A Survey of Ranging and Imaging Techniques for Precision Agriculture Phenotyping

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***Abstract*—Agricultural production must double by 2050 in order to meet the expected food demand due to population growth. Precision agriculture is the key to improve productivity and efficiency in the use of resources, thus helping to achieve this goal under the diverse challenges currently faced by agriculture mainly due to climate changes, land degradation, availability of farmable land, labor force shortage and increasing costs. To face these challenges, precision agriculture uses and develops sensing methodologies that provide information about the crop growth and health indicators. This paper presents a survey of the state of the art in optical visible and near-visible spectrum sensors and techniques to estimate phenotyping variables from intensity, spectral and volumetric measurements. The sensing methodologies are classified into three areas according to the purpose of the measurements: (i) plant structural characterization, (ii) plant/fruit detection, (iii) plant physiology assessment. This article also discusses the progress in data processing methods and the current open challenges in agricultural tasks in which the development of innovative sensing methodologies is required, such as pruning, fertilizer and pesticide management, crop monitoring and automated harvesting.**

***Index Terms*—Precision agriculture, advanced sensing in agriculture, phenotyping, morphology characterization, physiology assessment, fruit detection.**

I. INTRODUCTION

Precision farming has evolved towards an information approach, whose aim is to acquire as much data from the crop as possible to perform a customized management according to its needs. In this way, precision agriculture (PA) could be seen as a big control loop, where the machinery and the farm workers are the actuators which maintain a sustainable and profitable production. The farmers are in charge of taking the corrective actions according to both: the production needs and the environmental care. Sensing of the crop or the farm fields allows their status and health assessment, providing the loop feedback and therefore the loop closure. The latter is a cornerstone of any information process, since it provides the means to acquire data upon which any corrective action can be performed. There are several ways to assess the status of crops and plants, however, their morphology and physical description (e.g., volume, leaf area index, reflectance) have arisen as widely used parameters for these purposes. The non-invasive and non-destructive framework of crop sensing and characterizing in terms of these two features (morphology and physical description) provides a suitable approach for evaluating the vegetation conditions. In this context, three main applications can be recognized for agricultural phenotyping:

- Structural characterization: the estimation of parameters such as: canopy volume, plant height, leaf area coverage, biomass, among others, leads to take decisions in order to enhance the agricultural process. For example, canopy volume has been used to improve the spraying of phytosanitary products (i.e., pesticides and fertilizers) on fruit trees in terms of inputs saving and environmental costs [1], [2]. Additionally, the leaf area coverage has been used for crop growth monitoring and yield estimation since it reflects many aspects of the physiological processes of vegetation [3]. Further, biomass mapping and monitoring provide the means for detecting changes in the plantation status due to storms, drought or plagues [4], [5]. Moreover, since bio-energy obtained from specific crops has become one of the most frequently used power sources, estimating its biomass arises as a productivity evaluation parameter [6].
- Plant/Fruit detection: successful results in automated activities such as pruning, harvesting, seeding, among others, depend on an accurate localization of the object of interest within the environment. To achieve this aim, several features and properties of plants and fruits have been used, namely: color, shape and temperature. In robotic fruit harvesting, color is an attribute which can be used to identify the product within the canopy [7], [8] or in the crop field [9]. Moreover, for automatized robotic pruning, the shape of the stems is the feature which in most cases provides the cutting directives [10].
- Physiology assessment: the physical response of the canopy to sunlight results in characteristic spectral signatures, which provide insights about the physiological status of the plant. In this way, several indices based on the spectral responses of the crop have been developed to assess parameters such as: nitrogen deficiencies, chlorophyll concentration, water stress, pest infestation, among others[11], [12]. Additionally, other sensing devices (e.g., Infra-red gas analyzers) provide the means to measure directly a number of physiological parameters of the plants. Much of them require a direct contact with the crop, which results in more accurate readings, however, the measuring process follows an individualized path, which makes this approach time consuming in most cases [13].

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A classification of the sensors based on the previously-discussed applications is graphically depicted in Figure 1.

This manuscript reviews the most used sensors and sensing systems for crop phenotyping in terms of its morphology and physical appearance, along with the agricultural implications of the parameters estimated. The variety of approaches here revisited are intended to describe the integration of these sensing devices with mechanic designs in order to develop phenotyping applications such as sensing equipments or automated robots. Finally, it is noteworthy that previous notable works provided a review of sensing and robotics in PA, focusing on 3D imaging sensors [14], [15], challenges in robotic harvesting [16], and fruit detection [17]. In contrast, this work focuses on advanced phenotyping methods and a wide range of sensing methods, which allow the analysis of various agronomic implications and applications. This approach, along with the interpretation of the sensing systems in PA as the loop feedback in a classic control scheme represent the novelty of our work.

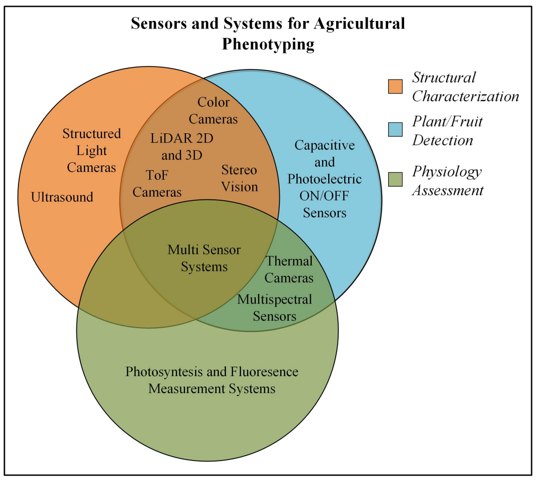

Fig. 1. Applications and sensors for morphological characterization, detection of plants and physiology assessment.

II. Sensing for Detection and Morphological Characterization of Vegetation

Several sensors and sensing systems provide relevant information which allows a characterization of the vegetation. Phenotyping is then addressed from the estimated or measured variables by finding a relationship between the characterization obtained and the status of the plants or crops. In this section we provide a discussion of the sensors used for: i) morphological characterization of crops, and ii) plant or fruit detection. According to the characteristics and measurement principles, such sensing devices can be divided in two broad categories: range and artificial vision sensors.

A. Range Sensors

1) Ultrasound: This type of sensor works by emitting an acoustic pulse of high frequency and short duration which propagates trough the air, impacts to the target and returns in form of echo. Electronics inside the sensor calculates the distance based on the time between the emission of the sound and receiving the echo signal. Ultrasonic sensors were widely used in the past, but the improvement and cost reduction of other sensing technologies have made their use less common. In this scenario, according to [18], there are some important drawbacks that made ultrasonic sensors less competitive: (i) when impacting against tilted surfaces, the sound diverts causing inaccuracies in the measurements; (ii) the interference produced when using sensors very close to each other, (iii) the measurement resolution, and (iv) the relatively slowness of sampling. However, the main advantages of this sensor are its low price and its robustness against fog and dust.

Despite of the disadvantages of this sensor, several works report its application to estimate geometric parameters of the crop such as volume, density, height width, among others. Specifically, in [19] is proposed a real time system to estimate the canopy density on apple trees and grapevines using four ultrasonic sensors mounted on a tractor. Previous works used the same measurement framework for estimating tree volumes, which provided information to adjust the dosing parameters of automatic spraying machines [20].

2) Time of Flight (ToF) Cameras: This type of range sensor provides 3D measurements of distance and intensity by using an array of detectors and a source of light. Due to its capabilities of accuracy, compactness and frame rate these sensors have been used in diverse applications. Concretely, in agricultural research, the structural characterization detection of plants or fruits have been addressed using these cameras. For example in [21] and [22] it is presented the use of a ToF camera for extracting geometrical variables of the plant that allows the modellling and monitoring of individual leaves. Both research works were carried indoors, in laboratory conditions, since field operation conditions (i.e., sunlight presence) can cause the saturation of the detectors, and therefore a poor performance, as reported in [23].

Incorporating color information provides important improvements for plant characterization and detection (Fig. 2). For example, the fusion of color and depth data to detect red sweet pepper in greenhouses is reported in [24]. The main processing is performed to RGB images; however, depth information was used to improve the detection accuracy, obtaining up to 90.9% of true positive rates when using natural light. Further, in [8] is detailed the use of depth and RGB cameras mounted in a mobile platform that acquires data in an over-the-row path within apple orchards. The sensing platform provided ideal illumination conditions so that the sensors would have good performance. The main processing of this work is performed on the color images, whereas depth information was used to filter duplicate detections; reporting up to 82% of detection accuracy. Having color and depth images obtained by different sensors allows an improvement in characterization and detection; however, when both are given by a single sensor, the sensing scheme becomes smoother. In this way, in [25] it is reported the use of a videogaming device (capable of providing color, depth and intensity of reflectance) to obtain a 3D reconstruction and modelling of apple trees.

3) LiDAR: Light Detection and Ranging is a non-destructive laser technology for measuring distances, which

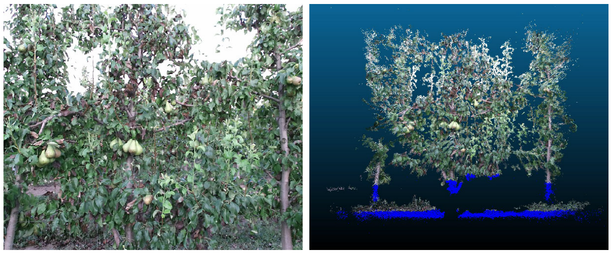

Fig. 2. Color image and its corresponding colorized 3D point cloud acquired with a commercial Time of Flight camera in a pear orchard. The blue points represent the absence of color information due to the limited vertical field of view of the color camera. Image courtesy of the Research Group in AgroICT & Precision Agriculture, University of Lleida, Spain.

has been used in agricultural research to estimate structural parameters of the crop such as volume, leaf area coverage, height, among others [4], [26]. Within the LiDAR sensors, two types of laser scanners can be distinguished: 3D and 2D; however, the latter are more used since they are cheaper and can be employed to get 3D measurements (with the appropriate hardware). Further, according to the distance measuring method, there are two types of laser scanners: (i) Time of Flight LiDAR, which employs the time that takes to the laser pulse to travel between the sensor and the target; and (ii) Phase-Shift LiDAR, which uses the phase difference between the incident and reflected laser beams.

The versatility for acquiring fast accurate measurements and quantifying the spatial variations of the vegetation have positioned LiDAR as a widely used sensing device for agricultural purposes. In this way, terrestrial and aerial applications have been reported to classify vegetation in large scenes or to obtain a geometric description of the crop [27], [28]. Regarding aerial applications, in [29] is reported the use of a full-waveform airborne laser scanner to classify orange trees, grass and ground based on the backscattering properties of the landscape. Additionally, in [30] returns from a full waveform LiDAR are used to build allometric models for estimating the stem volume and biomass of individual pine trees. The authors compared these models with others which do not rely on the waveform information and found that this parameter does not have a positive influence in the volume estimations. However, the accuracy of the biomass estimations was improved. Furthermore, the effects of the flying altitude and sensor configurations in the estimation of specific biophysical forestry parameters (i.e., Lorey's mean height and timber volume) of the canopies by using a small footprint aerial LiDAR is presented in [31].

A number of research works report the use of point clouds obtained from 2D or 3D terrestrial LiDAR to infer structural information of the canopy, such as the volume, area, leaf density, branch dimensions, among others. Some of them took place in laboratory or controlled environments emphasizing the data processing techniques or the validation of new LiDAR-based technologies [6], [12], [32]. However, once the method is validated in laboratory, the challenge lies in performing field experimentations. In order to sense large areas of the farm fields, laser scanners are usually placed over automatized or manually driven platforms, which allow the scanning of entire crops efficiently. In this way, a localization system, along with a 2D LiDAR mounted on such vehicles can be employed to generate a 3D point cloud of the environment, which can in turn be used to determine the structural variables of the canopy (Fig. 3). For example, in [33] this method of data acquisition is used to estimate the volume of fully and partially scanned pear trees in real time. Further, the leaf area coverage of plum trees was estimated using data from a 2D LiDAR placed in a tractor which offered a top view of the orchard in [34]. The results were compared with camera-based estimations, showing a strong correlation between both sensing systems. However, when comparing with hand-measured values, the correlation decreased in some extent, which implies that the proposed methodology could only partially describe the leaf area of the trees. Moreover, in [35] is described the relationship between canopy volume and leaf area density, both estimated from 3D data acquired applying the previously described measurement framework to vineyards, apple and pear trees. A non-linear relationship was obtained via logarithmic fitting of volume and leaf area estimations, obtaining a mean correlation coefficient of 0.87, and as high as 0.98 for the best case.

The use of moving 3D laser scanners have also been addressed for tree modelling. Particularly, in [36] is reported the geometric modelling and reconstruction of urban trees skeletal structures. The authors used a method based on a series of global least squares optimizations in order to fit the points to the resulting graphs, and thus automatically reconstruct the skeletal structure of the trees. In contrast, placing the laser scanners (especially 3D LiDAR) at fixed positions also allows the inference of important characteristics of trees or field farms. Specifically, in [28] is used a full waveform 3D LiDAR for detecting post harvest grown in a winter barley farm. Using the reflectance of the field, the authors corrected the range measurements and obtained up to 99% accuracy. Further, in [37] 3D data is employed to estimate the biomass of low-stature Arctic shrubs. To achieve such aim, two approaches were used: voxelization of the point cloud and a volumetric approximation, obtaining high correspondences between hand measured values and both methods. Regarding forestry applications, the detection of tree structural parameters (e.g., trunk diameter, leaf density) and biomass using LiDAR-based scanning systems mounted on a tripod have been studied with promising results [6].

Due to the versatility and good performance of LiDAR sensors, several improvements (much of them still in development) have been proposed. Particularly, the most novel, and still under research is the so-called Hyperspectral LiDAR (HL). This equipment is intended to join the benefits of the classical laser scanners with the capability of recognize multiple wavelengths [38]. The use of this sensor to agricultural applications have been studied in [39], where it is reported the using a HL to assess the status of vegetation in controlled environments. The results demonstrated the potential of using this type of LiDAR in spectral analysis of vegetation. Further, the estimation of parameters like nitrogen content (usually performed with spectral cameras or spectrometers) is possible with HL, as shown in [12] for rice leaves.

Table I summarizes the main characteristics of range sen-

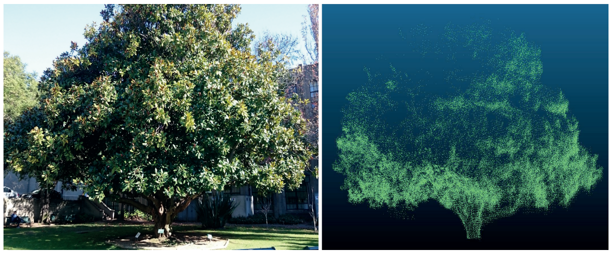

Fig. 3. Color image of an ornamental tree and its corresponding 3D point cloud acquired with a moving 2D LiDAR.

sors, highlighting their capabilities.

B. Artificial Vision Sensors

1) Structured Light Cameras: These sensors provide accurate measurement of distances by projecting an IR pattern over the scene and inspecting the distortion of the pattern received back. Structured light cameras are intended to work indoors, therefore for agricultural research they are mostly employed in laboratory conditions or greenhouses [41]. In [42] a leaf segmentation approach is presented using data from a commercial structured light camera (originally designed for videogaming purposes). This work also provides several crop monitoring applications of the leaf segmentation method proposed. Furthermore, the same sensor has also been used for detecting structural parameters including size, height and volume. Concretely, the characterization of sweet onions and cauliflowers is proposed in [43] and [44], respectively. Results shown good consistency and accuracy in both cases, proving to be suitable methods for quality assessment and harvesting directives. However, in both works is stated that illumination conditions seriously affect the sensor performance. In addition, in [45] a complete description of the application of structured light cameras for a variety of agricultural and livestock purposes is presented. This work provides a complete characterization of these sensors in changing illumination conditions (typical of farm fields), obtaining an inverse relationship between the number of points acquired and the illuminance received by the sensor.

2) Color Cameras: Color cameras have been widely used in agricultural detection and characterization. From the color information provided, additional parameters such as texture and geometrical features can be also obtained, which have proved to be suitable in certain applications (e.g., detection, positioning, guidance). However, the main drawback of using this type of sensors is the influence of the varying ambient lighting conditions, especially in outdoor environments. Despite this fact, when the conditions are suitable, they have proved to perform well in field conditions. For example, the detection of fruits or vegetables within the canopy using color cameras can be applied in automated harvesting tasks. In this context, a recent work reported the use of a number of segmentation techniques based on color features and shape to detect immature green citrus [46]. The results of this work showed an accuracy of 83.4% in the detection of 308 units, which is promising taking into account that the dataset was acquired with different illumination conditions. Furthermore, a real time guidance system for apple harvesting was developed in [7] for robotic harvesting activities. In this work, color and shape features extracted from color images were used, along with a supervised classifier, which resulted in 89% of successful detections. Additionally, a color camera with artificial illumination was used in [47], to present a system capable of detecting berries in a vineyard, for later estimating the yield of the crop. Results showed a high amount of true positive detections and the yield prediction with an error of maximum 11.5%.

Other classification and characterization activities also report the use of color cameras as the main sensing device. For example, a camera placed on an aerial vehicle was used in [29] to classify the land into orange trees, grass and ground, providing the ground truth for the main experiment which used a laser scanner. Furthermore, in [48] a method is presented for identifying plant diseases, based on color histograms of the training images and a supervised classifier. Maturity of fruits can also be assessed by using color images, as shown in [49] for mangoes. The authors developed a system to automatically sort the fruit in base of a correlation of fruit color features and their maturity. A conveyor belt and solenoid valves were used to store the mangoes according to the detected condition. Results of the proposed method were compared with ground truth provided by human expert workers, obtaining up to 93.10% of accuracy.

Three dimensional reconstruction of the environment is mostly addressed by using stereo vision systems. However, using a single camera and image registration algorithms (e.g., Structure from Motion) can provide 3D information of the environment. Specifically, in [50] it is described the estimation of height, diameter and volume of linden, walnut and maple trees from images acquired with a single hand-held camera. The authors report acceptable accuracies when comparing with hand measured values, proving the suitability of the proposed approach for assessing the structural parameters of small trees. Additionally, a camera placed on a manually driven platform was used in [51] to estimate height and leaf area of different plant species. The results were compared with destructive hand-measured values, obtaining a strong linear correlation. Nevertheless, the main drawback of these registration algorithms lies in the need of static structures to be reconstructed, since slight displacements (e.g., wind moving the trees or plants) of the objects cause poor 3D alignments.

3) Stereo Vision: This is a sensing system capable of providing a 3D color reconstruction of the environment, by using two or more monocular cameras in a fixed configuration. The level of description varies depending on the resolution of the camera; however, high resolution images results in a large amount of data to be stored, which make real-time applications a challenging task. The outcome of this measurement system is a 3D point cloud that renders the scene, similar to the approaches that use a color camera and a depth sensor together. In this way the applications in agricultural research are similar to those described earlier, by estimating structural parameters, representing the morphology of the plants and detecting plant or fruits. With this respect, in [52] it is reported

TABLE I
RANGE SENSORS: ADVANTAGES AND DISADVANTAGES IN MORPHOLOGICAL CHARACTERIZATION AND DETECTION

Sensor	Accuracy	Range	Advantages	Limitations	References
Ultrasound	From 60 mm	Up to 50 m	Low cost Robust in presence of dust, fog, water, sunlight Null influence of the optical properties of the target	Provide one range measurement per sensor Substancial accuracy reduction when increasing the distance to the object Accuracy reduction whith changes in target's orientation	[18], [20] [19], [40]
Time of Flight LiDAR	2D: from 10 mm 3D: from 1.2 mm	2D: up to 250 m 3D: up to 6 Km	Provides multi echo readings plus intensity returns in some cases Can work during day and night 2D: Versatility to acquire 3D measurements with the proper setup 3D: Provides raw 3D measurements	Sensitive to dust, fog and water Large amount of data is required to characterize entire crops or large farm fields Trade-off between accuracy and maximum range 3D: High cost	[33], [35] [36], [37]
Phase-Shift LiDAR	from 2 mm	Up to 330 m	High accuracy at large ranges Provides multi-echo readings and in some cases intensity returns Can work during day and night Provides raw 3D measurements	High Cost Only 3D sensors commercially available Sensitive to dust, fog and water	[27]
Time of Flight Cameras	From 10 mm	Up to 8 m	Provides depth information for each pixel Measure also the return intensity Do not have mechanical moving parts	Limited range Sensitive to dust, fog water and sunlight	[8], [24], [25]

the comparison of time of flight cameras and stereo vision systems for leaf imaging purposes under different illumination conditions. Fruit detection applications have also been studied using stereoscopic vision, as reported in [53] for red and green apples. The authors used image processing techniques based on the color information to detect the fruits in individual images. Depth information is used to remove duplicates based on the distance between two estimations. Results showed good accuracy, reporting errors of 3.2% when detecting red apples and 1.2% for green apples. Additionally, an example of blossom detection within the canopy of peach trees is reported in [54], obtaining an accurate positioning.

Table II summarizes the strengths and limitations of the vision systems described, including thermal cameras, described in the next Section.

III. SENSING FOR PHYSIOLOGICAL ASSESSMENT OF VEGETATION

A. Thermal Cameras

Temperature have proven to be an important parameter for some agricultural activities like crop diagnosing and fruit detection. For example, Fig. 4 shows the thermal characterization of an ornamental tree, which can provide means to segment the tree from the rest of the scene, and later assess the status of the canopy. Furthermore, the plant temperature has been recognized as an indicator of plant water availability [56], which would allow the development of site-specific irrigation technology based on the temperature of the plant. The relationship between temperature of the leaves and water stress or transpiration in the plant using thermal cameras have also been addressed, as reported in [11]. However, in the same work it is stated that the relation is not one to one since the modification in those physiological parameters of the crop also depends on other variables such as: ambient temperature, quality of the air and soil, etc. Hence, the water stress diagnosis of the crop requires the application of a multi-sensor approach.

Another use of thermal cameras is fruit detection, since fruits absorb and irradiate the solar radiation in a different way compared with leaves and trunks, allowing the design of accurate classification methods. Specifically, in [55] a thermal camera along with RGB imagery was used to detect green apples by applying image processing approaches. The authors reported an accuracy up to 74% when using together thermal and color camera images in the processing. Within this framework, one of the most important applications of fruit recognition on trees is the development of automated harvesting systems, as the reported in [7], for red apples. In addition, thermal imaging also represents an attractive solution to identify human operators or animals, especially when they are partially occluded or hidden in high vegetation [57].

Fig. 4. Color image of an ornamental tree and its thermal view.

B. Multi-spectral and Hyper-spectral Cameras

Absorption and reflection of radiation in certain bands of the electromagnetic spectrum are well related with a number of physiological variables such as, water stress, chlorophyll content, nitrogen deficiencies, among others. For example, the chlorophyll pigment absorbs light in the red (long wavelength) and the blue (short wavelength), whereas the green light is reflected. Furthermore, the reflectance in the mid-infrared (MIR) band is influenced by the water content of the crop. This reflectance information of the canopy can be measured by spectrometers and cameras. However, the additional spa-

TABLE II
REMARKABLE CHARACTERISTICS OF THE MAIN ARTIFICIAL VISION SYSTEMS USED FOR AGRICULTURAL CHARACTERIZATION AND DETECTION

Sensor	Advantages	Limitations	References
Structured Light Cameras	Low cost Provide color and depth information Provide good accuracy	Sensitive to variable illumination conditions Limited Range Provide low resolution images	[42], [44], [45]
Color Cameras	Low cost Provide color, texture and geometric information in 2D	Sensitive to changing in illumination conditions Need stable daylight conditions Unknown scale in raw data	[46], [47], [49]
Stereo Vision	Provide color, texture and geometric information in 3D	Sensitive to changing in illumination conditions Need stable daylight conditions Provide a big amount of data to process	[52]–[54]
Thermal Cameras	Do not rely on color attributes Provide also physiological insights of the plants	Need calibration to return accurate measurements Affected by the reflectance of the target object	[55], [56]

tial information also provided by a camera makes it more suitable for vegetation analysis. According to the span of the electromagnetic spectrum covered and the resolution and quantity of the bands that they are capable of measure, these sensing devices can be catalogued as multi-spectral (MS) and hyper-spectral (HS). Multi-spectral imagery can quantify the reflectance of the scene in a few broad bands, which are not necessarily contiguous, for example: Visible (VIS, 400-700 nm wavelength), Near Infra-Red (NIR, 700-1000 nm wavelength), Short Wave Infra-Red (SWIR, 1000-2500 nm wavelength), among others. On the other hand, hyper-spectral cameras allows a sort of continuous measurement of the spectrum, providing reflectance readings in contiguous narrow bands. In this context, Fig. 5 illustrates this difference between MS and HS imaging. Another important difference between these sensing systems lies in the amount of information to be processed. The level of spectral detail obtained with HS cameras produces larger quantities of data.

Satellite, aerial and terrestrial methodologies have been employed to collect MS and HS imagery for a number of applications [58], [59]. From this spectral information several broad and narrow band indices have proved to be suitable for evaluating specific physiological aspects of the canopy. A complete list of such indicators, its definition and the variables that they measure is detailed in [60]. Multi-spectral imagery along with aerial methods have been very popular to evaluate the status of the canopy using these indices. Water variability, vigour chlorophyll detection, crop yield, nitrogen stress and weed infestation are some of the aspects that have been evaluated using unmanned aerial vehicles [56], [61], [62].

Despite the good results obtained when using MS data, in some cases it can not provide conclusive information about the status of the vegetation. This is mainly because certain characteristics of the canopy are more correlated with its response in narrow bands, which are obtained with HS data. However, due to its high dimensionality, the bands that do not contribute with information are usually excluded from analysis by using statistical (e.g., Principal Component Analysis) [63] or Machine Learning techniques [64]. In this way, a number of works report the use of hyper-spectral vegetation indices for PA. Water and plant stress, pest infestation and soil properties are some of the characteristics that can be assessed employing HS imagery [65]–[67]. Furthermore, in [68] is detailed a review of the recent works about agricultural applications of HS imagery.

Multi-spectral and hyper-spectral information acquired with terrestrial methodologies have similar agricultural applications as explained before (e.g., nitrogen uptake levels, weed detection, pest infestation), as reported in various scientific works [69], [70]. However, fruit localization and quality evaluation are specific applications which can be better addressed using proximal sensing. For example, in [71] it is reported the use of a motorized HS camera to detect green citrus. The camera was moved by an electrically-driven pan head in order to cover more space. The results obtained high true positive detections for fruit located in the periphery of the canopy (up to 100%) and promising true detections when the fruit was occluded by the leaves of the trees (up to 79%). In addition, in [72] is presented a system capable of detecting skin imperfections in peaches. The sensing system consisted on a HS camera pointing to the fruit in a chamber illuminated by halogen lights. The results showed accuracies greater than 86% when classifying 9 types of peach skins. These spectral sensing systems could be used for yield estimation or to be part of harvesting units.

Figure 6 shows the evolution of range and vision sensing systems in the last fifty years, and their main contributions. Surprisingly, thermal and multispectral sensing are "old" solutions that were already proposed in the late sixties. Recently, the decreasing in the technology costs and the availability of powerful processing systems have arisen new interest and opened new applications including PA. The most recent sensors are structured-light cameras that represented a huge leap forward due to their high performance/cost ratio.

Table III provide a summary about the phenotype feature that can be measured or estimated using the sensors and sensing systems surveyed.

IV. Processing Techniques

Sensors in most cases provide raw data, which must be organized and processed in order to extract the information of interest for the specific application. For example, in [33], the volume of the canopy is estimated using four different approaches: convex hull, segmented convex hull, cylinder-based modelling and voxelization. In contrast, this parameter is calculated in [35] using the volume of the solid obtained when

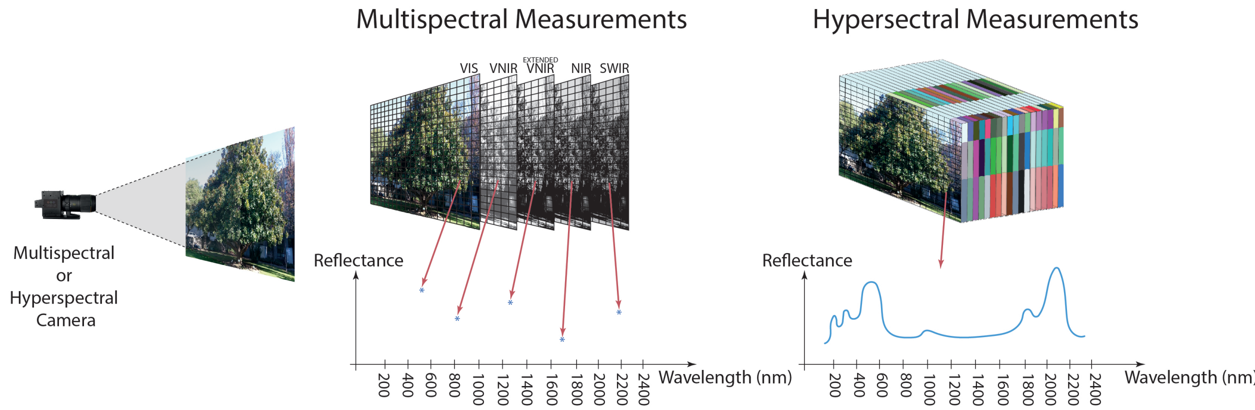

Fig. 5. Schematic representation of the measurements provided by multi-spectral and hyper-spectral cameras. MS imagery allows to determine reflectance in discrete broad bands of the electromagnetic spectrum, whereas HS imagery provides spectral information for narrow and contiguous bands.

Fig. 6. Evolution in the use of range and artificial vision sensors for morphological characterization and fruit/plant detection. The years report the first use of these sensing systems for agricultural purposes.

TABLE III
SENSING SYSTEMS COMMONLY USED TO ESTIMATE MOST OF THE IMPORTANT PHENOTYPE FEATURES

Feature Type	Phenotype Feature	Appropriate Sensor/Sensing System
Morphological	Leaf area coverage	2D-3D LiDAR, ultrasonic, stereo vision, color cameras
	Foliage Density	2D-3D LiDAR, ultrasonic, stereo vision, structured light cameras
	Stems shape and size	2D-3D LiDAR, stereo vision
	Plant height	2D-3D LiDAR, ultrasonic, color and structured light cameras
Physiological	Nutrient content	HS LiDAR, MS and HS cameras
	Water stress	Thermal, MS and HS cameras
	Biomass	MS and HS cameras
	Fruit Maturity	Color, thermal, MS and HS cameras

intersecting two scans from the front and the back of each tree. Moreover, when range sensors are used, clustering and matching techniques are most commonly applied to segment objects of interest and to obtain a representation of the entire scene or single objects, respectively [25], [36]. For data acquired from cameras, results are obtained using a wide range of processing techniques from the copmuter vision literature. Color-based features, color space transformation, image filtering, morphological operations, foreground segmentation, among others are the computer vision tools which have been used for detection and characterization [7], [47], [48].

An alternative set of approaches employ Machine Learning techniques, which by means of supervised and un-supervised classifiers provide adaptation and learning capabilities. K-means is a popular algorithm for unsupervised learning which is used for clustering and segmentation. This technique, along with neural networks, was used in [55] for detecting apples from color and thermal images. Regarding supervised classifiers, in [73] k-nearest neighbor and support vector machines algorithms were employed to distinguish 16 classes in HS satellite images of agricultural landscapes. In addition, a supervised classifier is also used in [74] to detect potato plants in a sugar beet crop by using color cameras under changing natural lighting conditions. Another example can be found in [75] where a self-learning classification approach based on radar readings is used for scene understanding. Nevertheless, a deeper description of the techniques and algorithms used in our review goes beyond the scope of this work.

V. Agricultural Challenges

The sensing of the morphology and structural distribution of the plants allows the automation of a number of agricultural tasks. Automatic mechatronic platforms capable to navigate and to perform activities of pruning, phytosanitary dosage, harvesting, among others, within the environment represent an improvement in the farming processes in terms of cost savings, environmental care and production rates. In plenty of cases, the automation is not an option but also a requirement due to the lack of human labor force since other activities are better paid and also offer more comfortable working conditions. This section focuses on the agricultural challenges that have been faced by using the sensing systems previously described.

A. Fertilizer and pesticide management

Supplying the optimal treatments according to the orchard characteristics provides an efficient management of the crop or farms. This approach allows a reduction in the environmental impacts produced by the agricultural activity. Mounting the sensors over tractors in order to estimate such features enables an efficient canopy characterization that can be used to configurate the sprayers (e.g., nozzles type, flow rates, pressure). In this way, plenty of the research has been carried out in the last years by fully developing (from laboratory design, to field tests) complete spraying systems mounted on manually driven vehicles. These systems are capable to characterize specific orchards and spray the product in real time according to the area or volume of the canopy [2], [40], [76]. However, the development of fully autonomous spraying vehicles is a topic still under study since the characteristics of the agricultural environment in much cases difficult the guidance and navigation tasks. Occlusion of GPS signal by the vegetation, reduced mobility, low-traction, deformable and steep-hill terrains, are some issues which can quickly degenerate the quality of the positioning and compromise the task execution.

B. Pruning directives

Performing an adequate pruning task provides a number of benefits to the orchard in terms of health and production, namely: avoids the growing of branches with poor health, encourages the renovation of branches, allows a good illumination of the tree and prevents harvesting difficulties. Identifying the correct branches to prune is usually done by specialized people; however, in large farms this task is especially time consuming. Thus, pruning automation arises as an alternative; for example, obtaining a three dimensional model of the tree from data acquired with different sensing systems is an approach which seems suitable to infer pruning directives [36]. Nevertheless, specific works report the characterization of trees for pruning activities. For example, in [10] a ToF camera was used to identify pruning branches in apple trees.

Despite of the advances in this topic, automatic pruning of plants and trees is still a challenging topic of research. The variability of the tree structure, the actuators needed to perform the cuts within the canopy and the accuracy of the pruning points detection are some of the main issues to be addressed.

C. Crop monitoring

The intensive information nature of PA technologies allows a constant control of the crop status. Crop monitoring can be seen as a consequence of the feedback provided by the sensors or sensing systems. Moreover, the physiological status of the crop, inferred from the information acquired can also be used to determine external parameters to the crop itself. Quality of the soil, illumination conditions, irrigation level, disease prevention, yield supervision are some of the variables and applications which can be addressed using the sensing systems reviewed. In this way, a correct and efficient management of a farm field must be capable of monitoring the crop in a long term (i.e., trough the seeding, the growing and the harvesting) using these developments. For example, in [77] is reported the use of radio transmitters and receivers along with GPS measurements in order to manually tag the locations of fruits when they are harvested by field workers. This information can be later used by the farmer to build yield maps of the crop based on the quantity of the production and its distribution within the canopy foliage. In this framework, building a database of the crop physiological and spatial parameters during the growing stages and the corresponding season would allow an integral management of the farm fields.

D. Breeding

In parallel to the applications that investigate the improvement of crop management during food production, plant phenotyping technologies are being used also to improve plant breeding. This application, in general, seeks to understand the mapping from the genetics of a plant (known as *genotype*), the physical characteristics of the plant (known as *phenotype*), and the environment to some plant performance phenotype such as yield or disease resistance. The standard practice to addressing this problem uses large scale experiments, where breeders use their experience and understanding of the plant genetics to create new plant varieties (known as *accessions*), which they then plant and observe over the course of successive growing cycles. The primary limiting factor in this type of breeding approach is the number of plants that a specialist can evaluate each growing cycle. Automated data collection has the potential to alleviate this bottleneck, increasing the quantity and quality of phenotype and environmental measurements collected throughout the growing cycle and hence accelerating the overall breeding process. This is commonly referred to as *high throughput phenotyping*, or HTP, and researchers are exploring its application within the PA framework. In this scenario, a number of works report the development of systems for automated field phenotyping from ground vehicles ([78]) as well as from umanned aerial vehicles ([79]).

VI. Conclusions

This paper presented a survey of the main sensing systems in Precision Agriculture for plant structural characterization, plant/fruit detection, and plant physiology assessment. Sensing methods for structural characterization rely mainly on color cameras, structured light cameras, 2D and 3D LiDAR sensors, time-of-flight cameras, stereoscopic vision or ultrasonic sensors for volumetric and morphological measurements. Some plant and fruit detection techniques employ color cameras and range sensors such as LiDAR, time-of-flight and stereoscopic cameras, but also include capacitive and photoelectric sensors, MS, HS and thermal cameras. The methodologies thus far developed for non-invasive plant physiology assessment employ photosynthesis and fluorescence measurement systems, as well as MS and thermal sensors. The accuracy of the approaches has improved significantly over the last decade, thanks to the improvement of the sensor's resolution and the decreasing in costs. The accuracy of the different approaches for morphological analysis, plant/fruit detection, and physiology measurement is in general above 80%. Provided that environmental conditions can be isolated or made comparable, the accuracy of each sensing methodology is often associated to the characteristics of the plant, such as stem/branch complexity, foliar density and contrast between fruits, leaves, and branches. Some challenges in precision agriculture which can benefit from the development of new sensing methodologies and the improvement of the process models include the measurement of the effectiveness of the spraying process of phytosanitary products, the development of automated perception methods for pruning that are capable of handling the variability and complexity of the branch structure of shrubs and trees, and the improvement of crop monitoring techniques and inference models not only for yield estimation, but also to manage irrigation, soil and illumination conditions, growth rates, plant nutrient uptake and assimilation. Novel mechatronic systems, including ground and aerial robotic platforms, for high throughput phenotyping will require improvements in the speed of algorithms and their ability to cope robustly with plant and environmental variability.

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