D1.15: Best Practices in Developing Open Platform for Agri-food Robotics

revised

WP1 – Competence Centers and Technical Expertise Management

Authors: Martijn Wisse, Ting-Chia Chiang, Gijs van der Hoorn

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Lead Author	Martijn Wisse	Email	M.Wisse@tudelft.nl
	TU Delft	Phone	
Other authors	Ting-Chia Chiang (TU Delft), Gijs van der Hoorn (TU Delft)		
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revised	December 2021	Revised		

Response to reviewers request:

'The deliverable should explain better why these are seen as best practices, the partners involved in the experiments are not clearly described.'

The deliverable is seen as a living document. The main argument for selecting the best practices is expert judgement of the authors who are active in the field. In D1.14 in the next version of this living document this is taken up. This deliverable gives more an overview of what is happening in robotics in agri-food. It is not dedicated to the innovation experiment. At the time of writing only the initial innovation experiments were running. The innovation experiments and industrial challenges resulting from the open call started all later.

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1 Introduction

This document is written for readers with an interest in agricultural robotics. Although robotics is not commonplace yet in the field of agriculture, there are already so many past and ongoing projects and products that it is difficult to decide where to start. What are the best practices to build upon? This document contains up-to-date overviews of potential examples as well as suggestions for best practices that can be used as a solid base for further developments.

As cited from a recent review paper [122], "practical agriculture robots rely not only on advances in robotics, but also on the presence of a support infrastructure. This infrastructure encompasses all services and technologies needed by agriculture robots while in operation, this include a reliable wireless connection, an effective framework for Human Robot Interaction (HRI) between robots and agriculture workers, and a framework for software sharing and re-use“. This statement is captured in the schematic representation in Fig. 1. Apparently, an integrated framework for software/hardware for agricultural robotics domain has not yet been in place, as there are lots of existing tools out there. However, lots of agricultural robotics problems may not use the best tools to solve them or are not aware of some tools. So listing and analyzing the existing open software/hardware tools will help improve the performance of common agricultural robotics problems.

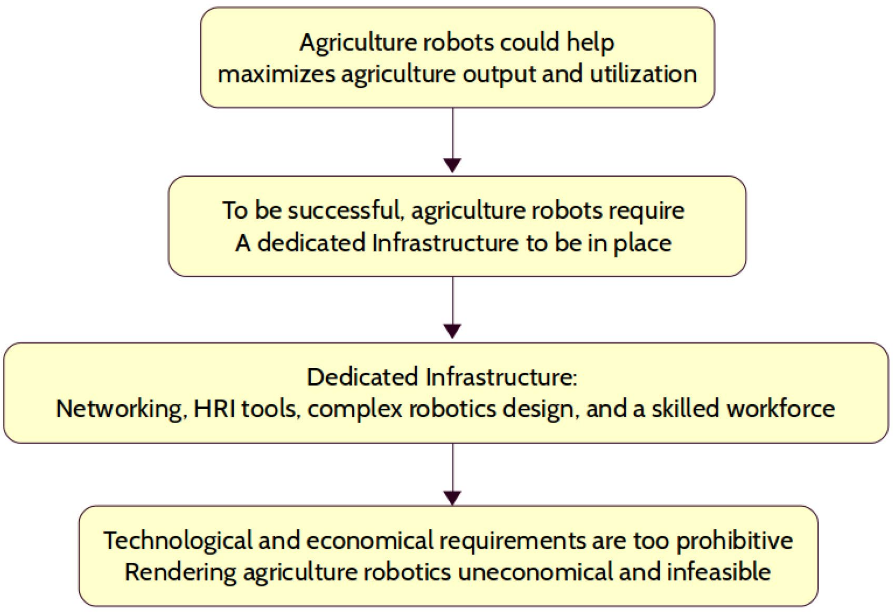

Fig 1: Schematic representation of the challenge of implementing agricultural robotics. From [122].

This document is a “live” document which will receive updates throughout the project. It is intended as a stand-alone document that can be used for a quick-jump into the state of the art of agriculture robotics. Nevertheless, it is part of a Europe-wide endeavor which is the agROBOfood project, which intends to connect all of Europe’s many high-quality projects on agriculture robotics. The following list of ongoing projects is taken from the EuRobotics Multi-Annual Roadmap on Robotics [97]:

- HUBRINA (HUman-roBot co-woRking IN Agricultural master-slave systems)
- ECHORD. Master-slave robot control for agricultural activities.
- FutureFarm
- ERA-NET ICT Agri. Typify current and new robot technology and their potential tasks in farming.
- CROPS (Clever Robots for Crops)

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- ERA-NET ICT Agri. Intelligent sensing and manipulation for sustainable production and harvesting of high value crops
- RHEA (Robot Fleets for Highly Effective Agriculture and Forestry management)
- ERA-NET ICT Agri. Design, development, and testing of a new generation of automatic and robotic systems for both chemical and physical –mechanical and thermal– effective weed management focused on both agriculture and forestry.
- GEOPAL (GNSS-based Planning system for Agricultural Logistics)
- QUAD-AV (Ambient Awareness for Autonomous Agricultural Vehicles)
- ERA-NET ICT Agri. Enhancing SaftetyLevel of autonomous agricultural vehicles during process in terms of threads to humans, animals and tangible goods.
- SmartBot - (here: Subproject AgroBot)
- INTERREG. Develop basic technologies needed for constructing multiple, agriculture, robotic demonstration models with different application

Future versions of this document may contain more diverse information than the current version. Specifically, the current version focuses on mobile ground-based robotic systems. Future additions might include aerial robotics as well as fixed (non-mobile) ground-based systems that operate on conveyor belts or move as large CNC machines [124]. Another intended future extension is to include more information on commercially available robots, platforms, and components. Due to the abundant availability of research project information as opposed to commercially available solutions, this is overrepresented in the current version of the document.

Despite the shortcomings of the current version of this document, we believe that it already contains highly valuable information for a quick yet complete overview of the state of the art in agriculture robotics. Chapter 2 focuses on the technological best practices, whereas Chapter 3 focuses slightly more on organizational aspects, yet still firmly connected to the robot technologies.

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2 Best practices from a technical point of view

2.1 Common use cases in Agri-Food domain

2.1.1 Introduction

There are many robotic applications in agri-food domains. Fig 2 shows a classification of tasks as proposed by [96]. In this deliverable, we focus on the subset of the three most occurring tasks as listed by a recent survey [1]. These three are, in order of robotic complexity,

(i) field scouting and data collection,
(ii) weed control and targeted spraying, and
(iii) automated harvesting robots.

A future version of this document may include best practices for other robot agriculture tasks.

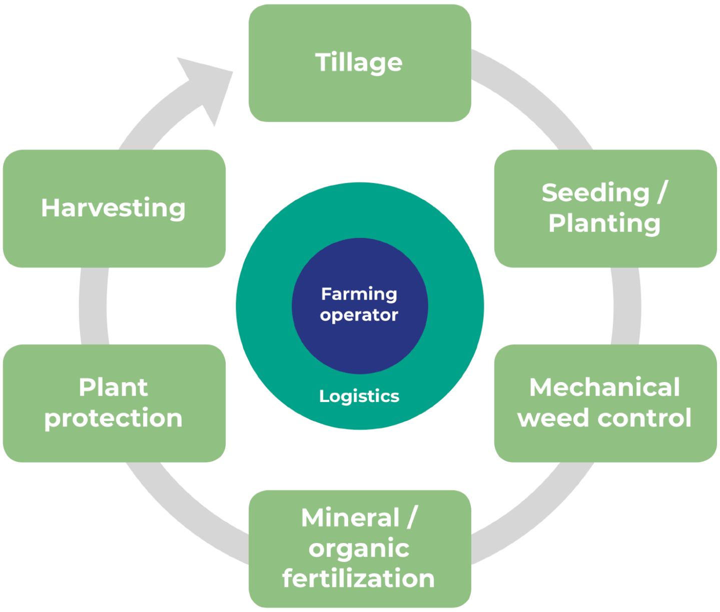

Fig 2: An overview of robot agriculture tasks, taken from [96].

2.1.2 (i) Field scouting and data collection

Table 2.1 provides an up-to-date overview of field scouting and data collection robots. Due to information availability, research projects are better represented than commercial solutions. This may be improved in a future version of this document. From this overview, we select Blok's orchard robot shown in Table 2.1.a [12] as the "best practice" example due to its extensive description as well as its coverage of most common components and packages.

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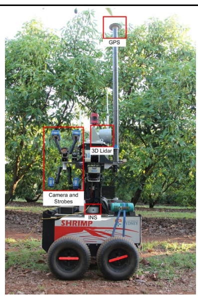
 a. Husky A200 robot with 2D LIDAR scanner used for orchard navigation [12]	 b. A prototype field survey mobile robot platform [135]	 c. Husky UGV for vineyard monitoring [10, 15]
 d. TrimBot2020 for automatic gardening [78]	 e. TerraSentia for in-field plant trait data collection; Source: https://www.earthsense.co	 f. Mobile Agricultural Robot Swarms (MARS) for seeding tasks [136]
 g. VINBOT – an all-terrain mobile robot for capturing and analyzing data in a vineyard; Source: http://vinbot.eu/	 h. SMP S4 – a surveillance robot to protect orchards from birds; Source: https://smprobotics.com/	 i. VineRobot for monitoring vineyards; Source: http://www.vinerobot.eu/
 j. Shrimp – a UGV for data collecion [145]		

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Table 2.1: An overview of field scouting and data collection robots

Besides common motion and sensing subcomponents, the specific robotic technology required for these robots is an exhaustive navigation system. Such a system comprises automatic and accurate navigation control, simultaneous localization and mapping, path planning algorithms, and three-dimensional environment reconstructions [1]. From the detailed list of technologies in Section 2.2, the following pertain specifically to field scouting and data collection robots:

- Mobile platform
- Simulation environment
- Navigation sensors
- Internal communication
- Software framework
- SLAM (Simultaneous Localization and Mapping)
- Environment reconstruction
- Path planning

2.1.3 (ii) Weed control and targeted spraying

One of the most demanded and common applications for agricultural robots could be weed control. The following weed control and targeted spraying robot projects can be used as examples and source of inspiration. We have obtained this list mostly from various survey papers [1, 3, 53, 54].

 a. BoniRob; Source: Deepfield Robotics [32]	 b. High speed electric in-row weeding machine; Source: Tillett and Hague Technology [33]	 c. Dino – an entirely autonomous weeding robot; Source: https://www.naio-technologies.com/en/
 d. AgBot II; Source: Queensland University of Technology [142]	 e. AVO performs autonomous weeding operations; Source: https://www.ecorobotix.com/en/	 f. RIPPA – a prototype robot for shooting weeds using a micro-dose

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		of liquid; Source: University of Sydney

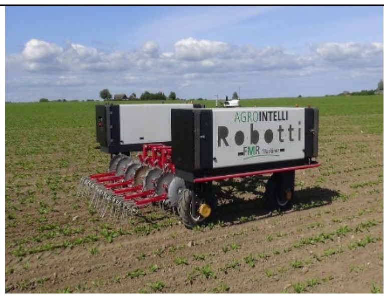
 g. Tertill – a solar powered weeding robot for home gardens; Source: https://franklinrobotics.com/	 h. S55 spray robot made for automatic spraying in a greenhouse; Source: http://www.hollandgreenmachine.com	 i. SwagBot [143] – an all-terrain, four-wheeled, solar-powered robot; Source: University of Sydney
 j. Hortibot [144 – a semi-autonomous weeding robot; Source: Aarhus University	 k. Ladybird – an omni-directional robot for targeted spraying and data colleciton [146]	 l. Robovator – a vision based robotic hoeing machine for controlling weeds in row crops; Source: https://www.robovator.com/
 m. Odd.Bot Weed Whacker – an autonmous weed-plucking robot that uses no chemicals ; Source: https://www.odd.bot/	 n. AgroIntelli Robotti – a diesel-hydraulics autonomous tool for both for sowing and spraying; Source: http://www.agrointelli.com/index.html#home	 o. Asterix – an light-weight, autonmous farm-bot desinged for spraying herbicides on weeds only; Source: https://www.asterixproject.tech/

Table 2.2: An overview of weed control and targeted spraying robots

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Weed control and targeted spraying robots are more complex than the category of field scouting and data collection robots. The additional technologies can be summarized as a targeted motion system together with a robust perception system which includes weed detection, weed and crop identification and crop localization. From the detailed technologies listed in Section 2.2, the following additional technologies pertain specifically to weed control and targeted spraying robots:

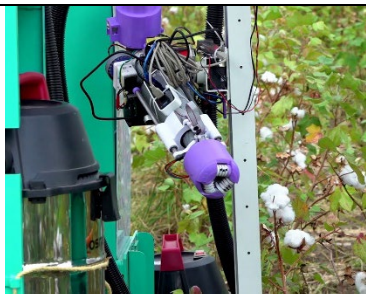
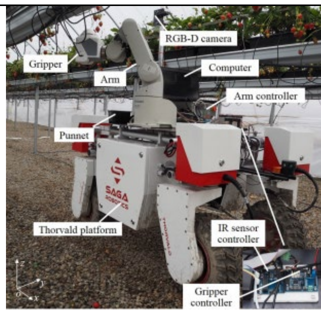
- Specific hardware components for weeding and targeted spraying
- Robot arms
- Perception hardware
- Weed/crop classification algorithms

The performance of state-of-art weed control robots is good in ideal conditions. However, in uncontrolled or semi-controlled environments, problems emerge due to the variety in lighting, density and species of weed plants, and occlusion of mixtures of plants [3]. This remains a major challenge to commercialization of weed control robots.

Although all examples in the Table 2.2 are useful sources for inspiration, at the time of writing we have selected BoniRob as the most useful example for "best practice" for weeding robotics. This choice was made based on the extensive descriptions [23, 55-58].

2.1.4 (iii) Harvesting

The third and most demanding main category of agriculture robotics is robotic harvesting. This not only requires all of the navigation capabilities of scout robots and all of the classification and positioning capabilities of weed removal robots, but adds three significant additional capabilities: crop detection, motion planning, and dexterous manipulation. The overview below shows a large number of research projects which can serve as inspiration for the development of high-performance harvesting robots.

		
a. SWEEPER – a robot for harvesting sweet pepper fruit in greenhouses [147]	b. Green Robot Cotton Harvester V 02 developed by Green Robot Machinery [139]	c. Strawberry-harvesting robot [31]

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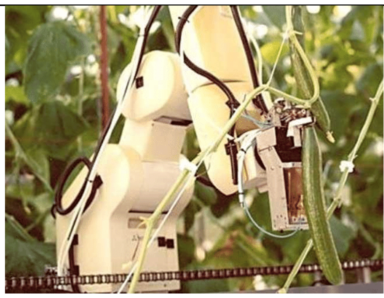
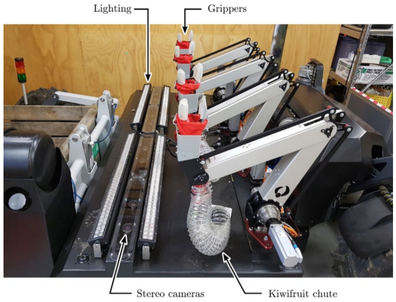
 d. Harvey – the robotic capsicum harvester [7]	 e. Cucumber harvesting robot [148]	 f. Kiwifruit harvester mounted on the base robotic platform [149]
 g. Apple-picking robot; Source: https://www.abundantrobotics.com/	 h. Tomato harvester; Source: https://metomotion.com/	 i. Energid citrus picking system; Source: https://www.energid.com/
 j. Dual-arm tomato harvesting robot testing in the greenhouse [150]	 k. Cherry-tomato harvesting robot [151]	 l. Panasonic AI-equipped tomato harvesting robot [152]

Table 2.3: An overview of harvesting robots

Compared to weeding and targeted spraying robots, harvesting robots are more complex. The additional capabilities that set harvest robots apart from scout or weeding robots, as detailed in Section 2.2, are the following:

- Harvesting end-effectors
- Crop detection and localization
- Grasp selection
- Robot manipulator path planning

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2.2 Open-source software/hardware components

2.2.1 Introduction

To avoid duplication of effort and reinventing the wheel, a great range of existing technologies from other robotics domains could be used to facilitate the transition of agricultural robotics into the field. Some technologies might need to be developed specifically for agriculture from scratch, while other technologies already developed for general robotics could be adapted to the agricultural domain, for example, autonomous vehicles, artificial intelligence and machine vision [4]. Hereby, in this section, we briefly review those technologies widely used in the agricultural domain, which are pertinent to aforementioned use cases. We also list the best practices regarding all of the specific components required for agriculture robotics. Although the focus of the document is on open-source components (which mostly entails software), we have included best practices for hardware component selection as well; not only does this provide a more complete overview of the state of the art, it also provides clarity how hardware decisions influence the use of open-source software components.

2.2.2 Hardware

Mobile platform

A common denominator in many projects is the use of a rugged, not-too-large, open-source-ready mobile platform. Examples include ClearPath's Husky robot [8] as used in projects [10,11,12,13,14,15,16] above, and Robotnik's Summit-XL [9] as used in project [17]. It is highly recommended to base at least the initial developments on such an existing, generic platform.

Hardware components specific for weeding and targeted spraying

The specific hardware for weeding and targeted spraying strongly depends on the crop and intended treatment. Although it is impossible to identify a single "best practice", one can find many inspirational examples in these papers [1,3,53,54].

Positioning hardware – robot arm

As soon as it is required to bring a spray head or mechanical weeding device to a specific position relative to the mobile base, one requires a positioning system for at least 3 degrees of freedom. Two best practices have been identified. First, for fast and lightweight motions with limited reach, a parallel robot construction is often used and the most popular type is "Delta robot" [59, 60]. Commercially available parallel robots are developed for static systems, so the best practice is that the hardware is developed specifically for the intended application, while the control software is taken from a common source (either commercial [61, 62] or open-source [63, 64]). Second, for motions which require larger reach and full orientation control, at the cost of operational speed, it is common to use a commercial serial robot manipulator arm. Due to the mobile weight and power limitations, the best practice is to use a lightweight industrial arm such as a Fanuc LR Mate [65], a Universal Robot [66], a Franka Emika Panda [67] or an even more lightweight wheel-chair specific robot arm [68]. Available ROS drivers make it fairly straightforward to integrate these robot arms into the mobile robot.

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End-effector for harvesting

From a thorough review of all available literature on harvesting robots, it is clear that the end effector will always be a very crop-specific and process-specific design. Each project has a unique gripper or cutter or other type of harvesting end-effector. The best practice here appears to be to take inspiration from all available publications, specifically those fully dedicated to designing (harvesting) end-effector [27, 31, 74, 78-82], and then to aim for a fast multi-prototype design process to handle unforeseen interactions with the crop [83, 84]. The end-effector must usually be moved in 6 dimensions for proper harvesting, and so we reiterate our previous best practice recommendation of using a standard and lightweight serial robot arm as commonly used in other industries. Efforts to make own robot arm designs to optimize for lower cost and higher speed (e.g. attempting to trade those off for lower required accuracy) usually don't succeed due to underestimation of the design efforts necessary for creating robust hardware and software.

2.2.3 Sensors

In robotics, sensors could be categorised into two groups: internal and external. Internal sensors are used to measure robot parameters relative to the reference frame of the robot, such as a joint angle, a linkage deflection, or a gripping force. External sensors are used to measure the environment and the position of the robot relative to that environment [137]. The sensors that are most widely used in robotics and supported by official ROS packages [121] can be summarized as follows:

· Inertial sensors (IMU)

· Orientation sensors (GPS)

· Laser range sensors (1D range finders, 2D range finders)

· 3D sensors (range finders & RGB-D cameras)

Navigation sensors

For outdoor navigation, a common best practice is the use of GNSS [125], typically Differential GPS for higher accuracy or RTK-GPS for extremely high accuracy [23]. Some research is done on purely vision-based navigation [24, 25] in order to prevent the perceived high cost for GPS, but this is not considered a best practice. For indoor (greenhouse) navigation, where GPS does not work well, there is no best practice yet that is commonly shared, and novel ideas such as Artificial Potential Fields are explored [26].

Additionally, field robots commonly use a LiDAR sensor [23, 27] to obtain a 3D scan of its near surroundings and an IMU sensor for orientation. There are many parallels with autonomous vehicle projects here, and many opportunities to reuse both research and available solutions.

Crop/weed perception sensors

Best practices include 2D and 3D image sensors and multi-spectral sensors [69-72]. In almost all systems, the developers have chosen to shield sunlight as much as possible, as this dramatically interferes with the sensors. A typical construction is that of a black, shielded casing around the sensors, which is being held as closely above the ground as possible [55, 73].

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2.2.4 Low-level communication protocol

Internal communication

Since CAN-bus has been adopted as ISO standard 11783 (also known as "ISOBUS"[34, 35]) for agriculture machinery, a best practice is to use this for the low-level communication between motion controllers, actuators, and other components. Unfortunately, this conflicts with the internal low-level communication inside common mobile research platforms such as the ClearPath's Husky as mentioned above. A best practice is to ensure the availability of ISOBUS-compatible communication for easy extension of the system with additional components. This is, however, limited to low-level communication only. For higher-level communication, a best practice is to adhere to the communication standards of a software framework as described below.

2.2.5 Overall software framework

ROS: overall software framework

One of the strongest common denominators of all field scouting and data collection robots is the use of ROS (Robot Operating System) as the software framework. Although there are many other frameworks as well [128, 129], ROS has become the de-facto standard. Besides an overwhelming amount of generic examples and tutorials to use ROS for mobile robots [36-39], there are a number of excellent descriptions of the specifics of ROS in agricultural settings [28, 40-42]. Best practices are collected and demonstrated in the open-source projects FroboMind [5, 43], AgROS [20], and ROS-Agriculture [29, 30]. The software framework allows an almost unlimited extension of the robot's capabilities through adding more and more (open-source) software packages written for this framework. For the current category of robots, which basically only need to navigate, the best practice includes packages for SLAM, path planning and environment reconstruction as elaborated below.

2.2.6 Navigation algorithm

SLAM algorithm

SLAM stands for Simultaneous Localization and Mapping, which is a category of algorithms that has various implementations [44-46, 130]. All mobile robotic devices including (semi-) self-driving cars use this type of algorithm. For the current version of this document, it is unclear if there already is a best practice regarding the choice and implementation of SLAM for agriculture robotics. The natural yet repetitive environment makes it hard to use landmarks for map-building and navigation, yet (at least for outdoor agriculture) the GNSS is highly accurate. A future version of this document should contain a clear recommendation.

Environment reconstruction

Best practice examples of agricultural robots typically use a LiDAR as illustrated above, which provides 3D information. The most common way for initial storage of that data is as a "Point Cloud". A collection of effective algorithms to process this kind of data is available through the open-source Point Cloud Library [47]. Good examples for the application of this library in agricultural robotics can be found in [48-51].

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Path planning algorithm

Path planning is the final type of generic algorithm that will be present in all mobile robots [52]. In agriculture, path planning is in some regards simpler than in challenging environments such as crowded public spaces. A difficult challenge remains the presence of foliage which should not be considered as a hard constraint, but can (and must) occasionally be pushed aside. Good examples of path planning in agriculture settings can be found in [10, 15, 27, 130].

ROS navigation stack

It's essential for an autonomous robot to navigate itself across a crop field without human assistance, e.g. field scouting robots for data collection. Generally speaking, an exhaustive navigation system is required a combination of three fundamental competences, that is, mapping, localization, and path planning [6]. There are many software toolboxes/packages capable of providing those competences. To the best of our knowledge, one of the most well-known software packages used in robotics is the *Navigation Stack* in ROS 1. Inputs generally required in Navigation Stack are odometry and sensor data such as a continuous stream of 2D/3D scans or 3D point clouds of the immediate environment. Outputs are velocity commands sent to a mobile base.

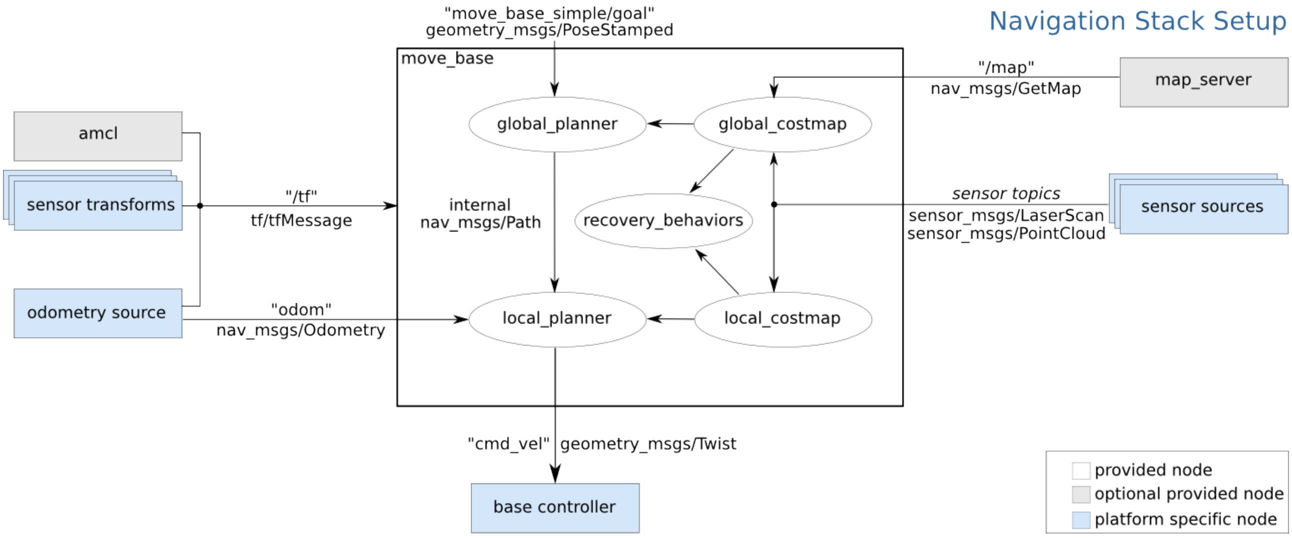

Fig 3: Overview of Navigation Stack in ROS 1

There is Navigation Stack in ROS 2 [138] as well. The main changes from ROS 2 is that the move_base (nav2_simple_navigator) has been split into multiple components (nav2_navfn_planner and nav2_dwb_controller) and a behaviour tree is implemented to orchestrate these components. These changes provide flexibility and extensibility of the navigation stack behaviour as it is possible to replace any of these nodes at launch/run time.

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2.2.7 Crop/weed sensing algorithms

Weed / crop classification algorithms

The choice for perception sensors is linked to the choice for classification algorithms. Currently, the best practice is to use Deep Learning algorithms. Within the span of just a few years, this approach has completely taken over from more "old-fashioned" classification algorithms which are still in use [73-75]. A few years ago, the best practice would probably consist of a combination of color segmentation and Bayes classification or Support Vector Machines, where the algorithm's parameter settings would be optimized with training data, which would need to be re-trained for each season.

Deep Learning is a generic term, and for agriculture applications many variations are in use [76]. Obtaining and properly labeling the training sensor data is crucial for success, [76] provides a list of available open datasets

Crop detection and localization

Compared to weeding, harvesting leads to much more complex tasks of detection, classification, and localization. Crops are often partially occluded [85], and misinterpretation of the cutting location of the crop might result in cutting vital parts of the plant and/or damaging the crop [86]. This is still an active field of research, and the best practice appears to be to aim for a combination of detection methods [87-89].

2.2.8 Simulation

Simulation

An essential aspect for effective robot development is the ability to test to high fidelity in simulation environments. [18] provides an excellent survey of simulation tools that allow initial development with little overhead cost. The survey "*concluded that V-REP <now CoppeliaSim> offers a higher number of useful features, such as multiple physics engine, comprehensive robot model library, and the ability of a user to interact with the world during simulation and, most importantly, mesh manipulation and optimization, however it is the most CPU resource-hungry of the simulators.*" Another favorite is the ROS-native Gazebo simulation environment which is used abundantly in (agriculture) robotics projects. In addition to the environments further listed in [18], we also encountered a specifically developed agriculture framework [19], an agriculture emulation framework AgROS [20], the possibility to use Unreal Engine [21] or the content-rich and popular "Farming Simulator" game environment [22]. For further testing towards successful real-world implementations, we see an increasing drive towards "hardware-in-the-loop" or "human-in-the-loop" simulations, where parts of the system are simulated and other parts are real [126, 127].

2.2.9 Manipulation

Grasp selection

Once the location and orientation of the crop has been determined, the robot must decide how to position the end effector. This is a constrained optimization problem where the stem should be cut but no other plant parts should be damaged. Within the field of generic robotics, a best practice we believe is to do grasp selection with a Deep Learning algorithm as well [90-94], Calculation time used to be a challenge, but very fast algorithms are becoming available [95].

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Manipulator: path planning

While weeding end-effectors can usually move in a straight line toward the weed, for crop harvesting there are often severe obstacles such as branches [77, 141] and other unripe or un(der)developed crops. This requires advanced path planning algorithms to avoid those obstacles. The current best practice is to use a randomized or optimizing motion planner as implemented in OMPL which can be used through the package MoveIt in ROS. New motion planning algorithms are still in development, and a very interesting research avenue is to plan motions that purposefully push parts of the obstacles away [31]. Retrieving the crop is yet another challenging motion planning problem, because now a collision-free motion for the manipulator *including the crop* must be found. A best practice example can be found in [96]. In a future version of this document, we should include best practices from other fields of application.

ROS MoveIt

MoveIt [132] is a user-friendly open-source robotics manipulation platform which runs on top of ROS. It leverages ROS software by providing high-level functionalities for robotics manipulation such as collision checking, inverse kinematic algorithms, trajectory processing, etc. To the best of our knowledge, it is one of the most widely used open-source robotics manipulation platforms for developing commercial applications, prototyping designs, and benchmarking algorithms. It has been recommended and used for agricultural robots especially on harvesting robots [7, 28, 41].

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3 Best practices from an organizational point of view

In this chapter, we provide an overview of the *non-technical* best practices to start working on agricultural robotics. The previous chapter listed all of the technical details to create a successful agricultural robot, but how should one get started from an organizational point of view? The suggestions in this chapter are useful for anyone in the agriculture value chain, and are probably most relevant for those interested in the actual development of robot systems.

3.1 Sources of inspiration

When starting from scratch or re-engaging in agriculture robotic development, it is good practice to be 'connected' with simultaneous developments and to have access to up-to-date information and involved communities. A good place to start are the high-quality review documents and other overviews that have been produced. We recommend the following sources as point of departure:

- "Scouting the Autonomous Agricultural Machinery Market". [96] This report identifies relevant factors that will influence the development, estimate their importance, understand the biggest uncertainties, and get a feeling of the state of the practice and the state of the art, as well as on how the experts see future developments. Elements of this report will appear in other paragraphs below.
- Multi-Annual Roadmap for Robotics. [97] This document was assembled with the help of a European-wide network of robotics experts and contains a timeline for technological developments. There is a full chapter dedicated to agriculture robotics.
- "Research and development in agricultural robotics: A perspective of digital farming." [1] This paper was used as one of the main sources for the overviews in Chapter 2. It contains inspiring examples and many useful references.

An additional best practice is to get 'connected' by participating in symposia and conferences. A number of such events cater exactly to the needs for agriculture roboticists:

- FIRA [98], every year in December in France.
- ROScon [99], fully focused on ROS.
- International Conference on Agricultural Robotics, Automation and Control [100]

Finally, the best way to stay connected and informed is to be(come) involved in the key online communities where open-source software and best practices are exchanged:

- ROS-Agriculture [101]
- FroboMind [43]
- IEEE Agricultural Robotics and Automation Technical Committee [102]

3.2 Open-source software/platforms/framework

There are a number of widely used open-source software platforms that deserve a more extensive description. We will briefly summarize the usefulness of these platforms for agriculture robotic

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applications, provide pointers to the organizational structure of these platforms, and illustrate the best practices to make use of these platforms.

3.2.1 ROS

The Robot Operating System (ROS) is an open-source, meta-operating system for writing robot software. It provides OS-like features such as hardware abstraction, low-level device control, implementation of commonly used functionality, message-passing between processes, and package management. It also provides a collection of tools, libraries, and conventions for performing different complex and robust robotic tasks across multiple computers/robotics platforms. ROS has become a de facto standard for robot application development.

From the start, ROS was developed and overseen mainly by Willow Garage. From 2013 till now, the primary development of ROS has been taken over by Open Robotics. Over the years, many other organizations/institutions have also made contributions to ROS development as it's an open-source project/framework. The worldwide approval and use of ROS can be attributed to the power and wisdom of the crowd. However, the governance framework in ROS community was not clearly identified earlier on. Therefore, starting from ROS2, in order to broaden participation to accelerate ROS 2 delivery, a Technical Steering Committee (TSC) has been established. TSC is responsible for effective planning, decision making and supervision for the technical direction that the project takes, i.e. determining the project roadmap, developing core tools and libraries, and establishing working groups to focus on important topics.

With regard to management and dissemination, ROS has a "ROS Discourse" which is a place to talk about ROS and ROS related things. There is also a site called "ROS Answers" which is dedicated to answering questions of the ROS community. In addition to these online forums, the following conferences and community meetups are also highly relevant:

- **ROSCon**
  ROSCon is a developers conference, in the model of PyCon and BoostCon. It has occurred every year since 2012 for ROS developers of all levels, beginner to expert, to spend two days learning from and networking with the ROS community. It is a must-attend event to meet world developers and keep abreast of ROS community. There are also national editions of ROSCon such as ROSCon Japan, ROSCon France, and ROSCon Hong Kong.
- **ROS-Industrial Conference**
- **ROS-Industrial Training**
- **ROS-A Community Meeting**

3.2.2 OpenCV, PCL

In addition to ROS as the main robotics framework in use in the best practices of today, a number of other open-source frameworks are in use. For image processing, most often one relies on OpenCV [102-106]. Modern machine learning approaches such as Deep Learning (next paragraph) do not replace OpenCV but work in harmony with it. Another key framework is the Point Cloud Library (PCL) [47-51] which contains algorithms for processing 3D image data.

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3.2.3 MRPT, OMPL, MoveIt, OpenRave

For motion planning, path planning, and grasp planning, there are a number of open-source projects available which are all linked well with ROS and which are being widely used in all robotics applications, such as MRPT for navigation [130], OMPL for robot arm motion planning [131], MoveIt [132] as a wrapper of that for ROS, and OpenRave [133] which is often used for grasp planning.

3.2.4 Deep Learning frameworks and datasets

Recently, Deep Learning took the field of robotics by storm, outperforming all other tools for image (or other data) classification. Although some state of the art agricultural robotic systems do not yet make use of Deep Learning (e.g. [73, 75]), we expect that this will change very quickly. The use of Deep Learning algorithms is clearly considered as a best practice for agriculture robotics [53, 76]. It has already been deployed successfully for various agriculture tasks [55, 56, 78, 110-112].

The robot developer currently has a choice between various Deep Learning frameworks such as Google Tensorflow [107], Caffe [108], or PyTorch [109] and some more. An overview of 40 agriculture robotics projects [76] shows that there is not yet a clear preference for any one of those frameworks.

Deep Learning algorithms are useful only if there is sufficient high-quality data available for training. From an organizational point of view, the best practice is to search for a proven combination of (1) a Deep Learning framework, and (2) an available dataset relevant for the specific application. A point of departure for re-using or creating agriculture-specific datasets is to first assess the most-used presently available datasets, as shown in Fig 4.

No.	Organization/Dataset	Description of dataset	Source
1.	Image-Net Dataset	Images of various plants (trees, vegetables, flowers)	http://image-net.org/explore?wnid=n07707451
2.	ImageNet Large Scale Visual Recognition Challenge (ILSVRC)	Images that allow object localization and detection	http://image-net.org/challenges/LSVRC/2017/#det
3.	University of Arcansas, Plants Dataset	Herbicide injury image database	https://plants.uaex.edu/herbicide/ http://www.uaex.edu/yard-garden/resource-library/diseases/
4.	EPFL, Plant Village Dataset	Images of various crops and their diseases	https://www.plantvillage.org/en/crops
5.	Leafsnap Dataset	Leaves from 185 tree species from the Northeastern United States.	http://leafsnap.com/dataset/
6.	LifeCLEF Dataset	Identity, geographic distribution and uses of plants	http://www.imageclef.org/2014/lifeclef/plant
7.	PASCAL Visual Object Classes Dataset	Images of various animals (birds, cats, cows, dogs, horses, sheep etc.)	http://host.robots.ox.ac.uk/pascal/VOC/
8.	Africa Soil Information Service (AFSIS) dataset	Continent-wide digital soil maps for sub-Saharan Africa	http://africasoils.net/services/data/
9.	UC Merced Land Use Dataset	A 21 class land use image dataset	http://vision.ucmerced.edu/datasets/landuse.html
10.	MalayaKew Dataset	Scan-like images of leaves from 44 species classes.	http://web.fsktm.um.edu.my/~cschan/downloads_MKLeaf_dataset.html
11.	Crop/Weed Field Image Dataset	Field images, vegetation segmentation masks and crop/weed plant type annotations.	https://github.com/cwfid/dataset https://pdfs.semanticscholar.org/58a0/9b1351ddb447e6abdede7233a4794d538155.pdf
12.	University of Bonn Photogrammetry, IGG	Sugar beets dataset for plant classification as well as localization and mapping.	http://www.ipb.uni-bonn.de/data/
13.	Flavia leaf dataset	Leaf images of 32 plants.	http://flavia.sourceforge.net/
14.	Syngenta Crop Challenge 2017	2,267 of corn hybrids in 2,122 of locations between 2008 and 2016, together with weather and soil conditions	https://www.ideaconnection.com/syngenta-crop-challenge/challenge.php

Fig 4: A list of publicly-available datasets related to agriculture [76]

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3.2.5 Best practice regarding open-source software licensing

As we have shown in the previous sections, the best practice examples typically include multiple (Free) Open Source Software (FOSS) packages. Although the internet has been running for decades on (F)OSS, with Linux being the primary example, only recently robotics companies have started to embrace (F)OSS. The fast access to state-of-the-art algorithms and collaborative (hence cheaper) developments outweigh the common not-invented-here attitude. Making use of (F)OSS for commercial robotic systems requires proper assessment of the software licences, for which we have collected the best practices. A first yet quite complete overview on licensing issues can be found on dedicated websites [113-115]

Importantly, a common misunderstanding about the "business friendliness" of open-source software licenses must be corrected [116]. Although *some* licenses, such as (L)GPL [140] live up to their difficult reputation that any new software also must be released as FOSS, this is not true for most licenses that are used for the recommended frameworks such as ROS. Most often, ROS packages are released under Apache 2.0, BSD, or MIT licenses [113] which *allow use of the free open-source software inside closed commercial software products.*

The recommended best practice before commencing agriculture robot product development is to conduct a thorough licensing trace to ensure that there are no hidden liabilities. Note that software packages *without* a license are more of a liability than those with a license, because the authors formally still have all the rights, even if they make their source code publicly available.

3.3 Standards

From [96] we copy the most well-known standards for agricultural robotics. Adhering to these standards and contributing to their development is considered as best (future-proof) practice.

The most well-known standardization efforts are the following:

• Machine-to-Machine Communications: The communications standard ISOBUS (ISO standard 11783) [35] is for standardizing farm equipment that creates and handles farm data. The ISO standard 11783 defines serial control and communications data networks for tractors and agricultural machinery. In order to achieve a large degree of autonomy, data produced by agricultural vehicles must be processed and reasoning needs to be performed. Such data might first be sent to the cloud infrastructure of the respective manufacturer before it is then shared between different clouds through standardized interfaces, semantics and data structures.

• SAE J3016: Taxonomy and Definitions for Terms Related to Automate Driving [117] defines terminology around automated driving such as automation levels.

• UL4600 – Standard for Safety for The Evaluation of Autonomous Products [118] provides a set of normative requirements on how to build a proper safety case for autonomous systems. The scope of this standard is mostly on autonomous driving with a focus on what things need to be assured. The standard is scheduled to be released in 2020.

• SOTIF – Safety of the Intended Functionality [119] deals with assuring the absence of unreasonable risk due to hazards resulting from functional insufficiencies of the intended functionality or from reasonably foreseeable misuse by persons. Practically, this refers to creating sufficient situational awareness and is targeted at finding problems induced by the incapability of sensors and sensor

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fusion to properly determine relevant properties of the environment. SOTIF is a very important standard for complex decision logic relying on complex situational awareness. As of its 2019 release, it deals only with automation levels L1 and L2 (according to SAE J3016 automation scale) explicitly, but the working group is currently extending the standard up to level 5 (highest level of driving automation).

3.4 Legal issues

Sources such as [96] indicate that currently, there is no comprehensive legal framework for the use of (semi/full) autonomous robots in agriculture. Safety, liability, privacy, and data management issues still need to be resolved. This document does not serve to solve these issues. Instead, we provide an overview of how the best practice examples in industry currently operate with agriculture robotics, given the current legal vacuum. In a future version of this document, we might expand on the following themes related to these legal issues:

- Maintaining human supervision
- Human robot collaboration (master-slave trucks)
- Confining the operational spaces for the robots
- Analyzing whether there are already agreements with insurance companies?
- Analyzing the tendency to outsource liability to the supplier?

3.5 Social aspects

Legal issues are not the only non-technical considerations that may hamper the widespread adoption of agriculture robotics. Devitt [120] analysed the social aspects that influence initial adoption and sustained use of robotics in agricultural enterprises. Although we are looking for best practices, the paper by Devitt provides the opposite; the cognitive factors that may lead to the lack of adoption of robotic and autonomous systems in agriculture. The main reasons for not adopting driverless tractors, agricultural crop picking robots, and UAV's are: i) inability to generate trust; ii) loss of farming knowledge; and iii) reduced social cognition. Although no concrete best practices are provided, we conclude that implementation success is highest if the robotic system performs a limited, well defined task, where all robot decisions are easy to interpret, and with a clear economic benefit.

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4. Conclusion and Future work

4.2 Conclusion

The purpose of this document is to provide an overview of the state of the art of agriculture robotics, with a focus on open-source best practices. The overall conclusion is that the best practice, as a basis for future open agriculture robots, contains the following elements (not all are needed, depending on the exact application):

- A commercial, open-source ready mobile platform
- A commercial delta-robot or 6-DoF serial manipulator
- A custom application-specific end-effector
- Low-level communication adherence to ISO standard 11783 (ISOBUS)
- ROS as the main software framework, OpenCV and PCL as additional frameworks
- A combination of GNSS, IMU, LiDAR, and RGB-D sensors
- SLAM and path planning algorithms for navigation
- Deep Learning for crop/weed classification
- Manipulator motion and grasp planning algorithms

The references section contains more than 100 literature sources with details about each of these elements.

4.2 Future work: ROS-Agriculture Europe

One of the identified topics for future work regarding the establishment of frameworks for software sharing and re-use would be to further apply the initial best practices more comprehensively in ROS-Agriculture Europe. Covering a great deal of wide-ranging information in agriculture robotics, we believe this deliverable should constitute clear objectives and guidelines for ROS-Agriculture Europe. The current ROS-Agriculture Europe Community has already been built and established on a small scale in line with the aforementioned element in the conclusion section, i.e. ROS as the main software framework.

We have monthly community meetings since January, 2020. Up till now, on the technical side, what has been started and set up in ROS-A Europe are the dataset working group, the simulation working group, and some initial pilot projects.

Dataset working group:

One of primary objectives of this working group is to establish an agricultural-specific common/standard annotation for datasets. We have broken down this goal into several actionable steps, i.e. (1) create a centralized index of all the available agriculture datasets (2) list the format of the annotations and annotation tools which have been used and (3) gather a collection of relevant publications [123].

As mentioned in Section 3.2.3, "deep learning algorithms are useful only if there is sufficient high-quality data available for training", however, collecting real data is tedious and time-consuming. This leads to the creation of another working group: the Simulation working group.

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Simulation working group:

The main advantage of using simulation is to accelerate development of intellectual property. If the simulation is fairly photo-realistic, we could transfer simulated images to real-world images or reduce the simulation-to-reality gap. Synthetic datasets could play an important role for testing machine learning algorithms. Therefore, we have realized the necessity of having a simulation setup which is representative for real world agriculture. One of our small pilot projects, as a proof of concept, is to use FarmSim19 [22] to tele-operate a vehicle using ROS.

On the other hand, in terms of the establishment of governance framework, ROS-A Europe is still in the conception and initiation phase. At the current stage, we agree that clear governance structure/ consortium should be a natural progression rather than an objective imposed forcibly. However, it is always nice to envision the future and keep long-term goals in mind, so we have touched upon the pros and cons of having a consortium based on the ROS-Industrial experience in several meetings. Based on the experience from other partners, we consider the Zephr project [134] as the best practice for governance structure. Although the Zephyr project is not pertinent to agricultural robotics, the governance framework is a mechanism for management applied in any organizations/ communities.

Zephyr project

The following texts were mostly taken from [134]:

"Zephyr was initially developed by Wind River Systems but has become a project of the Linux Foundation. The project is composed of two governing groups: administrative and technical. The administrative leaders meet in a Governing Board that approves the direction and initiatives for the project. The technical leadership consists of subsystem maintainers. The Technical Steering Committee (TSC) functions as a bridge between these groups. The TSC appoints a chair who represents the interests of the TSC on the Governing Board and also works with the TSC to find solutions per the direction of Governing Board.

The governing board chooses policies, articulates strategy and provides guidance to the technical steering committee. The technical steering committee serves as highest technical decision body consisting of project maintainers. It sets the technical direction for the project and coordinates cross-community collaboration. Each member organization provides an administrative representative to the project's Governing Board, and a technical representative to the Technical Steering Committee.

In choosing maintainers from the community of project developers, the TSC evaluates the needs of the project as a whole and the subsystem or component, taking into account the active participation of the individual. This results in a system of governance that relies on merit and trust as well as participation and transparency."

Even though we are currently at an early-stage of development, we strongly believe that, given the reinforcement by this deliverable, we will be able to coordinate with other partners and provide an open software platform with much higher level of reusability and robustness for the Agri-food robotics.

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