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Active perception fruit harvesting robots — A systematic review

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Abstract This paper studies the state-of-the-art of active perception solutions for manipulation in agriculture and suggests a possible architecture for an active perception system for harvesting in agriculture. Research and developing robots for agricultural context is a challenge, particularly for harvesting and pruning context applications. These applications normally consider mobile manipulators and their cognitive part has many challenges. Active perception systems look reasonable approach for fruit assessment robustly and economically. This systematic literature review focus in the topic of active perception for fruits harvesting robots. The search was performed in five different databases. The search resumed into 1034 publications from which only 195 publications where considered for inclusion in this review after analysis. We conclude that the most of researches are mainly about fruit detection and segmentation in two-dimensional space using evenly classic computer vision strategies and deep learning models. For harvesting, multiple viewpoint and visual servoing are the most commonly used strategies. The research of these last topics does not look robust yet, and require further analysis and improvements for better results on fruit harvesting.

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1 Introduction

Agriculture is a critical sector of the global economy. This activity has been adapted for years to fulfil the needs of the world's population, which has duplicated in the last 50 years [1]. Several studies predict the world population's continued growth, expecting to reach nine billion people by the year 2050, a 60% increase [2, 3]. Further, the prediction indicates an increment of people living in urban areas and a decrease in the ratio between working people and retired people [2]. Besides, there has been a substantial decrease in human resources for agricultural labour [4, 5]. This data indicates that the world's agriculture productivity must increase sustainably and more independent of handcraft work with the automatisation and optimisation of agricultural tasks. The technology was introduced to agriculture more than one century ago, with the first tractor presented in 1913. Nowadays, mechanical technology has had a considerable evolution, with a considerable amount of commercial technology available [6]. This evolution increased agricultural productivity and reduced the necessary amount of human labour in agriculture. However, this may not be enough to sustain the world's demand for future years. There are several studies performed since the 1990s to improve production efficiency [7], which originated the concept of "precision agriculture", a farm management notion based on the observation, measurement, and actuation to the variability in the crops, to optimise the returns while preserving resources.

The strategic European research agenda for robotics [8] states that robotic platforms will improve agriculture efficiency. Despite the increase of this area in the research domain [9], few commercial solutions are available [10]. Multiple works applied automation solutions for different agricultural tasks such as planting, harvesting, monitoring, spraying, and pruning [11–15]. For all of these processes, autonomous robot navigation is essential. This step consists of four requirements: localisation, mapping, motion control, and path planning [10, 16, 17].

To perform their tasks, such as localising themselves, harvesting, or pruning, people (and animals) always control their eyes and body actively, changing their pose and other intrinsic variables (as the field of view of the eyes) [18], to acquire the most available information of the environment. This information usually allows them to percept obstacles and free space for navigation and perceiving the best options to manipulate and grasp objects. On the other hand, in robotics, sensors, such as cameras or Light Detection and Rangings (LiDARs), are usually carefully placed in standing poses with fixed parameters [10]. The chosen poses and setting parameters for these sensors determine the robots' perception capability and their availability to recognise obstacles and estimate their dimensions.

From the literature we see a considerable advantage in using sensors actively in robotics [19]. Similarly to the way animals use their eyes, robots may adjust the sensors' pose to focus the computational resources on the aimed tasks [20]. Active perception allows the robots to change, actively, the distance and the orientation to the observed objects [21, 22], obtain multiple viewpoints [23–25], and others. Therefore, it allows the robots to gather the world's most relevant information and focus their computational resources on where it is needed. The implementation of active perception systems aware of the goal and the data interpretation demands the implementation of intelligent algorithms. These algorithms should select the best actions to move the robot towards the goal or task while controlling the different sensors and actuators for information-seeking and data augmentations, as made by Morrison et al. [26].

Active sensing systems have been explored in in industrial area [27]. However, they reveal more useful in unstructured environments [28], such as for precision agriculture's tasks [13, 29–33] (harvesting, *in-situ* monitoring or pruning).

Harvesting robots have several issues on detecting all fruits in the trees and catching them, due to occlusion of the fruit or the harvesting point. Selective harvesting also delivers to the producer additional advantages to optimise the crops quality and quantity, harvesting the fruit in the best maturity stage or avoiding to join bad quality fruits with healthier ones. Active perception systems develop strategies to allow dynamic readjustment of the sensor to improve the perception of fruits, trees and fruits properties.

1.1 Rationale

An overview of the literature about the topic of harvesting robots in the agricultural context reports that most of the publications in the subject are mainly using passive perception systems (even when using active sensors as LiDARs [34]). Although, most of the works are notably the first experiments and reports strategies to detect fruits in natural conditions [35–37]. The most complete works, considering partially or fully active perception approaches [23, 24, 32, 33, 38], seems to be more reliable and smarter under harvesting tasks.

Other reviews report to detection and segmentation algorithms to detect fruits in natural conditions [39–41]. Still, none of them assess active perception systems in agriculture for fruits harvesting. Because the fully active perception systems are rare in the literature, this systematic review assesses the gathered publications as part of a fully active perception system for harvesting fruits. Besides, this review also assesses the trends in the literature in the scope of the most common sensors and detection and segmentation strategies.

1.2 Systematic review objectives

The present systematic review assesses the literature about the application of active perception for harvesting robots. This research aims to understand:

- the main strategies used by the authors to detect the fruits under natural conditions;
- how the authors are overcoming the problem of occluded fruits and stems;
- what are the main strategies to harvest the fruits;
- what are the used sensors for detecting the fruits and the tree;
- how can the robots improve their knowledge about the scene.

Framing this research in the Population – Intervention – Comparision – Outcome – Context (PICOC) framework [42]:

Population: harvesting robots
Intervention: fruit detection, segmentation and harvesting using active perception
Comparison: *not applicable for the current study*
Outcome: A set of different and cascade algorithms able to perceive the environment and control the robot with the goal of acquiring information about the environment and actively detecting the most important key points for successfully harvesting the ripe fruits.
Context: For this research, it is mainly considered the primary publications of robots in the agricultural context.

As may be identified by the stated objectives, this review does not assess the harvesting tools but only the harvesting strategies within harvesting robotic components.

The following part of this manuscript is structured as: section 2 details the adopted researching strategy, and section 3 introduces and contextualises the topic of active perception, and formalises the problem to be approached; section 4 attempts to follow this architecture and highlights the most relevant work in each topic; section 5 analyses the performed review, discusses the results, states some gaps and the future work on the topic; finally, section 6 summarises the main conclusions.

2 Methods

There are different strategies to perform literature reviews. Systematic reviews are the most accepted ones because they assure the quality and full and organised analysis of all the publications on indexed platforms. Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) is the most common standard [43] for reporting these literature reviews. Therefore, this section will explore this standard and state the research and analysis strategy for this study.

2.1 Search strategy and selection and data collection processes

After a full inquiry of publications in scientific databases, thousands of articles should be reported for review. The stating of inclusion and exclusion criteria support this process and complies with a fair assessment of the publications. To keep the current review process, we used the online tool Parsifal [44] that allow systematising the whole research process: a protocol definition, duplication removal and screening, quality assessment and data extraction.

For this systematic review, we only considered the primary indexed publications about fruit harvesting robots between the period of 2016 and the inquiry day (21st of September of 2021). After removal of the duplicated publications, the remained publications were assessed and excluded based on the following criteria:

- The publication does not refer to a fruit harvesting robot in agriculture.
- The publication is not written in English.
- The publication is older than 2016.

– The publication is not a primary manuscript[1].

After screening the different publications, we fully read the manuscripts. Each read publication is quality assessed to validate whether the publication complies with the aims of the current work. Each question is evaluated into three parameters: Yes (1.0), Partially (0.5), and No (0.0). All the publications that did not sum up punctuation higher or equal 3.0 were deleted and not used for data extraction. For the current work, we considered the following questions for quality assessment:

– Does the paper refer to the sensory system?
– The work uses active perception?
– The authors used scene information increasing algorithm?
– The authors used detection, segmentation or detection and segmentation?
– The work is applied in agriculture and harvesting robots?
– The authors applied their work into a real scenario[2]?

Finally, in the data extraction phase, we gathered:

– fruits for which the work is applied;
– used sensory system;
– fruit Detection and Segmentation (DaS) strategy; and,
– additional active perception algorithms.

As could be concluded in the following sections of this manuscript, most of the publications report only to DaS. Therefore, unfortunately, this review should focus partially on this topic.

This review only considered the publications gathered from databases, and we performed the last full inquiry to the databases on 21st of September of 2021. The inquiry was made on five databases: ACM Digital Libray [45], EI Compendex [46], IEEE Digital Library [47], ISI Web of Science [48], Scopus [49]. The inquiry to the databases used the base string:

```
(robot*) AND (agricultur* OR harvest* OR open-field OR prun*) AND ("active
     perception" OR "active sensing" OR "active vision" OR "viewpoint" OR detect
     OR segment* OR "visual servoing") AND (fruit)
```

The term `robot` attempts to catch all the publications that contain the words robot, robots, robotic or robotics. In the population for this work, we set the interest in harvesting robots, so the terms `agricultur* OR harvest* OR open-field OR prun*)` catches the publications of robots for agriculture, harvesting or pruning, and robots designed to labour in open-field environments. Finally, we set a particular interest (intervention) on robots that use active perception for harvesting fruits. Therefore, the terms `("active perception" OR "active sensing" OR "active vision" OR viewpoint OR detect* OR segment* OR "visual servoing") AND (fruit)` catches this type of manuscripts and all the manuscripts about detection and segmentation. In the scope of this search, active sensing, active perception, and active vision are being understood as synonyms, and viewpoint (*aka* viewpoint selection) is a possible component of the active perception.

[1] We consider a primary manuscript whole the works that refer to an experiment publication, as a benchmark, that reports how the experiment was performed or a presentation of a new algorithm or method in the agricultural context for directly applied for fruit harvesting.

[2] The real-world scenarios are the open-field farms and agricultural environments and the greenhouses. Out of these scenarios are the simulations or tests made in testbeds at the laboratory.

2.2 Search results

The search by the base key string on the different databases reported 1034 publications between the stated period (2016–2021). Figure 1 reports the distribution ratio of the publications between the different databases. All the sources answered an even number of publications, except the IEEE Digital Library that is shorter and reported a lower number of results. On the other side, the Scopus library seems to be a more general database and reports more manuscripts from different publishers. Also, ISI Web of Science and EI Compendex are not publisher-specific databases, but they have more specific indexation criteria and can be scope specific (the case of EI Compendex).

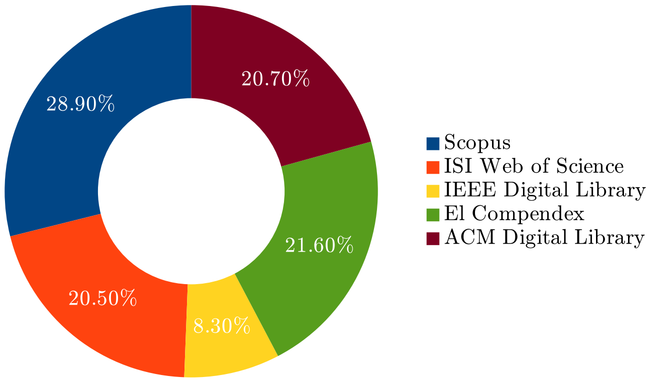

Fig. 1 Ratio of publications per database for the inquired search key

The reorganisation of the results by year, reports that the current review is surveying a hot point in its scientific scope (fig. 2). The results since 2016 show the increasing of the number of publications per year. The year of 2021 only reports a slight reduction of interest, but should be noticed that only the period until 21st of September is considered.

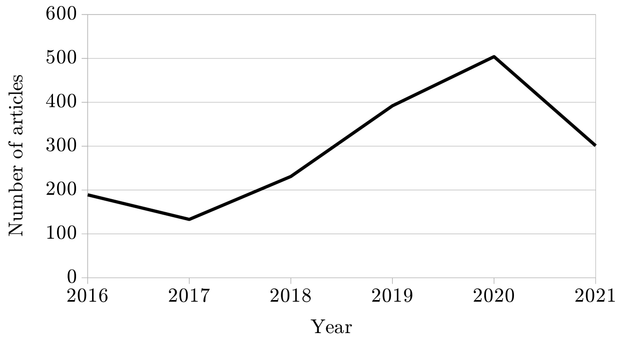

Fig. 2 Evolution of the number of publications per year for the inquired search key

Figure 3 reports the inclusion and exclusion process of publications for this systematic review, following the PRISMA standard's [43] flow diagram. After the identification of all the candidate publications, we matched them and deleted all the duplicates. The screening focused on the reading of the title, abstract and figures of the articles to identify the interest of the publications. The publications were removed by the exclusion criteria previously defined. The full reading of the publications allow to evaluate the quality of the different manuscripts and evaluate whether they can answer the questions which we are looking. Between the 1034 collected publications, just 195 publications were considered for inclusion in this review.

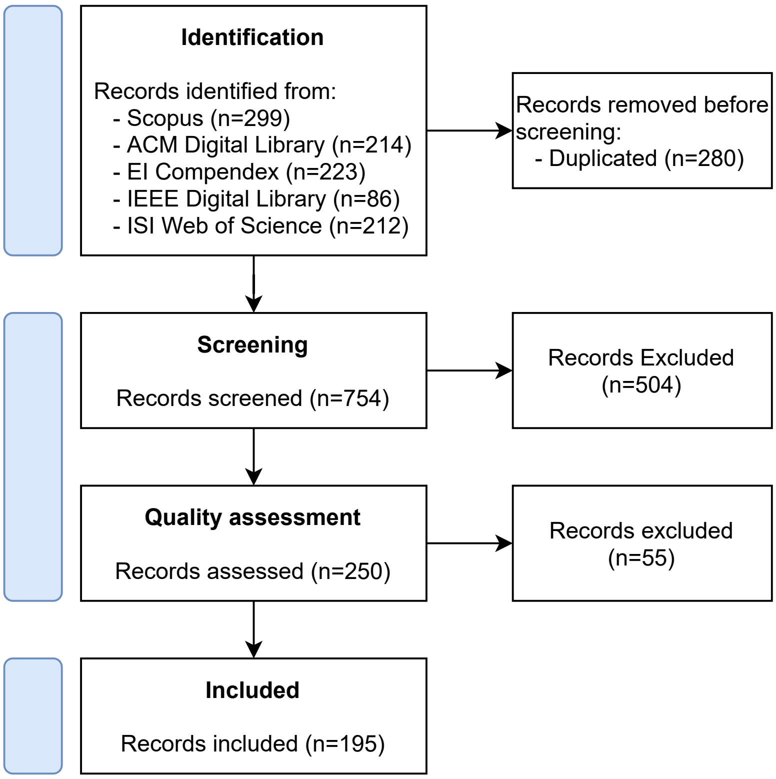

Fig. 3 PRISMA flow diagram for the current systematic review

3 Active Perception and Harvesting

The current section attempts to frame the reader in the definition of active perception, before moving on to the applications of active perception for fruits harvesting in agriculture.

3.1 Active Perception

Bajcsy [19] made the first formal approach to **active perception** in 1988. According to her, active perception (or active sensing [19]) is not restricted to the use of active sensors (like LiDAR, radar or sonar). Instead, she suggests that even passive sensors (e.g., cameras) may be used since they are applied in an active fashion. So, Bajcsy [19] stated active perception as a control problem applied to the data acquisition process. The control law should adjust the sensing apparatus according to the goal or the task and the current state of the data interpretation. A full active perception pipeline should include reasoning, decision-making and control steps [19].

At the time, the number of contributions to active sensing was reduced [19]. Because of that, Bajcsy [19] intended to formalise the concept, promote the contributions to the topic, and state the differences to active vision [50–53].

For Aloimonos et al. [50], not all active vision applications are active perception systems. Active vision is a standalone vision-based system that can only move the sensors [50]. An example of an active vision system is the pan and tilt (gaze control mechanisms) that makes the cameras move and change their position. If the movement of the camera is not aware of the environment and moves concerning its acknowledge of it, then this system is not an active sensing system [51]. However, Bajcsy [19] and Aloimonos et al. [50] both agreed that active vision may be useful for active perception applications.

A broad review in 2011, concerning the state-of-the-art of active perception in the past 15 years, concludes that active perception is the active application of vision sensors to gather and search for information in the environment [54]. At this age, Chen et al. [54] defined active perception as the ability to determine the pose and the configuration for the visual sensor cleverly, which implies the planning of multiple viewpoints to reconstruct the scene due to the limited field of view of the visual sensors. Using infinite viewpoints improves the reconstruction quality of the scene to perform tasks but increases the task time. Therefore, the robot should can to optimise the number of viewpoints to improve the task time [54, 55].

The reinforcement of the definition of active vision applied to active perception is made by Gualtieri et al. [55]. They also look for the active perception problem in the perspective of *where to look*. The robot should can to set different viewpoints during the plan strategy to increase their knowledge about the scene.

Vision systems are frequently actively controlled to track objects or adjust to environmental demands, such as the white balance or the camera's sensor's sensibility. In these cases, the sensor is being reactive and adjusting to predefined stimuli with previously configured responses. An active vision system in the scope of active perception hopes that the system has some knowledge to answer the stimulus smartly, choosing the sensors' best configuration to increase the perception. The sensor's behaviours may imply the sensor's repositioning to search for stimulus, change the view to increase the perception of a stimulus, among others. Commonly, to better manage the robot resources, stimuli are captured and processed by attention mechanisms [56], which respond as a filter that decides how sensory signals should be processed. So, in an active vision system, in the scope of active perception, the visual sensor has to move to a purposeful, visual perception pose, i.e., the system is purposeful to answer or search for stimuli.

The last formal definition of active perception was published in 2018. Bajcsy et al. revisited the topic and reformulated the initial concept due to the evolution of the state-of-the-art [20]. They specify the required components for any artificial agent [20] and affirm:

> "An agent is an active perceiver if it knows why it wishes to sense, and then chooses what to perceive, and determines how; when and where to achieve that perception." [20]

So according to Bajcsy et al. [20], an artificial agent, to achieve perception, should accomplish the pentuple of: *why*, *what*, *how*, *when* and *where*. The *why* concerns the motive. Based on the expectations and the current state, the agent chooses the next action to generate the new states. The new generated action maybe even remaining stopped. This evaluation would rely on any form of inductive inference. The *what* focus on the subset of the world (e.g. an object) which the observer is looking for. This process may be referred to as Scene Selection. The *how* is the set of actions that precede the observed actions. These preceding actions may be: (i) mechanical alignment, i.e., the positioning of the agent within the proper sensory field to observe the selected scene; (ii) sensory alignment, i.e., setting of the sensory apparatus and geometry for the best sensing of the scene (this may imply internal configuration of the apparatus, e.g. focus, light level, between other); (iii) priming, i.e., adaptation of the agent's perception mechanism to be most receptive for interpretation of the sensing results. The *when* concerns the temporal selection of expectation which validates when an expectation is valid and for how long it is valid. Finally, the *where* respects the viewpoint selection that chooses the best viewpoint and modality for each expectation.

In summary, an active perception system is a system that is purposive and information-seek [57] and involves the control of the sensor apparatus in the manner to fit the tasks, even that it implies remaining quiet.

3.2 Active Perception in harvesting

Harvesting is a fundamental task in agriculture. Robotic harvesting considers, typically, a robotic manipulator on the top of a mobile platform, equipped with specific end-effector tools and sensors. To be cost-effective is required to limit the use of sensors on the robot. Typically, the robotic platform considers three kinds of sensors [10, 58] – cameras, LiDARs and Global Navigation Satellite Systems (GNSSs) - which are mainly considered for localisation and mapping [58], and safety. On harvesting operations, these LiDARs and cameras may be considered for the first rough detection of the region of interest for harvesting, i.e., to detect the tree's fruits. However, these sensors do not supply the detailed and accurate information required for a reliable harvesting operation because the stem or the fruit may be occluded by the leaves or other fruits.

Reaching detailed and accurate information requires at least one sensor (e.g. camera or LiDAR) installed on the harvesting end-effector tool to complement the generic mobile robotics sensors data. So, the system requires procedures that:

1. Roughly attends the Region of Interest (RoI), i.e., fruits and stems, using the sensors of the mobile platform and the manipulator, to capture the attention of the robot for possible RoI, i.e., an **Attention Mechanism**;

2. For the detected RoI, it selects one of them and processes its information data, i.e. **Fixation Mechanism**;
3. From the rough detection – first step – move the robotic arm and its attached sensors to a generic approachable viewpoint;
4. Detects and segments the fruits and the stem for successful mapping and localisation of the RoI, i.e., **DaS**.
5. Moves the arm in well-defined motion to increase the information of the environment (3D mapping) – to obtain information of cutting point –, **Data augmentation** and **Viewpoint selection**;
6. Detects the stem of the selected fruit and chooses the best reachable cutting point,
7. Plans the best path to reach the cutting point, ensuring the observability of the cutting point in the stem, i.e., **Motion Planning**;
8. Generates the trajectory and controls the robot to the cutting point, involving online replanning of the path, considering the accurate available information of the cutting point in the stem, i.e., **Motion Plan and Control**.

These procedures result from analysing the future work and difficulties of the different reviewed manuscripts and framing them with the proposal of Bajcsy et al. [20] to create smarter systems. So, from these procedures emerge the need for active perception systems. These systems provide mechanisms to acquire smartly new information about RoI, look at it from different perspectives, and rebuild and aggregate all the available information. The role of active perception is to perform the smart selection algorithms, choosing the best approaches to acquire new data without overhead the system: attention, fixation, viewpoint selection and data augmentation mechanisms. These algorithms are complemented by others that control the robot (motion planning and control) or process the acquired data (DaS).

The development of the cognitive part for harvesting and pruning faces four main problems: (i) large variability of illumination conditions and target format; (ii) occlusions of the RoI; (iii) not stable or static RoI; and (iii) requirement of high manoeuvrability for end-effector tools. Find the solution for these issues may be relevant for the agricultural contexts.

4 Harvesting platform architecture

Active perception systems, as concluded in Section 3, imply the implementation of cognitive algorithms that allows a smart selection of actions to actively control the different sensors and actuators for information-seeking and data augmentation. Therefore, considering these requirements and the needed functions to harvest fruits, as established in the previous section, the fig. 5 proposes a generic framework for a mobile harvesting manipulator (a manipulator on the top of a mobile platform – fig. 4).

Through a quick and simplified algorithm, the attention mechanism searches for the main features of the RoI, i.e., fruits. In this case, these features may be the colour, looking for the red bunches of grapes, or the shape, looking for groups of circles or triangles (the generic shape of a bunch of grapes). Once detected a possible bunch of grapes, the manipulator is aligned with the RoI, which allows the perception of the RoI, i.e. a generic viewpoint that looks to the RoI. A DaS

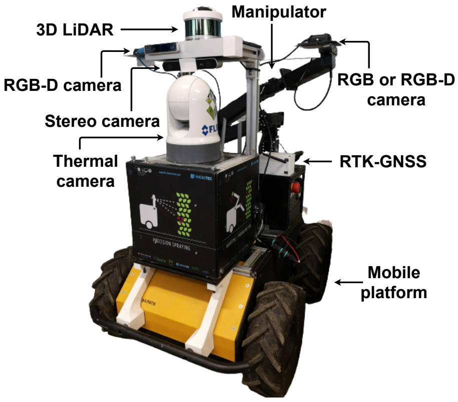

Fig. 4 Example of an agricultural robot for fruits harvesting from INESC TEC (see `http://agrob.inesctec.pt`)

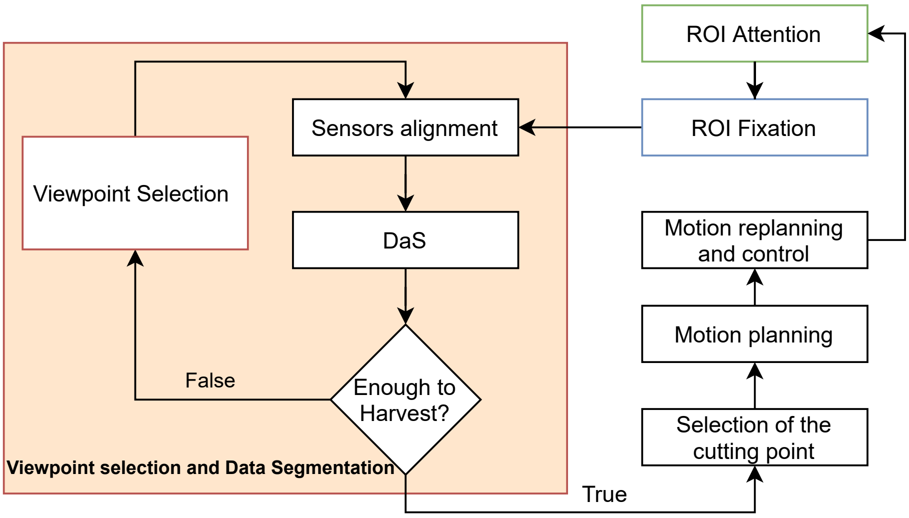

Fig. 5 Diagram of an active perception system's framework applied to harvest bunches of grapes in vineyards.

algorithm then captures the best perspective data and processes it to verify the attended RoI is a real RoI. Due to occlusions, the available information may not be enough to measure the shape and the size of the bunch of grapes and computes its position, observe the stem or the cutting point in the stem. The viewpoint selection algorithm is responsible for validating this information and selecting the next viewpoint to ensure the acquisition of the most available and relevant information to complement it. These algorithms that allow a smart data augmentation of the environment and quick selection of the RoI are the functions required for active perception systems [20, 56]. However, these implementations can be even expanded for additional algorithms that intend to track the RoI until harvesting, i.e., the motion planning and control algorithms. The motion planning, in this framework, is divided into two steps: a quick offline path planning algorithm [59, 60] is implemented, and then, while pursuing the planned path, the planned path is redefined with the improved acquired data; typically, this planning is ensured by online planning algorithms [61].

4.1 Sensors

Besides the expectations of Bajcsy [19] about the use of sensors in active perception, state-of-the-art is still focused on the applications of active vision systems applied to active perception (Fig. 6 and table 1), i.e., the active control of cameras to acquire and search data about the RoI cognitively. However, haptic and infrared (IR) sensors and spectrometers (table 1) also urged and seemed relevant to increase the information about the environment, mainly touch-sensitive information such as the roughness or other intrinsic properties of the material being sensed. Although, the complementary information given by the haptic sensors concerning the information provided by cameras [62, 63], for tasks like pruning or harvesting, is only relevant in the nearest of the RoI to correct and validate its position and validate the RoI with additional information, such as roughness.

Between the different used cameras, the Red, Green and Blue (RGB) digital cameras are the most common ones (table 1). This can be due to the very vegetative state of the research in most of the works about harvesting in agriculture, which mostly focus on fruit detection and segmentation. More advanced works for fruit detection, segmentation and localisation are using Red, Green, Blue and Depth (RGB-D) cameras or stereo cameras (usually referred as binocular cameras in the literature, see table 1). Tejada et al. [64] used a IR camera to detect peas. This camera makes the detection robust to other sources of light, but is sensible to the temperature variation and requires a dedicated source light.

Sensors	References
RGB cameras	[23–25, 36, 37, 61, 62, 65–179]
RGB-D cameras	[11, 12, 21, 22, 31, 38, 97, 108, 120, 158, 180–216]
Stereo cameras	[35, 133, 217–233]
Haptic Sensors	[33, 211, 234, 235]
LiDAR	[74, 98, 104, 124, 151, 175]

Table 1 Summary of the used sensors in the different publications

The use of RGB is sometimes associated with the use of Time of Flight (ToF) or LiDAR sensors (table 1). The joint of these kinds of sensors can be used to build low-cost RGB-D sensor to compute the distance between the sensory apparatus and the objects being detected or to build complex and complementary sensing systems to assess and validate the fruits. The LiDAR was also used as a single sensor to detect apples on the trees [34]. The author used the reflectance's index to distinguish the fruits from the leaves and background.

The use of haptic sensors is rare to assess the fruits, but some remarkable progress may guide future developments. The IR sensors are being used as proximity to sense the fruits [211, 235, 236]. Still, the use of spectrometers, besides detecting the fruits, also allow the assessment of their quality and properties [13, 33, 162], promoting selective harvesting.

Figure 6 and table 1 summarises the kind of sensors used to percept fruits. The authors divided their publications using mainly single RGB or RGB-D cameras. As we can conclude later, when the authors use RGB-D sensors, they perform three-dimensional (3D) localisation of fruits usually.

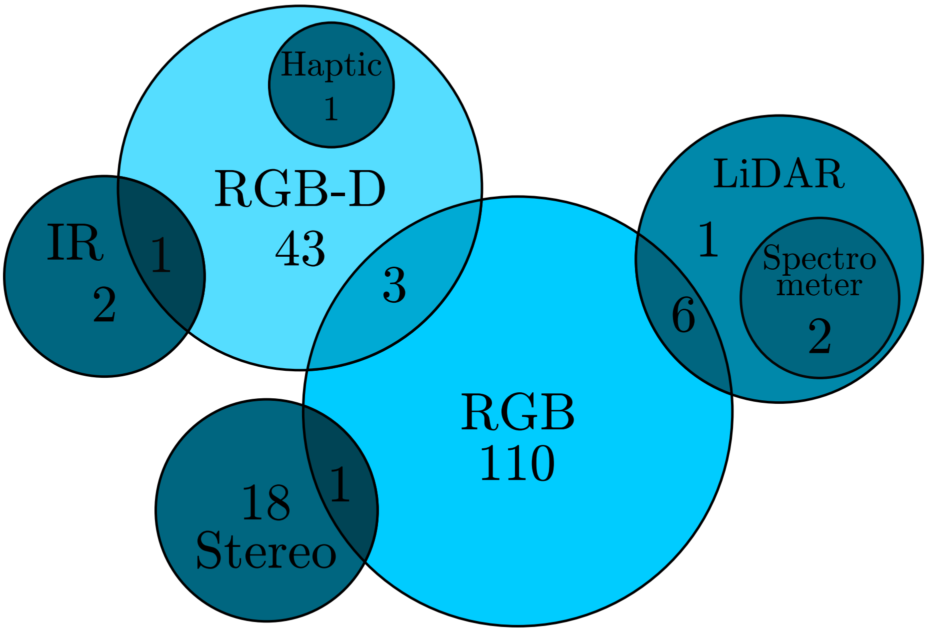

Fig. 6 Sensors used for fruit detection, segmentation, localisation and assessment

4.2 Attention and Fixation Mechanisms

Balkenius and Hulth [56] defined the attention mechanism as a decision mechanism responsible for filtering and deciding how the sensory signals should be processed. In these terms, the attentional mechanisms allow reducing the payload of processing data, processing the only ones who were captured and selected as an RoI. In this study, Balkenius and Hulth [56] stated the attentional mechanism as a robot's action manager and developed three fundamental principles for the attentional control of actions:

1. Attention as action;
2. Selection-for-action; and
3. Deictic reference.

Attention as action states that the attentional mechanisms to percept the target should be seen as the action itself and not as primary sensory processing. This step can also be referred to as attentional shifting. Whenever one or more are attended, they need to be selected for action. Balkenius and Hulth [56] also refers to this step as attentional fixation (i.e. the fixation mechanism). This fixation mechanism allows the system to focus only on the selected stimuli and ignore new stimuli, allowing for tracking the attended stimuli over time. Finally, the detected stimuli are generated by deictic references, i.e., the cues that allow perceiving the target without a full target object model. These cues may be characterised as internal or external; an internal cue is provided by the target, such as its dominant colour. An external cue is provided by an external factor such as a sound or a quick movement.

The attentional mechanisms may be modelled into two conditions: (i) bottom-up (how the RoI in the scene looks in consideration to its environment), and (ii) top-down (how the RoI in the scene relates to our goals) [56]. A combination of these two strategies for RoI detection may also be interesting when well-balanced [237].

The recent literature about the implementation of attentional shifting mechanisms for fruits detection is evenly divided between the use of Deep Learning (DL) (table 2 and Fig. 7) and classic computer vision algorithms (table 2 and Fig. 7), as colour features or morphological operators. Machine learning techniques (like Support Vector Machine (SVM) [150], Partial Least Square (PLS) [32, 33], k-means [148, 161] or wavelet [121]) for the detection of the fruits are becoming very frequent on the literature, despite of appearing as a single technique sometimes (table 2 and Fig. 7), they are commonly used with traditional computer vision algorithms (table 2), as colour features (changes in the colour space or colour threshold) or morphological operators. Rarely, the use of machine learning is associate to deep learning models (table 2). For this last case, the detection algorithms are related to cascade problems that intend to improve the post-processing, using for instance algorithms like acpls, SVM, or k-means to segment the detected fruits [193], detect secondary components as branches [199] or as redundancy procedures [129].

DaS strategy	References
Deep Learning	[11, 23, 35–38, 67–69, 71, 72, 84–87, 89–91, 93, 94, 99–102, 105, 109, 112, 113, 116, 117, 119, 120, 124–127, 135, 144, 146, 149, 152–155, 158, 159, 162, 163, 167, 169, 171, 174, 176, 176, 178–180, 182, 185, 195, 198, 200, 202–205, 207, 208, 216, 217, 221, 227, 228, 230–232, 235, 238–241]
Computer Vision	[12, 22, 64, 66, 78, 79, 81, 83, 88, 90, 96–98, 104, 106, 108, 111, 114, 118, 122, 123, 128, 130, 132, 136–138, 140, 142, 143, 151, 157, 158, 170, 175, 181, 188, 190–192, 194, 195, 197, 201, 206, 211, 212, 215, 218, 219, 222–225, 233, 242]
Machine Learning	[25, 31, 33, 62, 82, 110, 133, 148, 172, 229]
Computer Vision and Machine Learning	[65, 70, 74, 92, 95, 107, 121, 131, 139, 141, 142, 145, 147, 150, 160, 161, 164–166, 168, 173, 183, 186, 187, 189, 209, 213–215, 220, 226, 243]
Deep Learning and Machine Learning	[32, 77, 129, 193, 199]

Table 2 Summary of DaS application in the different publications

While most of the computer vision and machine learning algorithms refer to segmentation strategies that almost allow the harvesting of fruits, in the DL strategies, the threshold between the attentional mechanisms and segmentation is easier to define. Usually, in DL it is possible to classify the images, detect objects or segment objects. For the case of attentional mechanisms, the most interesting models are the classification and object detection models because they can compute quickly and are suitable for real-time application. On the other side, segmentation is time-consuming and resources demanding and requires slowing down the system. In the reviewed literature, the most common architectures are for object detection and are Faster Region-Based Convolutional Neural Network (Faster R-CNN), You Only Look Once (YOLO), Single Shot Multibox Detector (SSD) (table 3). YOLO is clearly the most used DL model in the literature, but Faster R-CNN is also getting some expressiveness.

DL algorithms	References
Faster R-CNN	[93, 99, 102, 105, 124, 127, 146, 154, 158, 180, 182, 198, 240, 241]
YOLO	[35, 38, 68, 84, 87, 89, 94, 100, 101, 109, 112, 116, 159, 163, 167, 176, 178, 182, 185, 193, 221]
SSD	[35, 72, 85, 86, 93, 227]

Table 3 Summary of the main used DL models in the different publications

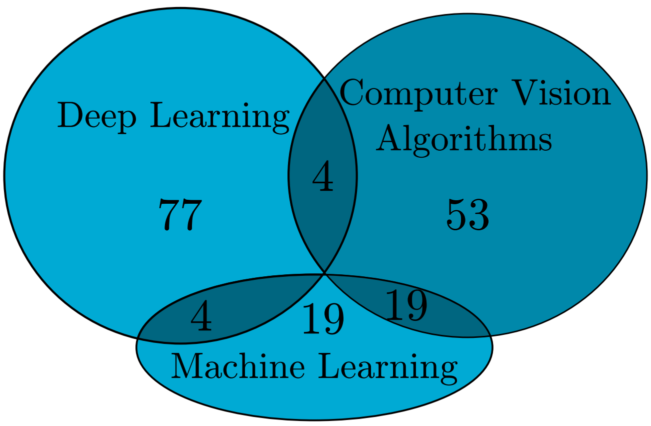

Fig. 7 Overview of the detection on detection and segmentation algorithms on the reviewed literature

The attentionnal shifting mechanisms are broad algorithms that allow to detect several RoIs at once. Therefore, once multiple RoIs can co-exist, and additional fixation mechanism is necessary to limit the hypothesis being considered [244].

In a strawberry greenhouse, [12, 211, 236] implemented the fixation mechanisms in a down-up way, i.e., the robot, due to construction constraints, selects first the lower strawberries to harvest and then the highest ones. This allows the robot to harvest all the strawberries, avoiding damage themselves. Other strategies may be used, such as selecting the nearest fruit or selecting the best confident RoI, i.e., selecting the RoI which has the highest confident rate to be a real fruit [56]. All the illustrated approaches seem plausible, considering the case of grapes harvesting. However, due to the high rate of occluded bunches of grapes in vineyards, the implementation of the highest confident RoI and the nearest ones seems more plausible and robust.

4.3 Viewpoint Selection and Fruits Segmentation

The natural behaviour of trees is to allow the fruits to grow up behind the leaves. By this way, the fruits get protected from the sun radiation and other bad weather conditions, avoiding to get burn or damage. This characteristic of the fruits let them occluded as well the stem. For supporting the harvesting process, active perception methods developed viewpoint selection algorithms to augment the information about the RoI, i.e., the fruit, and measure whether the collected information is sufficient to harvesting the fruit. Additional segmentation strategies are required to detach the RoIs from the background.

4.3.1 RoI Segmentation and Assessment

Before selecting the viewpoint, the system needs to be conscientious about the target, i.e., it needs to answer the question *What to percept?*. Moreover, at each viewpoint, the system should selectively collect the most information of that view, i.e. the available data of the fruit, peduncle, and other potential obstacles.

The collection of information about the fruits is typically assured by data segmentation algorithms that, similarly to the detection algorithms, may follow a classical analysis of the image and sensory data (such as region growing, erosion, dilatation, or other), machine learning algorithms or inferred by DL models. The study of the algorithms for fruits segmentation is not the aim of this publication, but some relevant recent works may be refereed.

The use of computer vision and machine learning techniques are very relevant for fruit segmentation. They have good results, and using state-of-the-art libraries, like OpenCV [245], they are easier to implement. The most common techniques are the use of colour features and threshold, corner and edge detectors as Canny edge detector or Harris corner detection (table 2). However, these methods rarely are helpful in the 3D space. While using classical methods, authors tend to use colour features and k-means or SVM to cluster the fruits pixels by colour or voxelization, based on the same principle (table 2).

The use of DL models is becoming a new trend in the segmentation context, mainly when considering the 3D space. Due to the high amount of data and their profile, the use of DL is easier to implement, and it can extract more and better features than the colour or shape profile. The most common Artificial Neural Network (ANN) for segmentation are Mask Region-Based Convolutional Neural Network (Mask R-CNN) and Detection and Segmentation Artificial Neural Network (DASNet) (table 2).

Between the reviewed publications, the problem of peduncle's identification is addressed by Lehnert et al. [11], Sa et al. [29], Benavides et al. [128], Yoshida

Algorithm or DL model	References
Colour features and threshold	[22, 65, 66, 75, 76, 83, 88, 95, 96, 104, 106, 108, 114, 117, 118, 121, 122, 128, 130–132, 136–138, 140–143, 145, 147, 150, 156, 160, 161, 164, 165, 186–189, 192, 194, 197, 206, 209, 211, 212, 214, 215, 218–220, 223–225, 233, 242, 243]
Circular Hough Transform	[88, 104, 111, 150, 151, 190, 209, 224, 229, 242]
Corner or edge detectors	[83, 97, 108, 132, 137, 160, 173, 210, 224]
colour features and SVM or k-means	[187, 206, 218]
Voxelization	[183, 184]
Mask R-CNN	[69, 90, 113, 120, 125, 152, 153, 162, 169, 203, 207, 232, 239]
DASNet	[195, 200, 202, 205]

Table 4 Summary of the main used strategies for 3D detection of fruits in the different publications

et al. [183], Luo et al. [246]. Sa et al. [29] developed a robot to harvest peppers in greenhouses. The robot used the SVM to identify the pepper's peduncle in a point cloud image of the environment, knowing that the peduncle is always near a pepper. Yoshida et al. [183] built, from the identified tomatoes, a directed acyclic graph to characterise the bunch of tomatoes. Using this graph and the voxalised image, they computed the cutting point position in the peduncle. Benavides et al. [128] followed a geometric and trigonometric approach to compute the stem's location based on the pose and computed size of the detected tomatoes. Lehnert et al. [11] used a lightweight agricultural Deep Convolutional Neural Network (DCNN) to compute and segment the stem's position in a pre-selected RoI.

As exposed in the section 4.1, the increasing of the knowledge about the environment is not only restricted to the best percept the RoI, acquiring more visual data about it. The system can also use other sensory apparatus and algorithms to assess the fruits' quality. Martins et al. [13], Wendel et al. [32], Zhao et al. [33] used a spectrometer to evaluate the quality of the fruits and open future possibilities to assess their health, predicting whether they can be infected with any disease. Additionally, the visual data can be used by complementary algorithms for selective harvesting, providing ripeness classification [65, 108, 118], harvesting the fruits only when they are ready.

4.3.2 Viewpoint selection

Bajcsy et al. [20] characterised the viewpoint in the *where* question of the pentuple (*why*, *what*, *how*, *when* and *where*), and divided it into two components: Agent pose and sensor pose. The agent pose refers to the control and the selection of the next best pose for the agent, i.e., robot or manipulator, to best percept and acquire complementary information about the RoI. Similarly, the sensor pose component refers to the active control of the sensor's pose (in the case of sensors pan and tilt – or similar – capabilities) and intrinsic parameters (focal length, zoom, white balance, between other) to the best percept the RoI. The selection of the viewpoint focus, i.e. RoI, is derived from the result of the fixation mechanism (see section 4.2), and all the viewpoint control, i.e., the changes between viewpoint poses, is supported by the attentional mechanism to allow the tracking of the object without losing it.

The contributions about active viewpoint selection for agriculture issues are not very explored in the literature. However, some contributions for industrial and domestic uses may be relevant [27, 247, 248] and useful for agriculture applications. In the agricultural context, some contributions can still be mentioned. Despite not having a clear selection of viewpoints, Sa et al. [29] developed a scanning strategy for augmenting the information about peppers to be harvested in order to clearly understand the fruit and peduncle position for harvesting using a self-designed gripper. Also, Barth et al. [22] implemented a visual servoing strategy to gather the most information of the plant, performing a full scan of the plant before any harvesting instruction. Although to assure a full model of the plant, this process proves time-consuming and computationally demanding. Jun et al. [38] based on passive 3D-perception to harvest tomatoes. Once detected the tomatoes, they approximate their shape by boxes and compute the Tool Centre Point (TCP) of these boxes. A hand-eye scheme is responsible for guiding the gripper until the fruit. The author concludes by referring that the estimation of the stem location is essential to successful harvesting in real scenes, and reinforcement learning approaches can improve the robot's movement. Visual servoing techniques are broadly used by many authors in the literature to successfully harvest the fruits [21, 22, 64, 103, 123, 133, 177, 228, 235]. These authors only rely on the current information that they have about the scene to guide the robot.

Authors, like Lehnert et al. [11], Arad et al. [194], Wu et al. [206] used a minimum of two viewpoints to assure and observe fruits. Soria et al. [31] developed a true viewpoint selection system. This system chooses the next best viewpoint based on the minimisation of the objective function that *'maximises the distance from the history of past poses, granting a good convergence of the mapping process'* [31]. The solution proposed by Soria et al. is similar to the framework here proposed (fig. 5). However, the authors do not consider the need for attentional systems to roughly detect the fruits, assuming that the sensor is already aligned with the fruits. Instead of fixating the task in a single RoI, the authors also opted first to model all the scene and then choose the fruit to harvest. This is more demanding and requires recovery and tracking systems to track the harvested fruits and search for all the detected and modelled fruits. Viewpoint selection for fruit harvesting and assessment is more challenging to implement than visual servoing, mainly when dynamic computation of viewpoints is considered [23–25]. However, they look more attractive in the literature because they allow gathering multiple perspectives of the fruit and joining them to assess different fruit's properties like maturity classification [108]. Sarabu et al. [185] describes a harvesting strategy using a dual-arm robot and multi-viewpoint approach. One of the arms is responsible for detecting and assessing the fruits using multiple viewpoints. When fruit is detected and selected, the arm selects another viewpoint for the same fruit or other previously detected and send the location and the harvesting strategy to the other arm for harvesting.

Lehnert et al.'s [249] solution, yet not based on viewpoint selection strategy, developed the 3D Move to See (3DMTS) method that allows continuous acquisition of information of the environment. The authors still built their self-made matrix of cameras to acquire multiple perspectives of the scene at once. The quality of each camera is individually rated. Then the manipulator moves through the gradient of the objective function, which computes all cameras' rate. Zapotezny-Anderson and Lehnert [228] presented an improved version of the 3DMTS algorithm called Deep 3D Move to See (Deep-3DMTS). This algorithm intends to increase the perceptibility of the occluded fruits using deep learning. Kurtser and Edan [61] presents disruptive research, presenting a planning algorithm that optimises the harvesting and fruit searching process. The travel salesman paradigm computes, online, the path for the manipulator, optimising a cost function to harvest and gather data. At every sensory pose, the new gathered target poses (poses with potential fruits to harvest) are added to the path, and the next best path is recomputed. The path between the target and sensory poses is computed using an offline algorithm, like Optimal Rapidly-exploring Random Tree (RRT*).

As can be observed, state-of-the-art still focuses on passive perception strategies for agricultural tasks. However, some of the implemented strategies can be transposed to active perception approaches because they are placed in the transition between the two paradigms. So, as performed by Barth et al. [22], many authors chose to consider full models of the scene, even knowing that it is time-consuming and computationally costly. An example of a full model of apple trees to harvest is presented by Kang et al. [195]. They used deep learning to detect and segment the fruits. Then, assuming that a spherical shape can approximate the tomatoes, they used the 3D Spherical Hough Transform (3D-SHT) to compute the apples' pose. The octree designed a 3D model of the apples and trees. Kang et al. [200] used the PointNet model to compute the pose grasp to harvest the apples, using the octree model.

5 Discussion

This systematic review assesses the publications since 2016 for fruits harvesting using active perception. Each fruit and cultivar have their properties and features that condition the harvesting. For instance, an apple can be easily grabbed and pulled off, but grapes' bunches require careful handling of the fruits and be cut by the stem. Table 5 reports the fruits' use cases in the literature. It is clear that the performed analysis is mainly conditioned by the researches on three kinds of cultivars: apple, pepper and tomato. In the reviewed literature, it is prevalent to produce pepper and tomato in greenhouses. Besides, most of the publications about the harvesting of apples report detection algorithms instead of effective harvesting. However, we can conclude that the interest in harvesting robots for different fruits has been growing in the last few years.

Most of the research for fruit detection is mainly made using detection and segmentation algorithms in the two-dimensional (2D) space. However, the literature does not support the effectiveness of using only this kind of sensor for successful harvesting. Indeed, most of the publications that use 2D sensors for harvesting complement the information with other types of depth's sensors like LiDAR or ToF [151, 175]. Concerning the used algorithms, the use of classic computer vision strategies and DL models are evenly distributed in the literature. Usually, the use of classical computer vision algorithms is associated with other machine learning strategies (like SVM or k-mean) and look to be more predictable because the developer plans the extraction of visual features, and the analysis is easier to track. However, these algorithms are slower because they are implemented in

Fruit	Number of publications	Fruit	Number of publications
Apple	58	Cucumber	2
Tomato	23	Eggplant	2
Pepper	21	Lime	2
Strawberry	12	Bitter Gourd	1
Orange	11	Blueberry	1
Litchi	9	Camellia Oleifera Fruit	1
Grape	6	Chestnut	1
Kiwi	4	Coconut	1
Mango	4	Date	1
Guava	3	Lemon	1
Peach	3	Muskmelon	1
Pomelo	3	Passion fruit	1
Almond	2	Peas	1
Aubergine	2	Persimons	1
Banana	2	Pineapple	1
Cherry	2	Plum	1

Table 5 Used fruits by publications

a cascade flow but not usually parallelised. The use DL models are winning expressiveness. They are easy to train and deploy but require dedicated resources (such as Graphics Processing Unit (GPU), TensorFlow Processing Unit (TPU), Field Programmable Gate Array (FPGA)) and a long training time. In the case of DL, the results of the trained model are data-dependent, and it is not easy to understand which image's features the model is using to predict the objects. Most of the publications are success focused and ignore the speed performance of the detection algorithm. Although we neglected this analysis on the current review, this is relevant, and DL could be an interesting approach due to new high-performance technologies as TPU, GPU or FPGA.

For harvesting, most of the researchers considered mainly visual servoing. However, the literature has noted the limitations of visual servoing, mainly in the scope of observability and the attribution of intelligent capabilities to the harvesting system. Because of that, some authors are implementing multiple viewpoint strategies with dynamic planning of the viewpoint to best percept occluded fruits and cutting points. The use of visual sensors and viewpoint planning strategies also brings additional advantages to the harvesting robots for selective harvesting, allowing better maturity classification and decease detection.

Therefore, given the present literature review, the next steps for the implementation of active perception strategies in agricultural field robots should be:

1. Implement effective and intelligent solutions for the data augmentation process based on the viewpoint selection technique;
2. Effective use of haptic sensors allied to vision (or other perceptive) sensors;
3. Implement smart strategies to select the best grasping pose to harvest or prune, without damage the RoI or the tree;
4. Implement active searching strategies to search for the fruits or other RoIs in occludes areas of the tree as behind the leaves, branches or other fruits, deviating the obstacles in the most promising areas of the trees.

Moreover, some gaps need to be researched to assure a robust active perception system to harvest fruits:

– Active and dynamic viewpoint selection;
– Fruits properties assessment;
– Cutting point detection;
– Database of fruits harvesting procedures;

Fruits in trees are, typically, very occluded to protect themselves from the sunlight and other weather conditions. This behaviour demands the development of active viewpoint selection algorithms capable of percepting these occlusions and remove them to percept the RoI. Like fruits, also the peduncle of each fruit is occluded behind leaves and trunks. However, there is some research on the topic of cutting point's detection in the fruit's peduncle, only one of them considers the problem of occluded cutting points and peduncles. Finally, a generic framework for fruit harvesting needs to adapt to different kinds of fruits and to different situations, which demands different harvesting procedures. Therefore, the development of a cloud database, as the RoboEarth Database [250, 251], to register the different procedures and allow the active learning by the robot from previous experiences, the experiences of other robots and taught procedures provided by human users.

6 Conclusion

The manuscript performs a systematic review of the indexed literature on active perception for harvesting robots in agriculture. The review collected publications from different sources and covered a wide range of topics inside the active perception topic, namely, fruit detection and segmentation, fruit assessment, multiple viewpoint selection and visual control.

The literature review used five online databases for manuscript gathering since 2016. We used the PRISMA flow diagram and the Parsifal tool to track publications' inclusion and exclusion process. After duplication removal, the publications were evaluated based on exclusion criteria as to whether the manuscript is not written in an understandable language or is older than 2016. Then each article was fully read and evaluated for quality assessment, validating whether the manuscript as the necessary information and quality for inclusion.

Between the manuscripts accepted for consideration in this review, most of the works reported on fruit detection using datasets of visual data acquired in cultures. The works that directly used harvesting robots are mainly using passive perception systems. However, a couple of publications report to some active perception systems, mainly using multiple viewpoint selection. These works report to the recent state-of-the-art and are mostly implemented under controlled environments as laboratory testbeds or simulation.

The use of active perception in harvesting robots looks to be the future path considering the evolution of the literature. The authors can easily highlight the advantages of using intelligent selection of viewpoints for fruits assessment, increasing the spatial information of the fruits for better harvesting, or estimating intrinsic properties, like the ripening stage.

From this review, we can conclude that the fruit detection and segmentation in the 2D space is widely researched. Further developments should focus essentially on the detection and segmentation in the 3D space, detection of occluded fruits, stems and cutting points, intelligent viewpoint selection and fruit assessment for intelligent harvesting, namely, maturity and decease detection.

Acronyms and Abbreviations

2D	two-dimensional
3D	three-dimensional
3DMTS	3D Move to See
ANN	Artificial Neural Network
DaS	Detection and Segmentation
DASNet	Detection and Segmentation Artificial Neural Network
DCNN	Deep Convolutional Neural Network
Deep-3DMTS	Deep 3D Move to See
DL	Deep Learning
Faster R-CNN	Faster Region-Based Convolutional Neural Network
FPGA	Field Programmable Gate Array
GNSS	Global Navigation Satellite System
GPU	Graphics Processing Unit
IR	infrared
LiDAR	Light Detection and Ranging
Mask R-CNN	Mask Region-Based Convolutional Neural Network
PICOC	Population – Intervention – Comparision – Outcome – Context
PLS	Partial Least Square
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RGB	Red, Green and Blue
RGB-D	Red, Green, Blue and Depth
RoI	Region of Interest
RRT*	Optimal Rapidly-exploring Random Tree
SSD	Single Shot Multibox Detector
SVM	Support Vector Machine
TCP	Tool Centre Point
ToF	Time of Flight
TPU	TensorFlow Processing Unit
YOLO	You Only Look Once

Declarations

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Author's contributions

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