Agricultural Robotics

Unmanned Robotic Service Units in Agricultural Tasks

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The application of agricultural machinery in precision agriculture has experienced an increase in investment and research due to the use of robotics applications in the machinery design and task executions. Precision autonomous farming is the operation, guidance, and control of autonomous machines to carry out agricultural tasks. It motivates agricultural robotics. It is expected that, in the near future, autonomous vehicles will be at the heart of all precision agriculture applications [1]. The goal of agricultural robotics is more than just the application of robotics technologies to agriculture. Currently, most of the automatic agricultural vehicles used for weed detection, agrochemical dispersal, terrain leveling, irrigation, etc. are manned. An autonomous performance of such vehicles will allow for the continuous supervision of the field, since information regarding the environment can be autonomously acquired, and the vehicle can then perform its task accordingly.

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The most important current abilities of automatic agricultural vehicles can be grouped into four categories:

- guidance (i.e., the way the vehicle navigates within the agricultural environment)
- detection (the extraction of biological features from the environment)
- action (the execution of the task for which the vehicle was designed, e.g., radicchio harvesting [2])
- mapping (the construction of a map of the agricultural field with its most relevant features) [3].

However, those four cores are not independent. For safe and successful navigation, the vehicle has to know its position within the field and the elements from the surrounding environment (mapping); bad detection could lead to an incomplete or unreliable map. Furthermore, if the elements from the environment are not properly located within the map, an agricultural vehicle may not be able to execute its tasks successfully. In addition, an incomplete map should not be used for navigation purposes because of the risk of collision. As can be seen, the knowledge regarding the location of a vehicle within the environment and the location of the elements in an environment plays a crucial role in an automatic agricultural vehicle design. Slaughter et al. [3] propose the main abilities for designing robotic vehicles for weed control only, without addressing the localization issues associated with such a design.

This article is aimed at presenting the four abilities mentioned previously for the design and implementation of an automatic agricultural vehicle for precision agricultural tasks. Special attention is given to the importance of a localization system for performing such agricultural tasks. In addition, the current open issues in robotics applied to agricultural environments (such as an automatic agricultural vehicle's interaction with field workers and priority task management) are also presented.

Agricultural Service Units

Growth in the world population has led to the need for an increasing level of sophistication in precision agriculture for both environment preservation and production optimization [4]. This need, in turn, has created a requirement for new methods, tools, and strategies for agricultural processes. Robotics and artificial intelligence achievements offer new solutions in precision agriculture to processes related to seeding, harvesting, weed control, grove supervision, chemical applications, etc. [4], to improve productivity and efficiency [2].

A service unit is an automatic vehicle for main or secondary tasks in the agricultural environment [3], [5], [6]. The relation between its four most important abilities—mentioned previously— is shown in Figure 1.

The guidance needs information regarding the surrounding environment (mapping) and the features currently detected (detection). For example, for seeding or harvesting, the service unit must be aware of the presence of trees or moving obstacles in its navigation. Thus, a map of the environment will allow a service unit to navigate safely, and the detected features will allow appropriate planning for performing actions (e.g., terrain leveling, chemical spreading, etc.). During mapping, a map of the surrounding environment is built and maintained to aid the navigation (guidance) process. Such a map is composed of the features or measurements acquired from the environment (detection) and the information regarding the location of the service unit within such a map (for guidance and action). The detection is the acquisition of information directly from the agricultural environment. This information is used at the mapping stage to build and maintain an updated map of the surrounding environment to guide the navigation process (guidance) or to perform a given action (e.g., weed detection, grove maturity inspection, or agrochemical disposal). Finally, the action stage represents the way the service unit interacts with the agricultural field. Such an action can be performed on the basis of a guidance process (e.g., harvesting or seeding), detection (e.g., weed removal), or mapping (e.g., agrochemical disposal based on previously acquired treetop information).

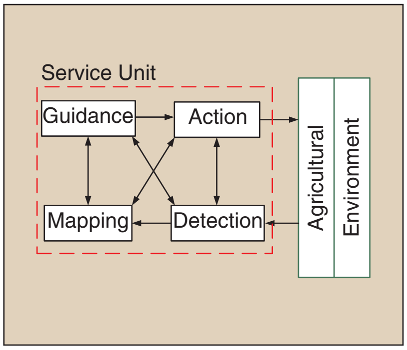

FIGURE 1 – Relation between the four most important implementations of a service unit.

Despite the relation shown in Figure 1 between the four main implementations of a service unit, such stages are intrinsically related to the localization problem. If the service unit has a bad localization system, then the vehicle's knowledge of its own location within the environment is not reliable (thus, it would not be able to perform path-following, path-tracking, or trajectory-tracking activities). Autonomous navigation without a precise knowledge about the actual position in the agricultural field is dangerous for the vehicle's integrity and, more importantly, could represent a risk for field workers. Additionally, the vehicle will not be able to perform any action associated with the agricultural task. For example, it will not be able to spread herbicides over selected trees or supervise a specific portion of a grove. If the localization system fails or is inaccurate, such an inaccuracy is propagated to the four abilities of the service unit, as will be shown later in this article. Each stage shown in Figure 1 and the localization problem are explained in more detail in the following sections.

Guidance

Control and motion-planning strategies applied to service units are aimed at driving the vehicle within the agricultural field for specific purposes, closely related to the action stage. For example, studies [7], [8] show the implementation of a multimachinery path-planning technique. The planning is done for one vehicle—which is considered the leader—and the rest of the vehicles follow it, maintaining their relative distances. Noguchi et al. [9] present a master–slave navigation system for general operations within a farm. In such a system, the master vehicle may or may not operate autonomously, although the slave vehicle always follows autonomously. A stable path-tracking controller for navigation between furrows of a grove is presented in [4]. Hagras et al. [10] present an online learning algorithm for agricultural machinery. It consists of implementing a life-long learning strategy. However, no analysis is presented regarding the robustness of the proposal to environment or task changes. A path-planning technique based on a gridded map of the agricultural environment is presented in [7]. The technique uses the grid information to plan feasible and optimal paths from the vehicle's starting position to a given destination in the environment. With the same insight, a three-dimensional (3-D) path planning for agricultural field machinery is presented in [11]. Despite the fact that the aforementioned works are examples of guidance applications of agricultural machinery, they are aimed at controlling the vehicle's motion problems in farms. Figure 2 summarizes the guidance stage in a service unit.

The planning stage in Figure 2 is associated with the action in Figure 1. Thus, the planning is related to the following question: How does the service unit drive to fulfill its agricultural purpose? For example, a service unit for weed detection in a field is shown in [3] and [12], whereas a service unit for treetop volume estimation is shown in [13] and [14]. Despite the nature of the vehicle, an unmanned service unit's motion usually fits one of the following two types: path following or trajectory following (including trajectory-tracking strategies) [15], [16]. The main difference between them is that path-following strategies do not have time constraints in the execution of the task. An example of a path-following case by an unmanned service unit with a previous path-planning process using environmental information is shown in [17], whereas an example of the trajectory-following case for a harvesting process is shown in [7]. Clearly, to navigate in an environment, the vehicle needs information regarding its location in the field (localization system stage in Figure 2). In addition, the localization system is used by the sensors for a correct localization of the extracted features within the map. It is worth mentioning that the map is used at the planning stage to plan feasible and safe paths or trajectories for the navigation process.

The controller stage represents the control strategy used for driving the vehicle following the previously defined trajectory or path. For example, a nonlinear controller for path tracking is proposed in [15], whereas a fuzzy-based controller for driving following a path within an agricultural environment is proposed in [18]. These are examples of controller design techniques. As the vehicle's model is highly nonlinear, both in kinematics and dynamics behavior, most control solutions are based on nonlinear design. Compensating for some effects that are present in agricultural applications, such as sliding of the vehicle, also relies on nonlinear design. The trajectory- and path-following control design is still an active area of research. As expected, the control commands are directly sent to the vehicle. The controller should, in all cases, include emergency stops and obstacle avoidance or other safety autonomous operations to protect the vehicle's and operator's integrity.

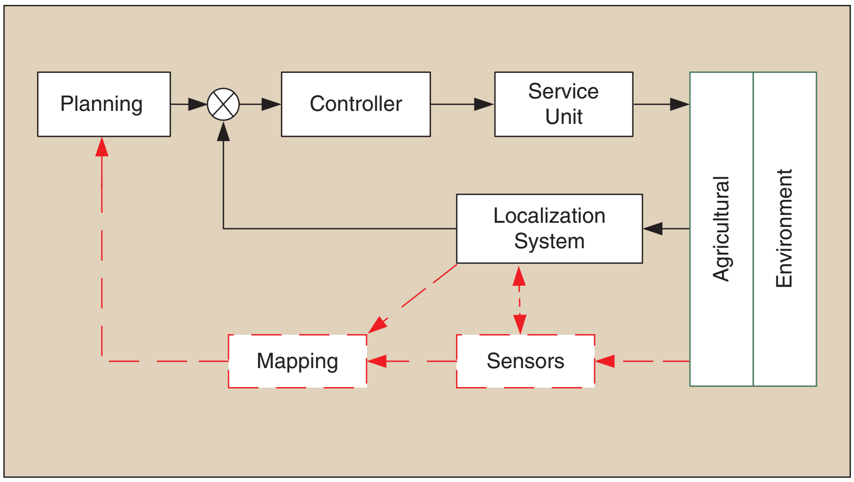

FIGURE 2 – Architecture of the guidance stage in a service unit.

Detection

The detection of the agricultural features is directly related to the purpose of the service unit design and the sensors incorporated on it. The detection stage in Figure 1 is aimed at answering the following two questions: Which is the biological feature of interest? How is such a feature extracted/detected? Artificial vision cameras, range lasers, and ultrasonic devices are widely used for acquisition of features [19]–[22]. In particular, image acquisition and processing is being increasingly applied in precision agriculture [23], [24]. Although most of the implementations are used for weed detection [25]–[27], artificial vision systems are also used for navigation. Such a case is shown in [28], wherein an autonomous robot used the Hough transform to navigate between the furrows of an olive grove. In a previous work of the authors [29], a monocular vision system was used to acquire stem information from an olive grove, based on support vector machines (this classification uses a linear kernel, which was previously trained with a positive image set—with olive stems—and a negative set—without olive stems). Subramanian et al. [30] integrate a range laser scanner with a vision system to obtain histograms of the environment. Such a histogram is a range-laser-based methodology for processing environmental information (it stores geometrical information in the form of angle and range histograms [31]). Hence, the histograms allow for a collision-free navigation of the agricultural machinery. Ultrasonic sensors have also been used to measure the range. For example, Zhao et al. [32] present a system to measure the harvest area by using ultrasonic sensors positioned at both sides of the harvest header—to detect the crops—and a GPS for machinery positioning.

The separation of weeds from crops is currently a main topic of study. Jones et al. [33] use a vision-based system to discriminate between the crops and the weeds for possible herbicide applications. The authors use a binary representation of the image that, after applying the Hough transformation, allows the differentiation of the weed from the crop in each furrow ([25] shows a similar approach). Gee et al. [26] and Piron et al. [27] used perspective and 3-D information with the same objective: weed discrimination. Weed discrimination is an important issue in an agricultural process and should be understood correctly to support the process in herbicide application decisions, harvest planning, crop volume estimation, etc.

In a grove, the size, disposition, maturity, volume, width, and height of the trees are important pieces of information [5], [10], [14], [24] that can be used to optimize the agricultural process. Zaman and Schumann [14] propose an ultrasound-based tree-volume measurement system that is limited by the height of the trees, whereas in [5], a light detection and ranging (LiDAR) system is used to estimate tree crops without extracting other features from the trees. Such information can be used for optimizing herbicide disposal. Figure 3 summarizes the detection stage in a service unit.

The sensors incorporated on a service unit acquire information about the surrounding environment. The acquired data are processed for extraction of biological features (such as crop maturity estimation [34], normalized difference vegetation index, foliage density [5], weed disposition [3], [35], etc.; see Figure 3). As stated in the "Guidance" section, the information extracted from the environment can then be used for guidance purposes. In addition, the information acquired from the environment is used for building (or completing) a georeferenced map of the agricultural field (as shown in [13], [29], and [32]). Nevertheless, exteroceptive sensors have drawbacks that should be taken into account while designing the detection stage of a service unit. Table 1 summarizes the pros and cons of the most common sensors used in service units.

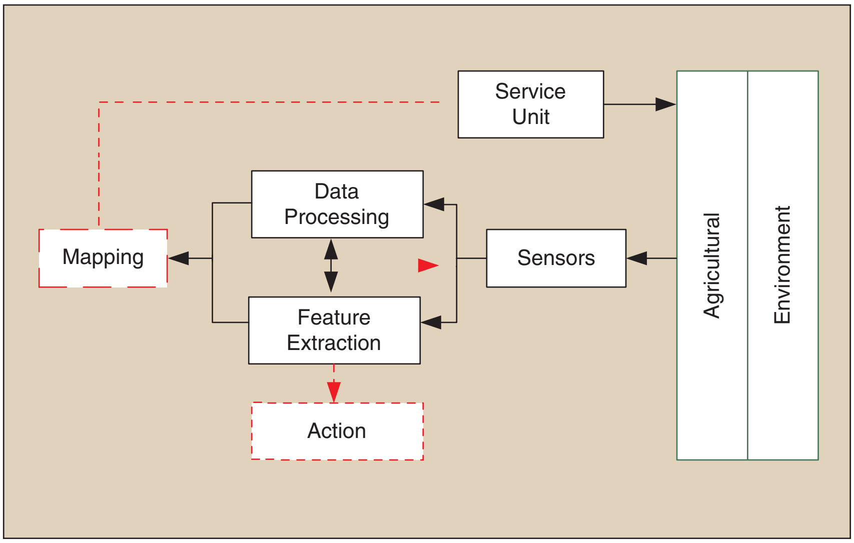

FIGURE 3 – Architecture of the detection stage of a service unit.

Action

The action stage in Figure 4 defines the purposes of the service unit in an agricultural field. It is aimed at answering the following question: What does the service unit do in the agricultural environment? At first sight, the action stage can be assumed to be separate from the detection stage. However, in some applications, the detection stage is the action stage. For example, a service unit for weed detection is presented in [35]; the proposed service unit for tree detection and treetop volume estimation in a grove is implemented in [5]; and the service unit is used for cherry detection in [36].

Nevertheless, there are cases where the action stage is different from the detection stage. Such a case shown in [2], wherein the service unit is used for radicchio harvesting. With the same insight, the service units are used in [37] for gardening within greenhouses. The agricultural vehicle is used for agrochemical disposal (such as herbicide spreading) in [38]. For example, Figure 5 shows a schematic of a service unit for grape harvesting. A vision system is used for both detection of grapes and vehicle navigation. A manipulator mounted on the top of the vehicle reaches the grapes, grasps them, and deposits them in a tank. Thus, the action stage is performed by the manipulator and not by the vehicle. Despite how the action stage is performed by a service unit, Figure 4 shows a summarized (and generalized) architecture of such stage.

The sensors on the vehicle acquire the environmental information, which, once processed, allows the extraction of biological features. As shown in Figure 4, the biological features extracted are used for mapping and action planning. The latter stage is directly related to the service unit agricultural task. Thus, if the agricultural task is related to the vehicle's navigation, then in the action planning stage in Figure 4, the set of actions to be executed by the service unit to fulfill the task is planned. For example, in [39], the service unit estimates wind velocity using a laser scanner and by positioning the service unit between two or more trees of a grove. Thus, the action in this case is to estimate wind and position the service unit. Therefore, a controller is in charge of the command motion generation to drive the vehicle for positioning in front of trees (hence, the wind-estimation process can be executed). In contrast, in [30], an artificial vision system is used

TABLE 1–PROS AND CONS OF EXTEROCEPTIVE SENSORS IN SERVICE UNITS.

SENSORS	PROS	CONS
LiDAR and range laser sensors	They cover a wide range of measurement (from 4 to 30 m) with a very high accuracy (e.g., ±0.02 cm in 30 m). They can be mounted on rotating platforms for 3-D acquisition. They are able to perform in both greenhouses and open fields. Some sensors are resistant to hostile climate conditions (direct sunlight, high temperatures, relative humidity, etc.). Their measurements can be used to model shapes and morphologies of plants.	Occasionally, they are sensitive to colors. Their prices are dependent on accuracy. They require further processing for the extraction of agricultural information. Sensitive features (such as texture of plants and fruits, maturity information, and colors) cannot be acquired by using range laser sensors.
Artificial vision systems (monocular, stereo, and multispectral cameras)	They provide the most important information about a grove (texture and color of plants and fruits, allow weed detection, maturity inspection, plant disposition, foliage estimation, etc.). In a stereo configuration, 3-D information can be acquired (as in the previous item) with color information.	Artificial vision systems (monocular, stereo, time-of-flight cameras, etc.) are sensitive to saturation due to lighting conditions. Therefore, operating the sensor under direct sunlight is not recommended. Additionally, when acquiring 3-D information, the range is very limited compared to LiDAR or range laser sensors. The 3-D vision systems can measure up to 10 m with a very reduced field of view. They require advanced processing algorithms and special hardware for data acquisition.
Range sonar sensors	The price of sensors is low. They are immune to hostile climate conditions; they are not affected by colors or sunlight and have high durability.	Their dispersion is too high, with low accuracy for higher ranges. Since one range sonar sensor acquires one single measurement, range sonar sensors are usually arranged in a matrix configuration. Their range varies, although they do not reach the ranges of LiDAR or laser sensors.

for planning feasible paths among furrows within an agricultural field. A path-following controller is then used to drive the service unit. In addition, in [40], a robot manipulator is used to handle heavy materials in agricultural environments. Therefore, the action planning is performed for the manipulator, and the controller drives the robot manipulator instead of the vehicle, shown as dashed black line in Figure 4. Nevertheless, the vehicle does not remain in an open-loop situation, since the guidance stage generates the control commands for driving the vehicle.

Mapping

The mapping stage is present in the three stages mentioned previously (see Figures 2 and 4). The mapping stage concerns the way the service unit interprets the surrounding environment and stores information regarding such an interpretation. As shown in Figure 6, the biological features extracted from sensor information (and the processed data) are used to generate a map of the surrounding environment. For example, remote sensing for mapping soil properties is used in [41]; information on treetops within a georeferenced map of the grove used for the experimentation is determined in [5]; with the same insight, ultrasonic sensors for estimating the treetop volume and distance between the trees in a grove are used in [14]. The information acquired in [14] is stored in a georeferenced map of the environment. In addition, a weed control system that is able to discriminate and localize weed within an agricultural field is shown in [42]. Regardless of the nature of the map (i.e., it can be topological, geometrical, hybrid, etc.), the environmental information is localized within the map in the localization system stage (Figure 6). With the available map information, the aforementioned abilities of a service unit (see Figures 2–5) can be used. It is worth mentioning that the aim of building and maintaining a map of an agricultural environment is to use it for improving the performance of the service unit in the execution of its assigned tasks. Thus, in works such as [42] and [28], wherein the navigation of the service unit within the agricultural field is purely reactive (its motion or action is not planned), the use of a mapping stage is unnecessary.

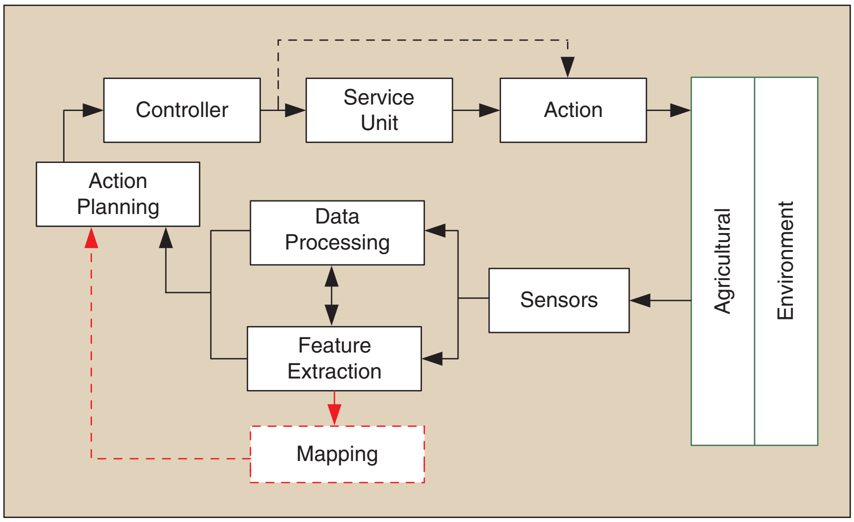

FIGURE 4 – Architecture of the action stage of a service unit.

The Importance of the Localization System

As stated in the "Agricultural Service Units" section, an error—and its associated covariance—in the localization system propagates to the four abilities of a service unit: guidance, detection, action, and mapping. Therefore, in some cases, the task performance of the service unit may become unreliable. Several approaches can be used as a positioning system, such as odometry.

Although an odometry-based positioning system is the most primitive approach, it is widely used in robotic applications. The main drawback of odometric systems is that their errors are also cumulative (i.e., as the vehicle drives within the environment, its positioning errors increase without bound). Figure 7 shows a case in which an odometry-based positioning is not reliable for navigation of the service unit.

Figure 7(a) shows an olive grove environment. Figure 7(b)–(d) shows three snapshots of the map obtained by the service unit as it navigates through the furrows of the environment. The red dots represent the detected olive stems obtained by the range laser scanner mounted on the service unit (as shown in [29]); the path traveled by the vehicle—estimated by dead-reckoning sensors (i.e., odometry)—is shown as a solid blue line. As can be seen in Figure 7(b)–(d), when the service unit turns 180° within the same furrow, the cumulative error in the positioning system becomes more evident, causing a bad reconstruction of the environment.

An inertial module unit (IMU) can be used to enhance an odometric system. The integration and fusion of IMU measurements in an odometric system decreases the error in the estimation of vehicle's position [43], [44] when using odometry. However, the IMU signal requires further processing to filter chassis vibrations and spurious measurements [45]. Nevertheless, the error obtained by using an IMU is conditioned by the accuracy of the IMU (e.g., to estimate position from an accelerometer, two integrations are needed, and the error in the acceleration is then accumulated two times). However, the IMU has been shown to be effective for detecting slipping situations [46]. Further improvement in the positioning system is achieved by using GPS receivers.

The field of precision agriculture has experienced increased growth since the implementation of GPS in agricultural machinery [5], [47]–[49]. The combination of GPS information with computer processing has allowed for the possibility of optimization of the agricultural process. For example, Norremark et al. [12] and Vougioukas et al. [50] show a path-planning technique for agricultural machinery that uses GPS information and georeferenced maps to calculate the best path for seeding or harvesting, minimizing the complexity of the mechanical movements. With the same insight, a path-planning algorithm for nonplanar terrains is shown in [11]. Thuilot and Cariou [51] present an automatic guidance system for a tractor following a set of waypoints and using a differential GPS as the only positioning sensor. However, relying only on GPS measurements for positioning presents difficulties in groves where dense tree canopies may block the GPS signal. Works such as [4], [6], [42], and [49] enhance the navigation system by using real-time kinematics (RTK) devices and exteroceptive sensors, such as artificial vision systems and range lasers.

The use of differential GPS or RTK devices has secondary problems in the design of a service unit: they increase its cost, which may prevent large-scale use of autonomous service units in the field of precision agriculture. However, it is worth mentioning that a bad positioning system will propagate its position error—and its associated covariance—to all the information acquired by the sensors on the vehicle. For simplicity, let us assume the covariance propagation model shown in (1) [52]. P_f is the covariance matrix associated with the detected feature according to the sensor's position within the environment, H_v is the Jacobian matrix of the motion model of the sensor (or the vehicle) and H_v^T is its transpose, H_f is the Jacobian matrix associated with the mathematical model of the detected feature, and R is the covariance matrix associated with the feature extraction procedure.

$$P_f = H_v P_v H_v^T + H_f R H_f^T. \qquad (1)$$

In (1), P_v is the covariance matrix of the localization system implemented on the vehicle. If we assume two localization systems ($P_{v,1}$ and $P_{v,2}$) implemented on the same vehicle, such that $P_{v,1} \succeq P_{v,2}$ (where $\succeq$ stands for positive semidefinite and $P_{v,1}, P_{v,2} \succeq 0$), then using the results shown in [53], we can see that $P_{f,1} = H_v P_{v,1} H_v^T + H_f R H_f^T \succeq H_v P_{v,2} H_v^T + H_f R H_f^T = P_{f,2}$. Considering that the determinant of a covariance matrix is associated with the volume of uncertainty of such a matrix [53], we can see that $|P_{f,1}| = |H_v P_{v,1} H_v^T + H_f R H_f^T| \geq |H_v P_{v,2} H_v^T + H_f R H_f^T| = |P_{f,2}|$. Thus, the volume of uncertainty associated with $P_{f,1}$ is bigger than the one associated with $P_{f,2}$. Hence, we can see that, if $P_{v,1}$ and $P_{v,2}$ are two different GPS receivers, the precision of mapping in GPS-based localization systems relies on the accuracy of the GPS sensor used.

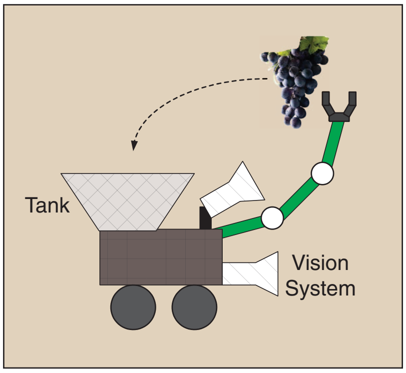

FIGURE 5 – Schematic of a service unit for harvesting grapes.

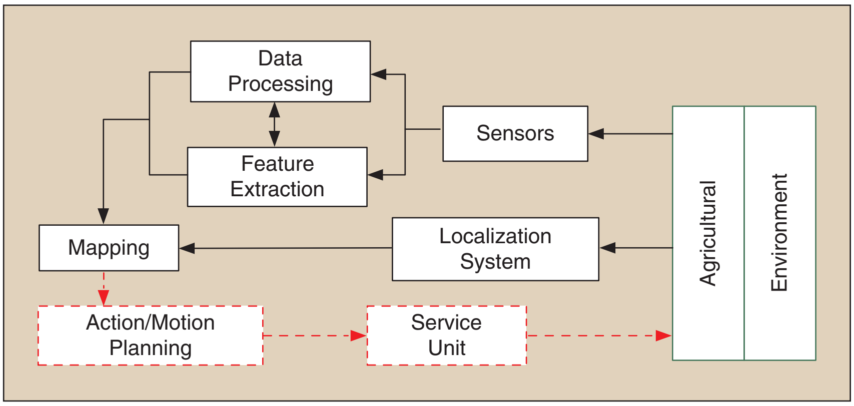

FIGURE 6 – Architecture of the mapping stage of a service unit.

As can be seen in (1), the accuracy of the four stages of a service unit implementation (shown in Figure 1) has a lower bound established by the accuracy of the positioning system (in case the feature extraction procedure cannot be further improved). Therefore, minimizing P_v in (1) would lead to a minimization of the propagation errors. With this insight, the simultaneous localization and mapping (SLAM) algorithm can be used to further reduce such propagation of the positioning errors.

The SLAM algorithms minimize the estimation errors in both the localization and the mapping processes [29], [52]. A SLAM algorithm concurrently estimates both the pose (position and orientation) of a vehicle and the map of the environment in which the vehicle is located. The sensors mounted on the vehicle extract features from the surrounding environment. Those features are then located within a map, which is maintained and updated by the SLAM algorithm. One of the main advantages of SLAM algorithms is that they can optimally perform in places where other positioning systems fail and can be used to further improve GPS-based localization systems.

SLAM: A Solution for Occluded GPS

GPS-based localization systems become inaccurate when GPS receivers are blocked by dense foliage. Thus, mapping and guidance applications like the ones shown in [5] and [54] would become unachievable. A SLAM algorithm can use exteroceptive sensors (such as the SLAM implementations shown in [29] and [55]) and can be enhanced by using a GPS-based localization system [56]. One of the main advantages of the SLAM algorithm is that it minimizes the errors in the estimation of both the pose and the map [29], [52], [55]. However, two of the main drawbacks are its high computational cost (which can be drastically reduced by using optimization criteria such as the ones shown in [29] and [57]) and meticulous design to avoid inconsistency and divergence in the estimation process. Such problems can be avoided by using GPS

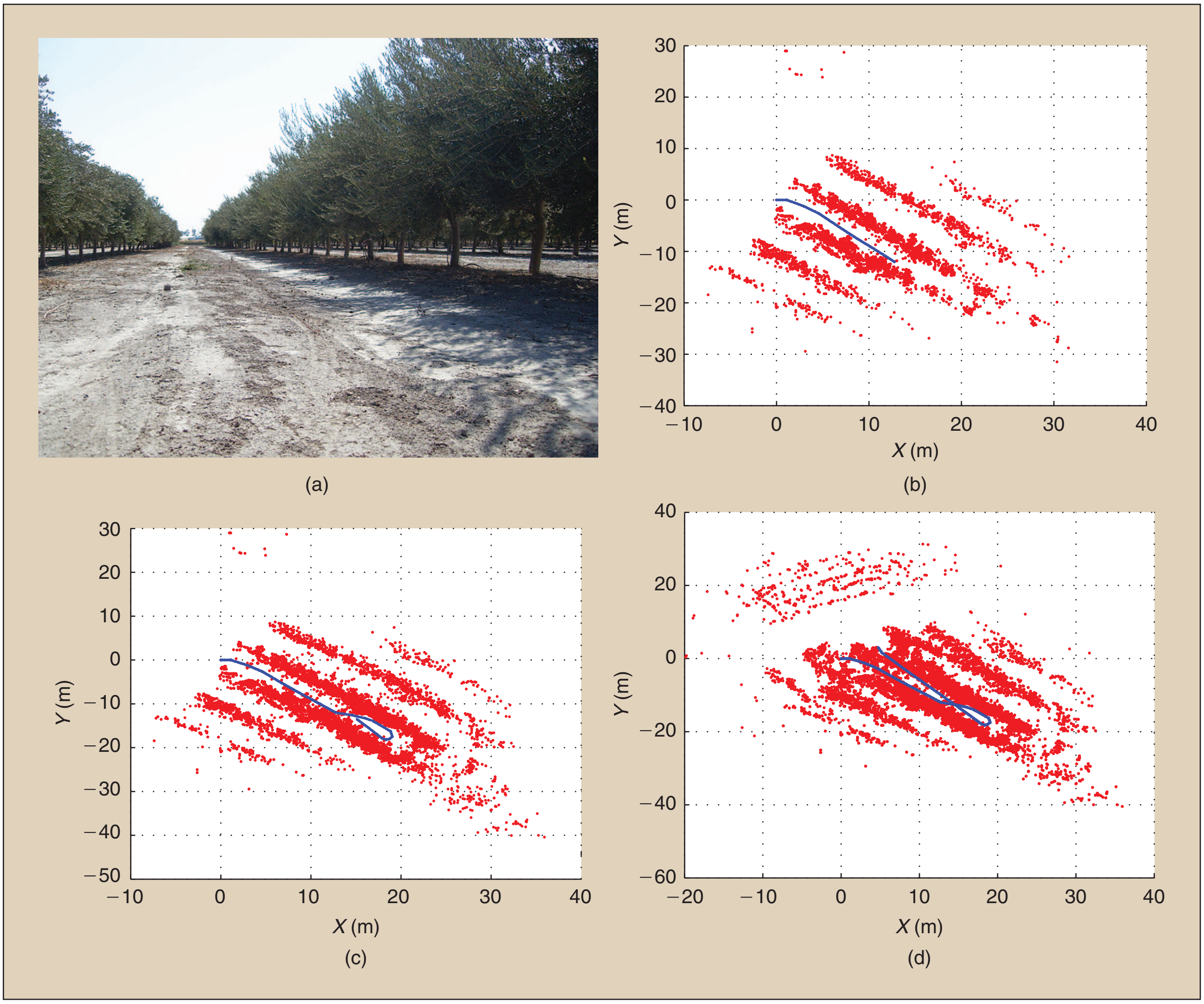

FIGURE 7 – An example of a bad positioning system. (a) The olive grove environment where the experimentation was carried out. (b)–(d) Snapshots of the reconstruction of the environment based on the positioning information. The solid blue line is the path (estimated by the odometry) traveled by the vehicle, whereas red dots represent the detected stems.

measurements from time to time to ensure convergence of the estimation process. The latter does not contradict the benefits of using SLAM algorithms as positioning methods, since GPS measurements are not mandatory at each sampling time [52], [56].

Several approaches can be used to overcome the shortcomings of the SLAM algorithm, such as using the extended Kalman filter (EKF) [52], [56] or the extended information filter (EIF) [29], including Gaussian-based filters, the particle filter [58], [59], etc. For example, a hybrid SLAM algorithm for farms is presented in [60], whereas an optimized EIF for real-time implementations in groves is presented in [29]. The features acquired from the environment are part of the map built by the SLAM process, and they are corrected and updated as the SLAM algorithm is executed. For instance, the stems of trees as features from the environment are used in [29], although other features can be used instead.

Considering the optimized EIF-SLAM formulation shown in [29], let ξ_t and Ω_t be the SLAM system state and its associated information matrix. ξ_t contains both the estimation of the pose of the vehicle in an agricultural field ($\xi_{v,t}$) and the features extracted from the environment (the map, $\xi_{m,t}$) [see (2)].

$$\xi_t = \begin{bmatrix} \xi_{v,t} \\ \xi_{m,t} \end{bmatrix}; \quad \Omega_t = \begin{bmatrix} \Omega_{v,t} & \Omega_{vm,t} \\ \Omega_{mv,t} & \Omega_{m,t} \end{bmatrix}. \quad (2)$$

In (2), suffix t represents the sampling time, $\Omega_{v,t}$ is the information matrix associated with $\xi_{v,t}$, $\Omega_{m,t}$ the information matrix associated with $\xi_{m,t}$, and $\Omega_{vm,t} = \Omega_{vm,t}^{T}$ are cross-information matrices. It can be shown that $\Omega_t \succ 0$ (Ω_t is positive definite) [29]. Considering the relation between the EIF and the EKF ($P_t = \Omega_t^{-1}$, where P_t is the covariance matrix associated with the EKF system state) and taking into account the convergence theorem for the EKF-based SLAM algorithm (it establishes that $\lim_{t\to\infty}|P_t| = 0$, i.e., the volume of uncertainty associated with the estimated process decreases as time tends to infinity), we can find that [29]

$$\lim_{t\to\infty}|P_t| = \lim_{t\to\infty}\frac{1}{|\Omega_t|} = 0. \quad (3)$$

Then, according to (3), it is possible to see that $\lim_{t\to\infty}|\Omega_t| = \infty$ (the information matrix diverges as time tends to infinity). Therefore, the estimation process performs properly [29], [52]. The latter means that the SLAM algorithms allows for the maximization of the information matrix associated with the EIF-SLAM system state, which, in turn, means that the volume of uncertainty associated with the estimation of the vehicle's pose [see (1)] can be minimized by the implementation of a SLAM algorithm in the service unit.

It should be noted that as new features are detected, they have to be properly added into the SLAM system state and its information (or covariance) matrix [52], [56]. Figure 8 shows an experimental result of implementing the EIF-SLAM shown in [29] in a service unit operating within an olive grove [shown in Figure 7(a)] for supervision purposes. As previously stated, the features acquired from the environment correspond to stems associated with trees in the grove. The solid black line is the path followed by the vehicle (and estimated by the SLAM algorithm); the solid magenta line is the path previously planned by the service unit; the red crosses are the estimated locations of the trees detected from the environment; and the blue triangles are the differential GPS locations of the trees and used for comparison purposes. The consistency tests of the EIF-SLAM algorithm mentioned herein are shown in [29].

Unmanned Service Unit in Olive Groves: A Case Study

The development of autonomous terrain vehicles for agriculture is still in the research and experimental stages, with practically no commercial vehicles on the market. Some experimental vehicles have been presented in the literature, such as the ATI platform developed at the Aalborg University in Denmark for weeding and spraying [61] or the HortiBot project by the Aarhus University, Denmark, for high-tech weeding in organic farms (http://www.hortibot.dk/). In this section, an experimental autonomous service unit developed recently at the Institute of Automatics, Universidad Nacional de San Juan, Argentina, for intensive agriculture applications is described. The vehicle shown in Figure 9 has been implemented on the basis of a standard utility four wheeler for agricultural applications. The aim of the project was to offer autonomy to the commercial vehicle by providing the abilities of guidance, action, detection, and mapping. The primary application of the vehicle is to capture vegetation information to construct georeferenced maps of the crop.

The general functional structure of the vehicle is shown in Figure 10 [29]. The vehicle is equipped with sensors for navigation, such as odometry encoders and IMU, stereo vision camera, laser range sensors, and RTK GPS, as well as sensors for capturing vegetation information such as multispectral cameras and laser range sensors. Also, it is equipped with electric actuators for acceleration, steering, and braking. The vehicle can navigate autonomously or be teleoperated and has four states of operation: start (initial conditions), normal (executing a task), standby (transitory suspension of operation), and emergency (emergency stop). Normal operation includes the control algorithms developed for path following and trajectory tracking. All operations can be supervised from a remote station, where a human–computer interface is developed to facilitate the supervision and teleoperation of the vehicle. The interface is accessible from the base station, at a remote location from the vehicle, where the tasks of planning, supervision, and teleoperation are executed. The vehicle is operated at an

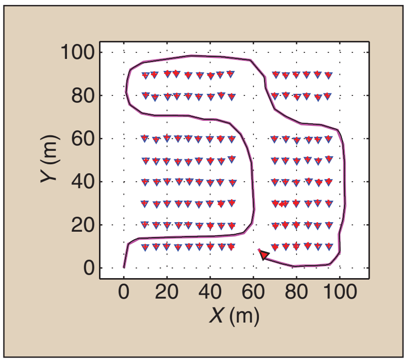

FIGURE 8 – Olive environment reconstruction using the EIF-SLAM shown in [29].

experimental field of olive groves in San Juan, Argentina.

The four core abilities mentioned in the "Agricultural Service Units" section are also present in the service unit shown in Figures 9 and 10.

- Detection: This stage is represented by the two range laser sensors, the stereo vision system, and the high-level CPU shown in Figure 10, which processes the sensors' information.
- Mapping: This stage is represented by the detection ability listed previously and the localization system (the DK-GPS, the internal sensors, and the low-level CPU). The high-level CPU generates a map of the environment based on the exteroceptive sensors and the localization information provided by the low-level CPU.
- Guidance: This stage is represented by the low-level CPU (which controls the mechanism of the service unit through a CAN bus), the positioning system (DK-GPS and the inertial sensors). The path controllers in the high-level CPU generate the driving motion commands based on the positioning and environmental information acquired by the sensors of the service unit (Figure 2). Obstacle avoidance and emergency stops are also included in this stage.
- Action: The service unit shown in Figures 9 and 10 was designed to monitor and supervise a grove. However, a robotic arm, controlled by a high-level CPU, can be mounted on the vehicle for manipulation purposes. Additionally, a ground station allows the teleoperation of the vehicle.

New Issues Under Study

Despite the service unit's abilities, some open issues still remain to be solved for autonomous vehicles in agricultural environments. The tools developed within the robotic field can be used as proposed solutions to such issues and for further improving the agricultural process. Nevertheless, the goal of agricultural robotics is not only to apply robotic technologies in the field of agriculture but also to use agricultural challenges to develop new techniques and systems.

Three open issues are described in the following sections. However, several others are present, particularly those strictly related to the nature of an agricultural field (e.g., the tools needed for autonomously harvesting a wheat field are not the same as those needed for harvesting an orange grove).

Service Unit Interaction with Field Workers

In the examples mentioned previously, a service unit was designed for use in harvesting, seeding, agrochemical dispersal, supervision, mapping, etc. However, one question still needs to be answered: How does the service unit interact with field workers? For example, a service unit is designed to give assistance to olive field workers. The workers have to load the service unit with olives as it navigates through the grove. The service unit must protect the workers' safety and fulfill its agricultural task.

Several robotic tools can be used to solve the problem, such as the studies in human–robot interaction, cooperative and collaborative work, control systems, etc. [62]–[65].

Maneuvering Problems

The width of the furrows is not necessarily ideal for the service unit's maneuvering abilities [66], [67]. Thus, navigation, positioning, orientation, and turning maneuvers require specific strategies that are directly related to the environment disposition and the vehicle's capabilities. For example, industrial olive harvesters are only appropriate for olive fields with specific width between the furrows and height of the treetops.

The kinematic and dynamic restrictions of the vehicle also play an important role. Service units are not usually unicycle-type vehicles. Instead, carlike configurations are more suitable for navigation in an agricultural environment [3], [5]. One of the main drawbacks of such a carlike configuration is that the vehicle is not able to turn over its point of control; therefore, it is restricted by a minimum radius of turning. The latter also means that not all the points from the environment can be reached by the service unit, and special care must be taken when planning (see the "Action" section) to avoid both risk (for the vehicle and the field workers) and expenditure of valuable resources trying to perform an action (e.g., trying to reach a point out of the vehicle's workspace).

Tasks: Which Tasks Should Be Performed First?

This issue is closely related to the versatility of the service unit and consists of having a hierarchical architecture based on the priorities

FIGURE 9 – The AGROBOT autonomous vehicle for agriculture.

and management of tasks. As previously stated, a service unit is usually developed for achieving a single task [68], [69]. A question arises when the service unit has to perform two or more tasks at the same time (e.g., harvesting and supervision of a grove). The system must be able to manage the available resources to optimize the agricultural tasks it is performing while the tasks are being executed successfully.

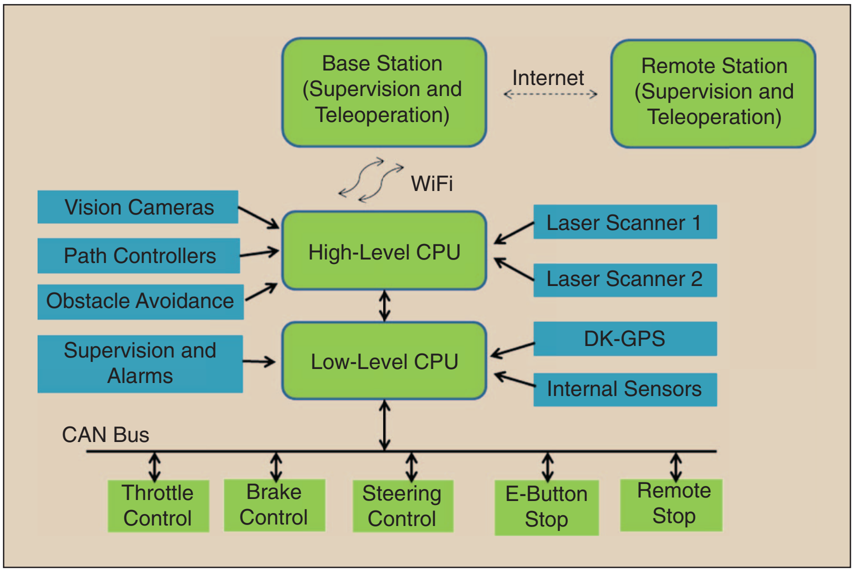

FIGURE 10 – Functional structure of the autonomous vehicle.

Conclusions

This article surveyed the state of the art in unmanned service units in agricultural environments and presented the four core abilities of such vehicles when performing agricultural tasks: detection, guidance, mapping, and action.

A detailed analysis of each ability was given, showing both how the four abilities are related to each other and how the accuracy of the localization system is crucial to ensure the success of an agricultural task. It was shown that a bad positioning system creates an unreliable map, risky driving, and the possibility of a failure of an agricultural task. In particular, the SLAM algorithm was presented as an inexpensive solution for the localization problem. In addition, a case study of an unmanned service unit for olive grove supervision was presented.

Hopefully, this article has provided sufficient information for an interested reader to further improve the field of unmanned service units to massive the use of such vehicles in main and secondary agricultural tasks.

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