for the design of nonlinear systems. The main idea of this approach is to algebraically transform the nonlinear system dynamics into a partially or fully linearised system so that feedback control techniques can be applied, as in Khamseh and Tôrres (2016) for FW-UAVs and in Martins, Cardeira, and Oliveira (2021) for quadrotors. Feedback linearisation is mentioned also in Kim, Kim, Ju, and Son (2019) as one of the control schemes typically exploited for UAVs in agriculture. To deal with nonlinearities, a backstepping controllers was applied to FW-UAVs (Sartori, Quagliotti, Rutherford, & Valavanis, 2014) and quadrotors (Glida, Abdou, Chelihi, Sentouh, & Hasseni, 2020), but within the agricultural field, it is mainly exploited for ground vehicles. When robustness against uncertainty and disturbance is sought, SMC controllers could represent a valid alternative, since they are characterized by low sensitivity to external disturbances, good tracking ability, and rapid response. A sampled-data second-order SMC scheme has been designed for as FW-UAV (Raza, Ahmed, Khan, Mumtaz, & Mumtaz Malik, 2017), proving robustness against external disturbances and capability of tackling with chattering issues. Runcharoon and Srichatrapimuk (2013) addressed the position and attitude tracking control for a small quadrotor UAV via multiple SMC controllers.

Another category is given by so-called adaptive controllers, which are able to automatically compensate for parameter changes in system dynamics by means of the controller's characteristics so that the overall system performance remains the same, or rather is maintained at an optimal level. An example is represented by the $L_1$ adaptive scheme in Capello, Guglieri, Marguerettaz, and Quagliotti (2012), which was designed for a mini-UAV autopilot, showing inherent robustness against external and internal parameter variations. For quadrotors, an example of adaptive control is represented by the approach described in Antonelli, Cataldi, Giordano, Chiaverini, and Franchi (2013).

The aforementioned controllers do not represent the complete range of control strategies that have been designed and implemented for UAVs. Indeed, an additional category can be identified, which includes 'intelligent' control schemes, i.e. algorithms that are able to handle a wider range of uncertainties than other control strategies. This category includes fuzzy logic (Zhang et al., 2020) and also neural-network (NN) based control techniques (see e.g. Bhandari & Patel, 2017; Dierks & Jagannathan, 2010).

Even if all the strategies discussed above could guarantee robustness against bounded modelled disturbances when properly designed, they are generally unable to explicitly take into consideration mission and system constraints. For these reasons, model predictive control (MPC) schemes (Kouvaritakis & Cannon, 2015; Mayne & Rawlings, 2009) have become widely used within the UAV path-following framework. The MPC philosophy can be simply described as follows: to predict future behaviour by using a system model, given the measurements or estimates of the current state of the system and a hypothetical future input trajectory or feedback control policy. In this way, the state and input constraints can be tackled directly. A first example is provided by Oettershagen, Melzer, Leutenegger, Alexis, and Siegwart (2014), where the authors combined a linear MPC, as an attitude controller, with an $L_1$

navigation loop for the altitude control. In Abdolhosseini, Zhang, and Rabbath (2013) an efficient MPC algorithm was proposed which deployed fewer prediction points and less computational requirements to control a small quadrotor UAV for trajectory tracking. Other examples were presented in Kamel, Burri, and Siegwart (2017), where different receding horizon methods for trajectory tracking were discussed, and in Michel, Bertrand, Valmorbida, Olaru, and Dumur (2017), where two different robust MPC schemes were proposed for the control of the FW-UAV's translational dynamics. In Raffo, Ortega, and Rubio (2008), the control structure envisioned a linear MPC for trajectory tracking and a nonlinear $H_\infty$ for rotational stabilisation. An explicit MPC was proposed in Liu, Lu, and Chen (2015) again for tracking a reference trajectory represented by using Bezier curves. Moreover, recent approaches to MPC have proved to be robust against system uncertainties, as for instance the so called tube-based MPC (see e.g. Limón, Alvarado, Alamo, & Camacho, 2010). The effectiveness, robustness and computational compatibility with low-cost hardware of this approach were already been proved in a simulation environment for an FW-UAV, as described in Mammarella and Capello (2020) and Mammarella et al. (2019), and experimentally for a space application as presented in Mammarella, Capello, Park, Guglieri, and Romano (2018). More advanced predictive control techniques were also been proposed for the FW-UAVs trajectory tracking problem, such as nonlinear MPC (Lindqvist, Mansouri, Agha-mohammadi, & Nikolakopoulos, 2020) or stochastic MPC (Mammarella, Capello, Dabbene, & Guglieri, 2018) but their computational burden may not be compliant with the autopilot's capability.

Thus in conclusion, it is possible to observe that, despite the multiplicity of control algorithms available in the literature describing UAV trajectory tracking, those that have been investigated for agricultural applications are (almost) all limited to classic schemes as PID and LQR. The main reason behind this choice lies in the following two aspects: i) these algorithms are typically provided with the autopilot of commercial UAVs; and ii) they are simple to implement, easy to tune and are characterized by a very limited computational burden. On the other hand, looking for completely autonomous aerial vehicles (i.e. no remote control) exploitable for innovative, unstructured and complex agricultural scenarios, one has to consider the possibility of employing and tailoring more complex control schemes that could provide better performances, robustness against internal and external uncertainty sources, and a higher level of safety. These aspects become more relevant if/when swarm architectures are envisioned within the Agriculture 4.0 framework.

#### 4.3.2. *Tracking controllers for UGVs*

For UGVs, Mohamed, El-Gindy, and Ren (2018) provided a literature survey on the control techniques that have been proposed and validated for the autonomous navigation of ground vehicles in various fields of application. In this survey, the authors highlighted how the UGVs autonomy and intelligence robustness mainly relies on control systems algorithms, which range from classic control to more advanced methods such as adaptive control, robust control, and intelligent control. Hence, also for UGVs, these algorithms can be split into three main categories: i) linear control; ii) nonlinear control; and iii) “intelligent” control.

The classic approach envisions the exploitation of PID controllers, which are easy to tune, reliable and light enough to be implemented onboard UGVs. In Soe and Tun (2014), a cascade of PID controllers is proposed for a UGV, which allowed to improve robustness thanks to a double closed-loop control system. In Haytham, Elhalwagy, Wassal, and Darwish (2015), the authors proposed an optimally-tuned PID controller as the steering controller for a 4WS UGV, by exploiting an optimal genetic algorithm to tune the vehicle's controller. In Gonzalez-de-Santos et al. (2017), a new PID controller was designed to follow the speed set point received from the trajectory controller of an electric UGV exploited for effective weed and pest control. An auto-tuning method for PID parameters was proposed in Koca, Aslan, and Gökçe (2021), where the authors were looking for a speed control PID-based configuration for the DC motor of an agricultural UGV. In Hang and Chen (2021), a linear parameter-varying (LPV) controller was used to obtain an adaptive path tracking control while a feedforward control was combined with an LQR to eliminate errors caused by disturbances. on the onboard implementation of an optimal LQR tracking controller is described in De Simone and Guida (2018), where an identification activity and a control application conducted on an electric UGV by using low-cost components and open-source software (i.e. Arduino) were presented. In Wu (2018), a path tracking controller was proposed for a robot-trailer system in which an LQR controller was designed to remove trailer position errors for both straight and curved reference paths and where the control parameters were tuned by exploiting particle swarm optimisation (PSO) with varying inertia. Ni, Hu, and Xiang (2019) proposed a robust path following controller, based on the robust $H_\infty$ output-feedback approach, which aimed at controlling an UGV to its handling and driving limits.

The path tracking accuracy of agricultural UGVs is one of the important factors that determine the results of the operation, as also discussed in Li, Yu, Guo, and Sun (2020). Currently, the commonly used path tracking methods for agricultural machines include the PID algorithm (Li, Sun, & Jin, 2016), pure tracking schemes (Guo, Zhang, Zhao, & Chen, 2020; Liu, 2018), and kinematic or dynamic model-based methods (see e.g. Bevly, Gerdes, & Parkinson, 2002; Eaton, Pota, & Katupitiya, 2009). Considering that the changes in soil hardness and the high-frequency dynamics of agricultural vehicle are difficult to model, the entire path tracking process is highly nonlinear. Hence, traditional linear control algorithms can provide unacceptable performance. For this reason, nonlinear and “intelligent” controllers are the best choice when the trajectory tracking problem is considered. In Hao, Lenain, Thuilot, and Martinet (2004), an SMC controller, robust not only against sliding effects but also against input noise, was proposed for farm vehicles and simulation results showed that this control law was able to guarantee high path-following accuracy even in the presence of sliding. The problem of sliding was also considered in Fang, Fan, Thuilot, and Martinet (2006), where the authors presented a trajectory tracking control based on a backstepping method, which provided, both in simulation and experiments, high longitudinal-lateral control accuracy, regardless of sliding. In Meng et al. (2015), an agricultural implement guidance system based on machine vision and fuzzy control was designed to achieve accurate mechanical inter-rows weeding. A compound fuzzy control was also proposed in Li et al. (2020) for unmanned agricultural vehicle path tracking. In this case, the proportional-derivative (PD) fuzzy controller was designed based on lateral and heading errors, and an integral compensation was adopted to solve the problem of low steady-state accuracy of traditional PD-type fuzzy controls, realizing high-precision path tracking of unmanned agricultural vehicles. An MPC-based path tracking control was proposed in Lin, Yin, Liang, and Wang (2018) for dealing with the peculiarities of an orchard terrain and the big turning radius characterising agricultural UGVs. A review of MPC applications in agriculture can be found in Ding, Wang, Li, and Li (2018), where the authors identified three main branches related to agricultural machinery that would benefit from the exploitation of MPC: i) *autonomous navigation*, i.e. controlling vehicle trajectory while maintaining it at a constant distance from the adjacent travel line, or placing the strip side by side in accordance with the agricultural conditions without overlaps or gaps (Coen, Anthonis, & De Baerdemaeker, 2008); ii) *path-tracking operations*, which could rely on distributed nonlinear MPC (NMPC) strategies (Kayacan, Kayacan, Ramon, & Saeys, 2014) for improving transport efficiency when dealing with multiple complex bodies, or on LTV-MPC to generate offline reference trajectories for high-precision closed-loop tracking as in Plessen and Bemporad (2017); and iii) steering operations, where the automation of the manoeuvres in a headland could reduce the burden on drivers and improve efficiency, e.g. see Cariou, Lenain, Berducat, and Thuilot (2010).

Lastly, when dealing with a 4WS configuration, it is necessary to address the control problem as a two-step procedure: first, a steering controller to define the desired steering angle and then, a velocity controller to assess the optimal velocity (and consequently the applied torque) of each wheel. Regarding steering controllers, several approaches have been proposed, ranging from simple proportional control laws or PID-like schemes (e.g. Marino, Scalzi, Orlando, & Netto, 2009) to predictive schemes (e.g. Falcone, Borrelli, Asgari, Tseng, & Hrovat, 2007) and neural networks (e.g. Deng, Xu, Yan, Zhang, & Song, 2017). For the second phase related to the definition of the velocity profile, one can rely on optimal control theory as proposed in (Higuchi & Saitoh, 1993) where the control feeds forward the steering wheel angle and feeds back the yaw velocity and the sideslip angle to the front and rear wheels.

## 5. Conclusions

Autonomous agricultural vehicles represent the next logical step in the automation of crop production, if safety and liability can be guaranteed. In that case, the exploitation of both aerial and ground vehicles for complex in-field operations such as spraying and shredding could become a reality in the near future.

In this paper, an overview of the agricultural scenarios that can benefit from using collaborative machines and the corresponding cooperative schemes typically adopted in this framework are presented. Moreover, a new multi-phase approach is proposed for long-cycle crops, in which heterogeneous agricultural aerial and ground vehicles operate. Then, a collection of kinematic and dynamic models for different categories of autonomous aerial and ground vehicles is provided, which are crucial for studying the vehicle behaviour. Lastly, a collection of state-of-the-art technologies for the autonomous navigation of drones is provided, summarising their peculiar characteristics, and highlighting their advantages and shortcomings with a specific focus on the Agriculture 4.0 framework.

Some of the aforementioned technologies were then selected to provide effective improvements on mission planning, autonomous navigation, and in-field operations, and later applied to a specific scenario, i.e. a Barolo vineyard on a sloped terrain, whose preliminary results are described in the companion paper, Mammarella et al. (2021).

## Funding

This research was partially funded by the project “New technical and operative solutions for the use of drones in Agriculture 4.0” (PRIN 2017, Prot. 2017S559BB).

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## REFERENCES

Aasen, H., Honkavaara, E., Lucieer, A., & Zarco-Tejada, P. J. (2018). Quantitative remote sensing at ultra-high resolution with UAV spectroscopy: A review of sensor technology, measurement procedures, and data correction workflows. *Remote Sensing, 10*, 1091. https://doi.org/10.3390/rs10071091

Abdolhosseini, M., Zhang, Y. M., & Rabbath, C. A. (2013). An efficient model predictive control scheme for an unmanned quadrotor helicopter. *Journal of Intelligent and Robotic Systems: Theory and Applications, 70*, 27–38. https://doi.org/10.1007/s10846-012-9724-3

Abrahão, G. Q. S., Megda, P. T., Guerrero, H. B., & Becker, M. (2012). AgriBOT project–comparison between the D* and focussed D* navigation algorithms. *In ABCM Symposium Series in Mechatronics, 5*, 1023–1031.

Aguiar, A. S., dos Santos, F. N., Cunha, J. B., Sobreira, H., & Sousa, A. J. (2020). Localization and mapping for robots in agriculture and forestry: A survey. *Robotics, 9*, 97. https://doi.org/10.3390/robotics9040097

Albiero, D., Pontin Garcia, A., Umezu, C. K., & Leme de Paulo, R. (2020). Swarm robots in mechanized agricultural operations: Roadmap for research. In *Brazilian congress of automatic*. Porto Alegre. https://doi.org/10.48011/asba.v2i1.1144.

Ambrosino, G., Ariola, M., Ciniglio, U., Corraro, F., De Lellis, E., & Pironti, A. (2009). Path generation and tracking in 3-D for UAVs. *IEEE Transactions on Control Systems Technology, 17*, 980–988. https://doi.org/10.1109/TCST.2009.2014359

Anjali, B. S., Vivek, A., & Nandagopal, J. L. (2016). Simulation and analysis of integral LQR controller for inner control loop design of a fixed wing micro aerial vehicle (MAV). *Procedia Technology, 25*, 76–83. https://doi.org/10.1016/j.protcy.2016.08.083
Antonelli, G., Cataldi, E., Giordano, P. R., Chiaverini, S., & Franchi, A. (2013). Experimental validation of a new adaptive control scheme for quadrotors MAVs. In *2013 IEEE/RSJ International Conference on Intelligent Robots and Systems* (pp. 2439–2444). https://doi.org/10.1109/IROS.2013.6696699
Arab, F., Shirazi, F. A., & Hairi-Yazdi, M. R. (2021). Planning and distributed control for cooperative transportation of a non-uniform slung-load by multiple quadrotors. *Aerospace Science and Technology, 117*, 106917. https://doi.org/10.1016/j.ast.2021.106917
Arguenon, V., Bergues-Lagarde, A., Rosenberger, C., Bro, P., & Smari, W. (2006). Multi-agent based prototyping of agriculture robots. In *International Symposium on Collaborative Technologies and Systems (CTS'06)* (pp. 282–288). https://doi.org/10.1109/CTS.2006.57
Bagheri, S., Jafarov, T., Freidovich, L., & Sepehri, N. (2016). Beneficially combining LQR and PID to control longitudinal dynamics of a SmartFly UAV. In *2016 IEEE 7th annual information technology, Electronics and mobile communication conference (IEMCON)*. https://doi.org/10.1109/IEMCON.2016.7746309
Barraquand, J., & Latombe, J. C. (1991). Robot motion planning: A distributed representation approach. *The International Journal of Robotics Research, 10*, 628–649. https://doi.org/10.1177/027836499101000604
Behringer, R., & Müller, N. (1998). Autonomous road vehicle guidance from autobahnen to narrow curves. *IEEE Transactions on Robotics and Automation, 14*, 810–815. https://doi.org/10.1109/70.720356
Berglund, T., Brodnik, A., Jonsson, H., Staffanson, M., & Söderkvist, I. (2010). Planning smooth and obstacle-avoiding B-spline paths for autonomous mining vehicles. *IEEE Transactions on Automation Science and Engineering, 7*, 167–172. https://doi.org/10.1109/TASE.2009.2015886
Bevly, D. M., Gerdes, J. C., & Parkinson, B. W. (2002). A new yaw dynamic model for improved high speed control of a farm tractor. *Journal of Dynamic Systems, Measurement, and Control, 124*, 659–667. https://doi.org/10.1115/1.1515329
Bhandari, S., & Patel, N. (2017). Nonlinear adaptive control of a fixed-wing UAV using multilayer perceptrons. *AIAA Guidance, navigation, and control conference*. https://doi.org/10.2514/6.2017-1524
Blender, T., Buchner, T., Fernandez, B., Pichlmaier, B., & Schlegel, C. (2016). Managing a mobile agricultural robot swarm for a seeding task. In *IECON 2016 - 42nd annual conference of the IEEE Industrial Electronics Society* (pp. 6879–6886). https://doi.org/10.1109/IECON.2016.7793638
Bonadies, S., & Gadsden, S. A. (2019). An overview of autonomous crop row navigation strategies for unmanned ground vehicles. *Engineering in Agriculture, Environment and Food, 12*, 24–31. https://doi.org/10.1016/j.eaef.2018.09.001
Bouabdallah, S., Murrieri, P., & Siegwart, R. (2004). Design and control of an Indoor micro quadrotor. In *, Vol. 4. IEEE International Conference on Robotics and Automation, 2004. Proceedings. ICRA* (pp. 4393–4398). https://doi.org/10.1109/ROBOT.2004.1302409
Brambilla, M., Ferrante, E., Birattari, M., & Dorigo, M. (2013). Swarm robotics: A review from the swarm engineering perspective. *Swarm Intelligence, 7*, 1–41. https://doi.org/10.1007/s11721-012-0075-2
Breivik, M., & Fossen, T. I. (2005). Principles of guidance-based path following in 2D and 3D. In *Proceedings of the 44th IEEE Conference on Decision and Control* (pp. 627–634). https://doi.org/10.1109/CDC.2005.1582226
Campion, M., Ranganathan, P., & Faruque, S. (2018). UAV swarm communication and control architectures: A review. *Journal of Unmanned Vehicle Systems, 7*, 93–106. https://doi.org/10.1139/juvs-2018-0009
Cao, R., Li, S., Ji, Y., Zhang, Z., Xu, H., Zhang, M., et al. (2021). Task assignment of multiple agricultural machinery cooperation based on improved ant colony algorithm. *Computers and Electronics in Agriculture, 182*, 105993. https://doi.org/10.1016/j.compag.2021.105993
Capello, E., Guglieri, G., Marguerettaz, P., & Quagliotti, F. (2012b). Preliminary assessment of flying and handling qualities for mini-UAVs. *Journal of Intelligent and Robotic Systems: Theory and Applications, 65*, 43–61. https://doi.org/10.1007/s10846-011-9565-5
Capello, E., Guglieri, G., & Quagliotti, F. (2013b). A waypoint-based guidance algorithm for mini UAVs. *IFAC Proceedings Volumes, 46*, 120–125. https://doi.org/10.3182/20131120-3-FR-4045.00005
Capello, E., Quagliotti, F., & Tempo, R. (2013). Randomized approaches and adaptive control for quadrotor UAVs. In *2013 international Conference on unmanned aircraft systems (ICUAS)* (pp. 461–470). https://doi.org/10.1109/ICUAS.2013.6564721
Capello, E., Sartori, D., Guglieri, G., & Quagliotti, F. (2012a). Robust assessment for the design of multi-loop proportional integrative derivative autopilot. *IET Control Theory & Applications, 6*, 1610–1619. https://doi.org/10.1049/iet-cta.2011.0275
Cariou, C., Lenain, R., Berducat, M., & Thuilot, B. (2010). Autonomous maneuvers of a farm vehicle with a trailed implement in headland. In *, 2. Proceedings of the 7th International Conference on Informatics in Control, Automation and Robotics* (pp. 109–114). https://doi.org/10.5220/0002875501090114
Casarosa, C. (2004). *Meccanica del volo* (Vol. 1). Plus-Pisa University Press.
Chakraborty, M., Khot, L. R., Sankaran, S., & Jacoby, P. W. (2019). Evaluation of mobile 3D light detection and ranging based canopy mapping system for tree fruit crops. *Computers and Electronics in Agriculture, 158*, 284–293. https://doi.org/10.1016/j.compag.2019.02.012
Chen, M., & Huzmezan, M. (2003). *A combined MBPC/2 DOF H infinity controller for a quad rotor UAV. AIAA guidance, navigation, and control conference and exhibit*. https://doi.org/10.2514/6.2003-5520
Chevalier, A., Copot, C., De Keyser, R., Hernandez, A., & Ionescu, C. (2015). A multi agent system for precision agriculture. In L. Busoniu, & L. Tamás (Eds.), *Vol. 42. Handling uncertainty and networked structure in robot control. Studies in systems, decision and control*. Cham: Springer. https://doi.org/10.1007/978-3-319-26327-4_15.
Coen, T., Anthonis, J., & De Baerdemaeker, J. (2008). Cruise control using model predictive control with constraints. *Computers and Electronics in Agriculture, 63*, 227–236. https://doi.org/10.1016/j.compag.2008.03.003
Comba, L., Biglia, A., Ricauda Aimonino, D., Barge, P., Tortia, C., & Gay, P. (2019). 2D and 3D data fusion for crop monitoring in precision agriculture. In *2019 IEEE International Workshop on Metrology for Agriculture and Forestry (MetroAgriFor)* (pp. 62–67). https://doi.org/10.1109/MetroAgriFor.2019.8909219
Comba, L., Biglia, A., Ricauda Aimonino, D., Barge, P., Tortia, C., & Gay, P. (2021). Neural network clustering for crops thermal mapping. *Acta Horticulturae, 1311*, 513–520. https://doi.org/10.17660/ActaHortic.2021.1311.65
Comba, L., Biglia, A., Ricauda Aimonino, D., & Gay, P. (2018). Unsupervised detection of vineyards by 3D point-cloud UAV photogrammetry for precision agriculture. *Computers and*

*Electronics in Agriculture, 155*, 84–95. https://doi.org/10.1016/j.compag.2018.10.005
Comba, L., Biglia, A., Ricauda Aimonino, D., Tortia, C., Mania, E., Guidoni, S., et al. (2020). Leaf Area Index evaluation in vineyards using 3D point clouds from UAV imagery. *Precision Agriculture, 21*, 881–896. https://doi.org/10.1007/s11119-019-09699-x
Comba, L., Zaman, S., Biglia, A., Ricauda Aimonino, D., Dabbene, F., & Gay, P. (2020). Semantic interpretation and complexity reduction of 3D point clouds of vineyards. *Biosystems Engineering, 197*, 216–230. https://doi.org/10.1016/j.biosystemseng.2020.05.013
Davoodi, M., Mohammadpour Velni, J., & Li, C. (2018). Coverage control with multiple ground robots for precision agriculture. ASME. *Mechanical Engineering, 140*, 4–8. https://doi.org/10.1115/1.2018-JUN-4
De Luca, A., & Oriolo, G. (1995). Modelling and control of nonholonomic mechanical systems. *Kinematics and dynamics of multi-body systems*, 277–342. https://doi.org/10.1007/978-3-7091-4362-9_7
De Simone, M. C., & Guida, D. (2018). Identification and control of a unmanned ground vehicle by using Arduino. *UPB Scientific Bulletin, Series D: Mechanical Engineering, 80*, 141–154.
Deng, J., Xu, D., Yan, W., Zhang, Q., & Song, X. (2017). Adaptive neural network automatic parking constrained control via anti-windup compensator. *Advances in Mechanical Engineering, 9*, 1–10. https://doi.org/10.1177/1687814017700830
Dierks, T., & Jagannathan, S. (2010). Output feedback control of a quadrotor UAV using neural networks. *IEEE Transactions on Neural Networks, 21*, 50–66. https://doi.org/10.1109/TNN.2009.2034145
Ding, Y., Wang, L., Li, Y., & Li, D. (2018). Model predictive control and its application in agriculture: A review. *Computers and Electronics in Agriculture, 151*, 104–117. https://doi.org/10.1016/j.compag.2018.06.004
Dong, Y., Zhang, Y., & Ai, J. (2017). Experimental test of unmanned ground vehicle delivering goods using RRT path planning algorithm. *Unmanned Systems, 5*, 45–57. https://doi.org/10.1142/S2301385017500042
Dusadeerungsikul, P. O., & Nof, S. Y. (2019). A collaborative control protocol for agricultural robot routing with online adaptation. *Computers & Industrial Engineering, 135*, 456–466. https://doi.org/10.1016/j.cie.2019.06.037
Eaton, R., Pota, H. R., & Katupitiya, J. (2009). Path tracking control of agricultural tractors with compensation for steering dynamics. In *Proceedings of the 48h IEEE Conference on Decision and Control (CDC)* (pp. 7357–7362). https://doi.org/10.1109/CDC.2009.5399528
Escolà, A., Martínez-Casasnovas, J. A., Rufat, J., Arnó, J., Arbonés, A., Sebé, F., et al. (2017). Mobile terrestrial laser scanner applications in precision fruticulture/horticulture and tools to extract information from canopy point clouds. *Precision Agriculture, 18*, 111–132. https://doi.org/10.1007/s11119-016-9474-5
Etkin, B., & Reid, L. (1996). *Dynamics of flight: Stability and control*. New York: John Wiley & Sons.
Falcone, P., Borrelli, F., Asgari, J., Tseng, H. E., & Hrovat, D. (2007). Predictive active steering control for autonomous vehicle systems. *IEEE Transactions on Control Systems Technology, 15*, 566–580. https://doi.org/10.1109/TCST.2007.894653
Fang, H., Fan, R., Thuilot, B., & Martinet, P. (2006). Trajectory tracking control of farm vehicles in presence of sliding. *Robotics and Autonomous Systems, 54*, 828–839. https://doi.org/10.1016/j.robot.2006.04.011
Fox, D., Burgard, W., & Thrun, S. (1997). The dynamic window approach to collision avoidance. *IEEE Robotics and Automation Magazine, 4*, 23–33. https://doi.org/10.1109/100.580977
Gao, G., Xiao, K., & Jia, Y. (2020). A spraying path planning algorithm based on colour-depth fusion segmentation in peach orchards. *Computers and Electronics in Agriculture, 173*, 105412. https://doi.org/10.1016/j.compag.2020.105412
Garrido-Rubio, J., González-Piqueras, J., Campos, I., Osann, A., González-Gómez, L., & Calera, A. (2020). Remote sensing-based soil water balance for irrigation water accounting at plot and water user association management scale. *Agricultural Water Management, 238*, 29–35. https://doi.org/10.1016/j.agwat.2020.106236
Gebbers, R., & Adamchuk, V. I. (2010). Precision agriculture and food security. *Science, 327*, 828–831. https://doi.org/10.1126/science.1183899
Glida, H. E., Abdou, L., Chelihi, A., Sentouh, C., & Hasseni, S. E. I. (2020). Optimal model-free backstepping control for a quadrotor helicopter. *Nonlinear Dynamics, 100*, 3449–3468. https://doi.org/10.1007/s11071-020-05671-x
González-Briones, A., Castellanos-Garzón, J. A., Mezquita-Martín, Y., Prieto, J., & Corchado, J. M. (2019). A multi-agent system framework for autonomous crop irrigation. In *2019 2nd International Conference on Computer Applications & Information Security (ICCAIS)* (pp. 1–6). https://doi.org/10.1109/CAIS.2019.8769456
Gonzalez-de-Santos, P., Ribeiro, A., Fernandez-Quintanilla, C., Lopez-Granados, F., Brandstoetter, M., Tomic, S., et al. (2017). Fleets of robots for environmentally-safe pest control in agriculture. *Precision Agriculture, 18*, 574–614. https://doi.org/10.1007/s11119-016-9476-3
González, D., Pérez, J., Milanés, V., & Nashashibi, F. (2016). A review of motion planning techniques for automated vehicles. *IEEE Transactions on Intelligent Transportation Systems, 17*, 1135–1145. https://doi.org/10.1109/TITS.2015.2498841
Guan, T., Tean, C., Oh, S., & Lee, K. (2019). Caterpillar equipped mobile robot navigation with dynamic windows approach for outdoor agriculture application. *Korean Society of Agricultural Machinery, 24*, 178.
Guo, C. Y., Zhang, S., Zhao, J., & Chen, J. (2020). Research on autonomous navigation system of orchard agricultural vehicle based on RTK-BDS. *Journal of Agricultural Mechanization Research, 8*, 254–259.
Hameed, I. A. (2017). Coverage path planning software for autonomous robotic lawn mower using Dubins' curve. In *2017 IEEE international conference on real-time computing and robotics (RCAR)* (pp. 517–522). https://doi.org/10.1109/RCAR.2017.8311915
Hang, P., & Chen, X. (2021). Path tracking control of 4-wheel-steering autonomous ground vehicles based on linear parameter-varying system with experimental verification. In *, 235. Proceedings of the Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering* (pp. 411–423). https://doi.org/10.1177/0959651820934572
Hao, F., Lenain, R., Thuilot, B., & Martinet, P. (2004). Sliding mode control of automatic guidance of farm vehicles in the presence of sliding. *International Symposium on Robotics and Automation, ISRA, 4*, 582–587.
Haytham, A., Elhalwagy, Y. Z., Wassal, A., & Darwish, N. M. (2015). Modeling and simulation of four-wheel steering unmanned ground vehicles using a PID controller. In *2014 International Conference on Engineering and Technology (ICET)*. https://doi.org/10.1109/ICEngTechnol.2014.7016751
Higuchi, A., & Saitoh, Y. (1993). Optimal control of four wheel steering vehicle. *Vehicle System Dynamics, 22*, 397–410. https://doi.org/10.1080/00423119308969039
Hsieh, M. F., & Özguner, Ü. (2008). A parking algorithm for an autonomous vehicle. In *2008 IEEE Intelligent Vehicles Symposium* (pp. 1155–1160). https://doi.org/10.1109/IVS.2008.4621317

Hu, J., Bhowmick, P., Jang, I., Arvin, F., & Lanzon, A. (2021). A decentralized cluster formation containment framework for multirobot systems. *IEEE Transactions on Robotics*, 1–20. https://doi.org/10.1109/TRO.2021.3071615

Hwang, Y. K., & Ahuja, N. (1992). A potential field approach to path planning. *IEEE Transactions on Robotics and Automation, 8*, 23–32. https://doi.org/10.1109/70.127236

Ivić, S., Andrejčuk, A., & Družeta, S. (2019). Autonomous control for multi-agent non-uniform spraying. *Applied Soft Computing Journal, 80*, 742–760. https://doi.org/10.1016/j.asoc.2019.05.001

Jin, J., & Tang, L. (2011). Coverage path planning on three-dimensional terrain for arable farming. *Journal of Field Robotics, 28*, 424–440. https://doi.org/10.1002/rob.20388

Joelianto, E., Christian, D., & Samsi, A. (2020). Swarm control of an unmanned quadrotor model with LQR weighting matrix optimization using genetic algorithm. *Journal of Mechatronics, Electrical Power, and Vehicular Technology, 11*, 1–10. https://doi.org/10.14203/j.mev.2020.v11.1-10

Ju, C., & Son, H. I. (2019). Modeling and control of heterogeneous agricultural field robots based on Ramadge–Wonham theory. *IEEE Robotics and Automation Letters, 5*, 48–55. https://doi.org/10.1109/LRA.2019.2941178

Kamel, M. S., Burri, M., & Siegwart, R. (2017). Linear vs nonlinear MPC for trajectory tracking applied to rotary wing micro aerial vehicles. *IFAC-PapersOnLine, 50*, 3463–3469. https://doi.org/10.1016/j.ifacol.2017.08.849

Karaman, S., & Frazzoli, E. (2011). *Sampling-based algorithms for optimal motion planning*. arXiv preprint. arXiv: arXiv:1105.1186v1.

Kavraki, L. E., Švestka, P., Latombe, J. C., & Overmars, M. H. (1996). Probabilistic roadmaps for path planning in high-dimensional configuration spaces. *IEEE Transactions on Robotics and Automation, 12*, 566–580. https://doi.org/10.1109/70.508439

Kayacan, E., Kayacan, E., Ramon, H., & Saeys, W. (2014). Distributed nonlinear model predictive control of an autonomous tractor–trailer system. *Mechatronics, 24*, 926–933. https://doi.org/10.1016/j.mechatronics.2014.03.007

Kerkech, M., Hafiane, A., & Canals, R. (2020). Vine disease detection in UAV multispectral images using optimized image registration and deep learning segmentation approach. *Computers and Electronics in Agriculture, 174*, 105446. https://doi.org/10.1016/j.compag.2020.105446

Khaksar, W., Sahari, K. S. M., & Hong, T. S. (2016). Application of sampling-based motion planning algorithms in autonomous vehicle navigation. *Autonomous Vehicle, 735*. https://doi.org/10.5772/64730

Khaliq, A., Comba, L., Biglia, A., Ricauda Aimonino, D., Chiaberge, M., & Gay, P. (2019). Comparison of satellite and UAV-based multispectral imagery for vineyard variability assessment. *Remote Sensing, 11*, 436–452. https://doi.org/10.3390/rs11040436

Khamseh, H. B., & Tôrres, L. A. B. (2016). A comparative study of four feedback linearization schemes for motion planning of fixed-wing unmanned aerial vehicles. *Journal of Aerospace Technology and Management, 8*, 63–72. https://doi.org/10.5028/jatm.v8i1.542

Kharim, M. N. A., Wayayok, A., Shariff, A. R. M., Abdullah, A. F., & Husin, E. M. (2019). Droplet deposition density of organic liquid fertilizer at low altitude UAV aerial spraying in rice cultivation. *Computers and Electronics in Agriculture, 167*, 105045. https://doi.org/10.1016/j.compag.2019.105045

Kim, J., Gadsden, S. A., & Wilkerson, S. A. (2020). A comprehensive survey of control strategies for autonomous quadrotors. *Canadian Journal of Electrical and Computer Engineering, 43*. https://doi.org/10.1109/CJECE.2019.2920938

Kim, J., Kim, S., Ju, C., & Son, H. I. (2019). Unmanned aerial vehicles in agriculture: A review of perspective of platform, control, and applications. *IEEE Access, 7*, 105100–105115. https://doi.org/10.1109/ACCESS.2019.2932119

Koca, Y. B., Aslan, Y., & Gökçe, B. (2021). Speed control based PID configuration of a DC motor for an unmanned agricultural vehicle. In *2021 8th International Conference on Electrical and Electronics Engineering (ICEEE)* (pp. 117–120). https://doi.org/10.1109/ICEEE52452.2021.9415908

Kouvaritakis, B., & Cannon, M. (2015). Model predictive control: Classical, robust and stochastic. In *Advanced textbooks in control and signal processing*. Springer.

Kulbacki, M., Segen, J., Knieć, W., Klempous, R., Kluwak, K., Nikodem, J., et al. (2018). Survey of drones for agriculture automation from planting to harvest. In *2018 IEEE 22nd International Conference on Intelligent Engineering Systems (INES)* (pp. 353–358). https://doi.org/10.1109/INES.2018.8523943

Kunchev, V., Jain, L., Ivancevic, V., & Finn, A. (2006). Path planning and obstacle avoidance for autonomous mobile robots: A review. *Lecture Notes in Computer Science, 4252*, 537–544. https://doi.org/10.1007/11893004_70

Kurita, H., Iida, M., Suguri, M., & Masuda, R. (2012). Application of image processing technology for unloading automation of robotic head-feeding combine harvester. *Engineering in Agriculture, Environment and Food, 5*, 146–151. https://doi.org/10.1016/S1881-8366(12)80011-5

LaValle, S. (1998). *Rapidly-exploring random trees: A new tool for path planning*.

Limón, D., Alvarado, I., Alamo, T., & Camacho, E. F. (2010). Robust tube-based MPC for tracking of constrained linear systems with additive disturbances. *Journal of Process Control, 20*, 248–260. https://doi.org/10.1016/j.jprocont.2009.11.007

Lindqvist, B., Mansouri, S. S., Agha-mohammadi, A. A., & Nikolakopoulos, G. (2020). Nonlinear MPC for collision avoidance and control of UAVs with dynamic obstacles. *IEEE Robotics and Automation Letters, 5*, 6001–6008. https://doi.org/10.1109/LRA.2020.3010730

Lin, Y., Yin, G., Liang, Q., & Wang, L. (2018). Cross-line-turn path tracking of intelligent agricultural vehicle based on MPC in standard orchard. In *2018 Chinese Control and Decision Conference (CCDC)* (pp. 4786–4791). https://doi.org/10.1109/CCDC.2018.8407959

Li, L., Sun, L., & Jin, J. (2016). Survey of advances in control algorithms of quadrotor unmanned aerial vehicle. In *2015 IEEE 16th International Conference on Communication Technology (ICCT)* (pp. 107–111). https://doi.org/10.1109/ICCT.2015.7399803

Liu, L. (2018). *Research and implementation of path tracking algorithm of rice transplanter with autonomous walking*. Anhui Agricultural University.

Liu, C., Lu, H., & Chen, W. H. (2015). An explicit MPC for quadrotor trajectory tracking. In *2015 34th Chinese Control Conference (CCC)* (pp. 4055–4060). https://doi.org/10.1109/ChiCC.2015.7260264

Li, Y., Yu, J., Guo, X., & Sun, J. (2020). Path tracking method of unmanned agricultural vehicle based on compound fuzzy control. In *, 9. 2020 IEEE 9th Joint International Information Technology and Artificial Intelligence Conference (ITAIC)* (pp. 1301–1305). https://doi.org/10.1109/ITAIC49862.2020.9338981

López, J., Dormido, R., Dormido, S., & Gómez, J. P. (2015). A robust H∞ controller for an UAV flight control system. *Scientific World Journal*, 403236. https://doi.org/10.1155/2015/403236

Lowenberg-DeBoer, J. M., Behrendt, K., Godwin, R., & Frankin, K. (2019). The impact of swarm robotics on arable farm size and structure in the UK. *Agricultural Economics Society*. https://doi.org/10.22004/ag.econ.296492

Madari, S. B. S., Adlinge, S. D., & Sharmila, A. T. (2019). Multi fusion path planning algorithm for UGV. *Asian Journal for Convergence in Technology*.

Mammarella, M., & Capello, E. (2020). Tube-based robust MPC processor-in-the-loop validation for fixed-wing UAVs. *Journal of Intelligent and Robotic Systems, 100*, 239–258. https://doi.org/10.1007/s10846-020-01172-6

Mammarella, M., Capello, E., & Dabbene, F. (2018a). Sample-based SMPC for tracking control of fixed-wing UAV: Multi-scenario mapping. In *arXiv preprint arXiv:1805.05879*.

Mammarella, M., Capello, E., Dabbene, F., & Guglieri, G. (2018). Sample-based SMPC for tracking control of fixed-wing UAV. *IEEE Control Systems Letters, 2*(4), 611–616. https://doi.org/10.1109/LCSYS.2018.2845546

Mammarella, M., Capello, E., Park, H., Guglieri, G., & Romano, M. (2018b). Tube-based robust model predictive control for spacecraft proximity operations in the presence of persistent disturbance. *Aerospace Science and Technology, 77*, 585–594. https://doi.org/10.1016/j.ast.2018.04.009

Mammarella, M., Comba, L., Biglia, A., Dabbene, F., & Gay, P. (2021). *Cooperation of unmanned systems for agricultural applications: A case study in a vineyard. (submitted to biosystem engineering, under review)*.

Mammarella, M., Ristorto, G., Capello, E., Bloise, N., Guglieri, G., & Dabbene, F. (2019). Waypoint tracking via tube-based robust model predictive control for crop monitoring with fixed-wing UAVs. In *2019 IEEE international workshop on metrology for agriculture and forestry* (pp. 19–24). https://doi.org/10.1109/MetroAgriFor.2019.8909260

Marino, R., Scalzi, S., Orlando, G., & Netto, M. (2009). A nested PID steering control for lane keeping in vision based autonomous vehicles. In *2009 American Control Conference* (pp. 2885–2890). https://doi.org/10.1109/ACC.2009.5160343

Martins, L., Cardeira, C., & Oliveira, P. (2021). Feedback linearization with *zero dynamics* stabilization for quadrotor control. *Journal of Intelligent and Robotic Systems, 101*, 7. https://doi.org/10.1007/s10846-020-01265-2

Mayne, D. Q., & Rawlings, J. B. (2009). *Model predictive control: Theory and design*. Nob Hill Publishing.

Mazur, M. (2016). *Six ways drones are revolutionizing agriculture* (Vol. 23). MIT Technology Review.

Mazzia, V., Comba, L., Khaliq, A., Chiaberge, M., & Gay, P. (2020). UAV and machine learning based refinement of a satellite-driven vegetation index for precision agriculture. *Sensors, 20*, 1–16. https://doi.org/10.3390/s20092530

McAllister, W., Osipychev, D., Davis, A., & Chowdhary, G. (2019). Agbots: Weeding a field with a team of autonomous robots. *Computers and Electronics in Agriculture, 163*, 104827. https://doi.org/10.1016/j.compag.2019.05.036

McNaughton, M., Urmson, C., Dolan, J. M., & Lee, J. W. (2011). Motion planning for autonomous driving with a conformal spatiotemporal lattice. In *2011 IEEE International Conference on Robotics and Automation* (pp. 4889–4895). https://doi.org/10.1109/ICRA.2011.5980223

Meenakshisundaram, V. S., Gundappa, V. K., & Kanth, B. S. (2010). Vector field guidance for path following of MAVs in three dimensions for variable altitude maneuvers. *International Journal of Micro Air Vehicles, 2*, 255–265. https://doi.org/10.1260/1756-8293.2.4.255

Meng, Q., Qiu, R., He, J., Zhang, M., Ma, X., & Liu, G. (2015). Development of agricultural implement system based on machine vision and fuzzy control. *Computers and Electronics in Agriculture, 112*, 128–138. https://doi.org/10.1016/j.compag.2014.11.006

Messina, F., Faedda, F., Di Pietra, V., & Lingua, A. (2021). Validation of UGV autonomous navigation based on an adapted path planning algorithm using UAV imagery. In *Advances in Localization and navigation*. https://doi.org/10.31490/9788024845050-4

Michel, N., Bertrand, S., Valmorbida, G., Olaru, S., & Dumur, D. (2017). Design and parameter tuning of a robust model predictive controller for UAVs. *Ifac World Congress, 2017*, 4865–4869.

Millard, A. G., Ravikanna, R., Groß, R., & Chesmore, D. (2019). Towards a swarm robotic system for autonomous cereal harvesting. *Towards Autonomous Robotic Systems, 11650*, 458–461. https://doi.org/10.1007/978-3-030-25332-5_40

Miranda-Colorado, R., & Aguilar, L. T. (2020). Robust PID control of quadrotors with power reduction analysis. *ISA Transactions, 98*, 47–62. https://doi.org/10.1016/j.isatra.2019.08.045

Mohamed, A., El-Gindy, M., & Ren, J. (2018). Advanced control techniques for unmanned ground vehicle: Literature survey. *International Journal of Vehicle Performance, 4*, 46–73. https://doi.org/10.1504/IJVP.2018.10009708

Morellos, A., Pantazi, X.-E., Moshou, D., Alexandridis, T., Whetton, R., Tziotzios, G., et al. (2016). Machine learning based prediction of soil total nitrogen, organic carbon and moisture content by using VIS-NIR spectroscopy. *Biosystems Engineering, 152*, 104–116. https://doi.org/10.1016/j.biosystemseng.2016.04.018

Nguyen, H. T., Quyen, T. V., Nguyen, C. V., Le, A. M., Tran, H. T., & Nguyen, M. T. (2020). Control algorithms for UAVs: A comprehensive survey. *Industrial Networks and Intelligent Systems, 7*, 164586. https://doi.org/10.4108/eai.18-5-2020.164586

Ni, J., Hu, J., & Xiang, C. (2019). Robust path following control at driving/handling limits of an autonomous electric racecar. *IEEE Transactions on Vehicular Technology, 68*, 5518–5526. https://doi.org/10.1109/TVT.2019.2911862

Noordin, A., Mohd Basri, M. A., Mohamed, Z., & Mat Lazim, I. (2021). Adaptive PID controller using sliding mode control approaches for quadrotor UAV attitude and position stabilization. *Arabian Journal for Science and Engineering, 46*, 963–981. https://doi.org/10.1007/s13369-020-04742-w

Oettershagen, P., Melzer, A., Leutenegger, S., Alexis, K., & Siegwart, R. (2014). Explicit model predictive control and L1-navigation strategies for fixed-wing UAV path tracking. In *22nd mediterranean conference on control and automation* (pp. 1159–1165). https://doi.org/10.1109/MED.2014.6961532

Ögren, P., & Leonard, N. E. (2005). A convergent dynamic window approach to obstacle avoidance. *IEEE Transactions on Robotics, 21*, 188–195. https://doi.org/10.1109/TRO.2004.838008

Pfaffmann, S., de Moraes Boos, F., Tarasinski, N., & Kegel, V. (2019). Swarm unit – development of a fully electric agricultural machine with external power supply. In V. D. I. W. GmbH (Ed.), *LAND.TECHNIK AgEng 2019: The forum for agricultural engineering innovations* (pp. 401–408). VDI Verlag.

Pitt, J., & Mamdani, A. (2000). Communication protocols in multi-agent systems: A development method and reference architecture. In *Issues in agent communication* (pp. 160–177). Berlin, Heidelberg: Springer.

Plessen, M. M. G., & Bemporad, A. (2017). Reference trajectory planning under constraints and path tracking using linear time-varying model predictive control for agricultural machines. *Biosystems Engineering, 153*, 28–41. https://doi.org/10.1016/j.biosystemseng.2016.10.019

Popović, M., Hitz, G., Nieto, J., Sa, I., Siegwart, R., & Galceran, E. (2017). Online informative path planning for active classification using UAVs. In *2017 IEEE International Conference on Robotics and Automation (ICRA)* (pp. 5753–5758). https://doi.org/10.1109/ICRA.2017.7989676

Potrino, G., Serianni, A., & Palmieri, N. (2019). Drones coordination protocols in the precision agriculture context. *Autonomous Air and Ground Sensing Systems for Agricultural Optimization and Phenotyping, IV*, 11008. https://doi.org/10.1117/12.2518973

Powers, C., Mellinger, D., & Kumar, V. (2015). Quadrotor kinematics and dynamics. *Handbook of Unmanned Aerial Vehicles*, 307–328. https://doi.org/10.1007/978-90-481-9707-1_71

Quan, L., Han, L., Zhou, B., Shen, S., & Gao, F. (2020). Survey of UAV motion planning. *IET Cyber-Systems and Robotics, 2*, 14–21. https://doi.org/10.1049/iet-csr.2020.0004

Raffo, G. V., Ortega, M. G., & Rubio, F. R. (2008). MPC with nonlinear $\mathscr{H}\infty$ control for path tracking of a quad-rotor helicopter. *IFAC Proceedings Volumes, 41*, 8564–8569. https://doi.org/10.3182/20080706-5-KR-1001.01448

Raza, A., Ahmed, N., Khan, R., Mumtaz, F., & Mumtaz Malik, F. (2017). Sampled-data higher order sliding mode control of fixed wing UAV. In *Proceedings - The Fifth International Academic Conference for Graduates*.

Rose, D., & Chilvers, J. (2018). Agriculture 4.0: Responsible innovation in an era of smart farming. *Frontiers in Sustainable Food Systems, 2*.

Rossi, F., Bandyopadhyay, S., Wolf, M., & Pavone, M. (2018). Review of multi-agent algorithms for collective behavior: A structural taxonomy. *IFAC-PapersOnLine, 51*, 112–117. https://doi.org/10.1016/j.ifacol.2018.07.097

Rubí, B., Pérez, R., & Morcego, B. (2019). A survey of path following control strategies for UAVs focused on quadrotors. *Journal of Intelligent and Robotic Systems, 98*, 241–265. https://doi.org/10.1007/s10846-019-01085-z

Runcharoon, K., & Srichatrapimuk, V. (2013). Sliding mode control of quadrotor. *2013 the international Conference on technological Advances in electrical. Electronics and Computer Engineering (TAEECE)*, 552–557. https://doi.org/10.1109/TAEECE.2013.6557334

Sabatino, F. (2015). *Quadrotor control: Modeling, nonlinear control design, and simulation.* EES Examensarbete / Master Thesis.

Santos, L., Santos, F., Mendes, J., Costa, P., Lima, J., Reis, R., et al. (2019). Path planning aware of robot's center of mass for steep slope vineyards. *Robotica, 38*, 684–698. https://doi.org/10.1017/S0263574719000961

Sartori, D., Quagliotti, F., Rutherford, M. J., & Valavanis, K. P. (2014). Implementation and testing of a backstepping controller autopilot for fixed-wing UAVs. *Journal of Intelligent and Robotic Systems, 76*, 505–525. https://doi.org/10.1007/s10846-014-0040-y

Shamshiri, R. R., Hameed, I. A., Balasundram, S. K., Ahmad, D., Weltzien, C., & Yamin, M. (2018). Fundamental research on unmanned aerial vehicles to support precision agriculture in oil palm plantations. *Agricultural Robots-Fundamentals and Application*, 91–116. https://doi.org/10.5772/intechopen.80936

Shimoda, S., Kuroda, Y., & Iagnemma, K. (2005). Potential field navigation of high speed unmanned ground vehicles on uneven terrain. In *Proceedings of the 2005 IEEE International Conference on Robotics and Automation* (pp. 2828–2833). https://doi.org/10.1109/ROBOT.2005.1570542

Soe, T. T., & Tun, H. M. (2014). Implementation of double closed-loop control system for unmanned ground vehicles. *International Journal of Scientific & Technology Research, 3*.

Song, Y., Fang, X., Liu, B., Li, C., Li, Y., & Yang, S. X. (2020). A novel foraging algorithm for swarm robotics based on virtual pheromones and neural network. *Applied Soft Computing, 90*, 106156. https://doi.org/10.1016/j.asoc.2020.106156

Stentz, A. (1994). Optimal and efficient path planning for partially-known environments. In *, 4. Proceedings of the 1994 IEEE International Conference on Robotics and Automation* (pp. 3310–3317). https://doi.org/10.1109/ROBOT.1994.351061

Sufendi, Trilaksono, B. R., Nasution, S. H., & Purwanto, E. B. (2013). Design and implementation of hardware-in-the-loop-simulation for UAV using PID control method. In *2013 3rd International Conference on Instrumentation, Communications* (pp. 124–130). Information Technology and Biomedical Engineering (ICICI-BME). https://doi.org/10.1109/ICICI-BME.2013.6698478.

Sujit, P. B., Saripalli, S., & Sousa, J. B. (2014). Unmanned aerial vehicle path following: A survey and analysis of algorithms for fixed-wing unmanned aerial vehicles. *IEEE Control Systems Magazine, 34*, 42–59. https://doi.org/10.1109/MCS.2013.2287568

Sunay, A., Altan, A., Belge, E., & Hacioglu, R. (2020). Investigation of route tracking performance with adaptive PID controller in quadrotor. *European Journal of Technic, 10*, 160–172. https://doi.org/10.36222/ejt.652828

Sylvester, G. (2018). E-agriculture in action: Drones for agriculture. *Food and agriculture Organization of the united Nations (FAO), Bangkok*. http://www.fao.org/3/I8494EN/i8494en.pdf.

Tanner, H. G., Kyriakopoulos, K. J., & Krikelis, N. I. (2001). Advanced agricultural robots: Kinematics and dynamics of multiple mobile manipulators handling non-rigid material. *Computers and Electronics in Agriculture, 31*, 91–105. https://doi.org/10.1016/S0168-1699(00)00176-9

*Tevel Aerobotics Technologies Ltd.*(2021). https://www.tevel-tech.com/.

Tokekar, P., Vander Hook, J., Mulla, D., & Isler, V. (2013). Sensor planning for a symbiotic UAV and UGV system for precision agriculture. In *2013 IEEE/RSJ International Conference on Intelligent Robots and Systems* (pp. 5321–5326). https://doi.org/10.1109/IROS.2013.6697126

Ulus, S., & Ikbal, E. (2019). Lateral and longitudinal dynamics control of a fixed wing UAV by using PID controller. In *4th International Conference on Engineering and Natural Sciences*.

Vu, Q., Raković, M., Delic, V., & Ronzhin, A. (2018). Trends in development of UAV-UGV cooperation approaches in precision agriculture. *Interactive Collaborative Robotics, 11097*, 213–221. https://doi.org/10.1007/978-3-319-99582-3_22

Wang, H., Yu, Y., & Yuan, Q. (2011). Application of Dijkstra algorithm in robot path-planning. In *2011 Second International Conference on Mechanic Automation and Control Engineering* (pp. 1067–1069). https://doi.org/10.1109/MACE.2011.5987118

Wu, T. (2018). Path tracking control for a robot-trailer system with parameter tuning using particle swarm optimization. In *2018 IEEE International Conference on Mechatronics and Automation (ICMA)* (pp. 1257–1262). https://doi.org/10.1109/ICMA.2018.8484577

Xuan, P., & Lesser, V. (2002). Multi-agent policies: From centralized ones to decentralized ones. In *Proceedings of the first international joint conference on Autonomous agents and multiagent systems: Part 3* (pp. 1098–1105). https://doi.org/10.1145/545056.545078

Xue, X., Lan, Y., Sun, Z., Chang, C., & Hoffmann, W. C. (2016). Develop an unmanned aerial vehicle based automatic aerial spraying system. *Computers and Electronics in Agriculture, 128*, 58–66. https://doi.org/10.1016/j.compag.2016.07.022

Yan, X. T., Bianco, A., Niu, C., Palazzetti, R., Henry, G., Li, Y., et al. (2020). The *AgriRover*: A reinvented mechatronic platform from space robotics for precision farming. *Reinventing Mechatronics*, 55–73. https://doi.org/10.1007/978-3-030-29131-0_5

Yingkun, Z. (2018). Flight path planning of agriculture UAV based on improved artificial potential field method. In *2018 Chinese Control and Decision Conference (CCDC)* (pp. 1526–1530). https://doi.org/10.1109/CCDC.2018.8407369

Zhang, F., Li, N., Xue, T., Zhu, Y., Yuan, R., & Fu, Y. (2019). An improved dynamic window approach integrated global path planning. In *2019 IEEE International Conference on Robotics and Biomimetics (ROBIO)* (pp. 2873–2878). https://doi.org/10.1109/ROBIO49542.2019.8961684

Zhang, X., Wang, Y., Zhu, G., Chen, X., Li, Z., Wang, C., et al. (2020). Compound adaptive fuzzy quantized control for quadrotor and its experimental verification. *IEEE Transactions on Cybernetics, 51*, 1121–1133. https://doi.org/10.1109/TCYB.2020.2987811

Zhao, J., Li, Y., Hu, D., & Pei, Z. (2016). Design on altitude control system of quad rotor based on laser radar. In *2016 IEEE International Conference on Aircraft Utility Systems (AUS)* (pp. 105–109). https://doi.org/10.1109/AUS.2016.7748029

Please cite this article as: Mammarella, M et al., Cooperation of unmanned systems for agricultural applications: A theoretical framework, *Biosystems Engineering*, https://doi.org/10.1016/j.biosystemseng.2021.11.008