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Sensor network applications in precision agriculture

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Abstract
The challenges of feeding the exponential growth of world population with limited agriculture resources require innovation in sustainable, efficient farming. The practice of precision agriculture offers many benefits towards addressing these challenges, such as improved yield and efficient use of such resources as water, fertilizer and pesticides. Sensor Network plays a very basic and essential role in any kind of automation. Internet of Things (IoT) based automation of agricultural field can change the agriculture sector from not only static to dynamic but from manual SMART. It will result in leading enhanced production with reduced human efforts. Precision Agriculture (PA) along with Sensor Network is the main driver of automation in the agriculture sector. PA uses specific sensors and software to ensure stress management in crops. It will optimize productivity and sustainability of agriculture domain. PA includes retrieving real data about the conditions of soil, crops and weather from the sensors incorporated in the fields. In this paper, a review of sensor networks for various ranges in the agriculture domain is presented along with applications and installations. This survey includes sensors and wireless communication technologies used in PA.

Keywords: Sensors, automation, precision farming, UAV, robotics

Introduction

The rapidly-growing human population has increased food demands for human survival on the Earth. Meeting the food requirements with limited resources of the planet is a big challenge. Several state-of-the-art technologies are being incorporated in the agriculture domain to enhance the productivity to cope with this challenge. Precision Agriculture (PA) is comprised of near and remote sensing techniques using IOT sensors, which help to monitor crop states at multiple growth levels [1, 2]. Agriculture production systems have benefited from incorporation of technological advances primarily developed for other industries. The industrial age brought mechanization and synthesized fertilizers to agriculture. The technology age offered genetic engineering and automation. The information age brings the potential for integrating the technological advances into precision agriculture (PA) [3, 4].

PA is based on innovative systems approach and these new systems approach depends on a combination of fundamental technologies such as Geographic Information System (GIS), Global Positioning System (GPS), computer modelling, ground based/airborne/satellite remote sensing, variable rate technology and advanced information processing for timely in-season and between season crop management. Protocols for PA implementation can be encapsulated in three general steps: (1) Gathering information about variability, (2) Processing and analyzing information to assess the significance of variability and (3) Implementing change in the management of inputs. PA is integrated, information-and production based farming system that is designed to increase long term, site-specific and whole farm production efficiency, productivity and profitability while avoiding the undesirable effects of excess chemical loading to the environment or productivity loss due to insufficient input application. The inference is that better decision making will provide a wide range of benefits in economic, environmental and social aspects that may or may not be known or measurable at present [5-7].

Traditionally, remote sensing satellites and airborne sensing with winged aircraft have allowed scientists to map large farmlands and forests through acquisition of multispectral imagery and 3-D structural data. However, data from these platforms lack the spatio-temporal resolution necessary for precision agriculture. For example, a typical remote sensing satellite image may have a pixel resolution of hundreds of meters, and airborne sensing may provide resolutions of a few meters. Monitoring orchard or vineyard health however requires data at a centimeter scale - the resolution necessary for observing stems, leaves, and fruits [8-10]. There are several ways to assess the status of crops and plants; however, their morphology and physical description (e.g., volume, leaf area index, and 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. They are Structural Characterization, Plant/Fruit Detection and Physiology Assessment. Structural characterization includes the estimation of parameters such as canopy volume, plant height, leaf area coverage, biomass etc. Plant/Fruit detection includes automated activities such as pruning, harvesting, seeding etc. To achieve this aim, several features and properties of plants and fruits have been used, namely, colour, shape, and temperature. Physiology assessment includes the physical response of the canopy to sunlight results in characteristic spectral signatures, which provide insights about the physiological status of the plant [11-13].

Along with this, constantly changing environments are often unfavourable or stressful for growth and development of plants. These adverse environmental conditions include biotic stress, such as pathogen infection and herbivore attack, and abiotic stress, such as drought, heat, cold, nutrient deficiency, and excess of salt or toxic metals like aluminium, arsenate, and cadmium in the soil. Drought, salt, and temperature stresses are major environmental factors that affect the geographical distribution of plants in nature, limit plant productivity in agriculture, and threaten food security. The adverse effects of these abiotic stresses are exacerbated by climate change, which has been predicted to result in an increased frequency of extreme weather [14, 15].

This paper presents the applications of relevant sensors in precision agriculture and their role in improvising the mechanization in agriculture sector.

Material and Methods

One of the most important objectives of farmers is the optimization of profit for each field. One approach is to minimize inputs. This benefit is directly correlated to yield and crop quality. For a long time, this improvement has been obtained through a thorough crop selection for specific climates, and for an increased resistance to pest infections. Better fertility management supported these improvements. Higher yields are sometimes accompanied by an increased leaching of pollutants to the environment. Misapplication of fertilizers and pesticides results in pollution and increased pressure on the environment. Farmers are under increasing legislative pressure to reduce fertilizer, pesticide and herbicide inputs. Precision farming is likely to provide a solution for these problems. During the growing season, one can visually detect differences in a field. Different growing conditions result in varying grain yield, weed infestation etc. Fertilizer and herbicide application can be adapted to this variation in a site-specific manner to obtain maximum economic yield. To evaluate this profit, yield has to be determined site-specifically. With cereal grains, the only place to measure the latter is the combine harvester. So within precision farming, combine harvesters play an important function [16]. Biotic and abiotic stress, yield, land mapping, grading of fruits, grain storage etc. are the different areas in precision farming to look upon to increase the income of farmers. Sensors and measurement methodologies of some of these key areas are listed in following section.

A. Stress measurement

Plant stress may be of different types i.e. organellar, ER, chloroplast, mitochondrion and peroxisome, cell-wall, ionic, osmotic, cold and heat stress etc. Understanding stress signalling and responses will increase our ability to improve stress resistance in crops to achieve agricultural sustainability and food security for a growing world population [17].

Remote sensing technologies have advanced significantly over the past 10 to 15 years. With the development of hyper spectral remote sensing technologies, researchers have benefited from significant improvements in the spectral and spatial properties of the data, allowing for more detailed plant and environmental studies. These technologies acquire many hundreds of spectral bands across the spectrum from 400 nm to 2500 nm, using satellite, airborne or hand-held devices. The Casi or Hymap airborne imagers are examples of commonly used hyper spectral imagers which acquire high spectral and spatial resolution images. A distinct advantage of most air- borne imagers is their capability to acquire at least 200 or more spectral bands at less than 5 m spatial resolution. Advances in spectrometry have also resulted in state-of-the-art portable field instruments which allow for the collection of hand-held hyper- spectral signatures. The Hyperion sensor is currently the only hyper spectral satellite system available for research [18].

The spectral characteristics of vegetation are governed primarily by scattering and absorption characteristics of the leaf internal structure and biochemical constituents, such as pigments, water, nitrogen, cellulose and lignin [19-20]. Pigments are the main determinants controlling the spectral responses of leaves in the visible wavelengths [21]. Chlorophyll pigment content, in particular, is directly associated with photosynthetic capacity and productivity [21-22]. Reduced concentrations of chlorophyll are indicative of plant stress [22]. On the other hand, cellular structure and water content of leaves are the main determinants in the near- and mid-infrared wavelengths.

Plant water content at the leaf and canopy scales is often estimated using specific spectral reflectance bands and spectral reflectance indices from near infrared, middle infrared (MIR) and short-wave infrared (SWIR) regions of the electromagnetic spectrum [23-30]. The water band index is derived from the ratio of reflectance measured at 900 nm and 970 nm [31]. This spectral index has been correlated with ground-based measurements of plant water content at both the leaf and canopy scales. It is, however, more sensitive to leaf water content than the water content of the whole plant. This is advantageous in agricultural applications, where leaf water content changes more noticeably in response to drought conditions than the water content of the entire plant foliage [32].

B. Field mapping

Nowadays, lot of researchers are using large scale digital maps and there are many technologies available for robot mapping application including GPS, RF beacons, encoder or odometer (dead reckoning), sonar, etc. Price and availability of the sensors are important element in achievement of getting data for localization and mapping [33]. Sonar sensors that used for indoor mapping are usually for sensing sectors such as planes, corners, edges and unknown sector. Distance between transmitter and receiver are close to reduce the error and increase the accuracy [34]. For this paper, the sensors used were from EZmax where transmitter and receiver are built in together, therefore the accuracy is greater. Other research uses single rotating Polaroid sonar with resolution of 22.5° mounted on mobile robot used both adaptive control of motion and also sensing in comparison to straight-line motion and random motion [35]. There is also research using sonar sensors which used grid-based localization technique for mapping [3]. The used of the grid localization is to reduce computer processing for localization [36].

Coil based geophones are a proven technology that has been used for a long time by the industry. Recent advances in micro-machined sensors now provide adequate sensitivity, low noise, and dynamic range to be applicable to seismic acquisition. MEMS have the potential to provide broader bandwidth, more accurate amplitude, and less sensitivity to planting tilt. Together with the renewed interest for 3C recording, triggered by the success of OBC surveys, these trends have incited manufacturers to develop and market new digital sensors based on MEMS accelerometers [37].

Collecting information over a grove or orchard has been greatly facilitated in the past few decades with the development of different types of sensors within the scope digital horticulture. Digital horticulture is a recent terminology that refers to the use of a range of digital technologies (including plant sensing devices) used in different horticultural applications such as the high-throughput phenotyping and precision horticulture (often referred as site-specific management). Among different types of sensing technologies applied in digital horticulture, ranging sensors, mostly light detection and ranging (LiDAR) and ultrasonic sensors gained attention from researchers and practitioners for their applications in fruit and nut crops. Ranging sensors are designed to measure the distance to the nearest object by emitting an electromagnetic signal (an ultrasonic wave for ultrasonic sensors or a laser beam for LiDAR sensors) in a given direction; the time between emitting and receiving the signal is used to calculate distance to the target. As long as appropriate acquisition and data processing is applied, these sensors can be used to estimate geometrical parameters such as canopy height, width, volume, and other structural parameters. These parameters are useful to site-specific management because they usually relate to plant development, health, yield potential, and, consequently, with input requirements. With such information, growers can identify zones with different characteristics within the grove/orchard and apply appropriate management in each zone. If the data are provided with sufficient spatial resolution, trees can be treated individually using automated variable rate application of inputs [38].

The canopy volume of tree row crops can be estimated by different methods. One that is often used to calculate spraying dose rates is based on the tree-row-volume concept which traditionally uses manual measurements of canopy height, width, and length to calculate volume [39-41]. Early studies on ranging sensors applied to tree crops aimed to make such measurements more accurate and rapid. In the studies of McConnell *et al*., in West Virginia and Giles *et al*. in California, USA, ultrasonic sensing systems were designed and evaluated. The sensors were arranged in different heights along a vertical pole, facing a side of the tree row. Each ultrasonic unit measured its distance to the canopy as the system moved along the alleyway at constant speed. By combining the measured distances from the sensors, the system provided estimates of canopy volume for each section along the tree row [42-45].

C. Yield monitoring sensors

Rice is one of the staple foods for more than three billion people worldwide. Rice paddies accounted for approximately 11.5% of the World’s arable land area during 2012. Rice provided ~19% of the global dietary energy in recent times and its annual average consumption per capita was ~65 kg during 2010-2011. Therefore, rice area mapping and forecasting its production is important for food security, where demands often exceed production due to an ever increasing population. Timely and accurate estimation of rice areas and forecasting its production can provide invaluable information for governments, planners, and decision makers in formulating policies in regard to import/export in the event of shortfall and/or surplus. The most commonly applied optical sensors include: Landsat (mainly MSS, TM and ETM+), SPOT-VGT, NOAA/AVHRR, MODIS, etc. These satellite sensors have the potential of obtaining multi-temporal and multi-spectral reflectance data over croplands that can be used for deriving time-series of vegetation indices (VIs), calculated as a function of red, blue, and infrared spectral bands [46].

B/W cameras were used in some of the earliest studies in detecting fruit based on geometric features. However, the B/W camera was replaced later with colour camera and an accuracy of 90.0% on fruit detection was reported with a 5.0% false detection. The major disadvantage of B/W cameras was that colour information was not available, which is one of the most prominent features of fruit. Thus, limited feature information of fruit makes it difficult to achieve desired level of accuracy on fruit identification using B/W camera [48]. Colour is one of the most important features used in machine vision system to distinguish fruit from leaves, branches and other background objects in the orchard environment. Fruit localization in trees is another important part of machine vision system for robotic harvesting and sizing of fruit for crop-load estimation. The major challenges in localizing fruit are the displacement of fruit by wind or other factors during imaging and occlusion of fruit [49]. Colour cameras, consisting of either CCD sensors or CMOS sensors have been used for localizing fruit and for tracking the trajectory of harvesting robots. The relationship between the focal length of the camera, pixel size, and centre of the apples in the image plane was used to calculate the distance between the camera and the fruit [50]. Laser range finders operate on the principle of Time-of-Flight (TOF) of light. A laser range sensing unit consists of a laser source to emit pulsed laser beams and a sensor to receive the beam reflected back from the objects. The time taken by the laser beam to reflect back from the objects is proportional to the distance between the object and the sensor. Laser range finders can provide range information of an entire scene using a scanning sensor. The scene can be scanned horizontally and vertically to create 3D coordinate map of the scene [51]. Stereovision systems consist of two or more cameras separated by a certain distance. Multiple images captured by individual cameras are matched together to estimate spatial displacement (or disparity) of the object in two images. Image disparity is then converted to distance to objects from the camera using relative camera locations and orientations, and focal lengths of the cameras [52]. Thermal cameras capture temperature signature of objects, which may be helpful in differentiating fruit and background. The fruit absorbs more heat and radiates more heat in comparison with leaves and other parts of the plant canopy, which allows for distinction between those plant materials with thermal imaging [53].

D. Soil moisture measurement

Quantification of spatial variability of soil parameters is important to the successful implementation of Site-Specific Management (SSM). Soil parameters are known to vary spatially, and with the availability of Global Positioning System (GPS) technology, changes in a soil parameter can be precisely mapped. Research has shown a need for geo-referenced data on more soil parameters, to be able to identify which soil parameter, e.g. nutrient deficiency, soil compaction level, etc. is limiting crop productivity at each grid point or cell throughout the field [54].

The oven-drying technique is probably the most widely used of all gravimetric methods for measuring soil moisture and is the standard for the calibration of all other soil moisture determination techniques. This method involves removing a soil sample from the field and determining the mass of water content in relation to the mass of dry soil. Although the use of this technique ensures accurate measurements, it also has a number of disadvantages: laboratory equipment, sampling tools, and 24 hours of drying time are required. In addition, it is a destructive test in that it requires sample removal. This makes it impossible to measure soil moisture at exactly the same point at a later date. Eventually, measurements will become inaccurate because of field variability from one site to another [55].

Neutron scattering is widely used for estimating volumetric water content. With this method, fast neutrons emitted from a radioactive source are thermalized or slowed down by hydrogen atoms in the soil. Since most hydrogen atoms in the soil are components of water molecules, the proportion of thermalized neutrons is related to soil water content. This method offers the advantage of measuring a large soil volume, and also the possibility of scanning at several depths to obtain a profile of moisture distribution. However, it also has a number of disadvantages: the high cost of the instrument, radiation hazard, insensitivity near the soil surface, insensitivity to small variations in moisture content at different points within a 30 to 40 cm radius, and variation in readings due to soil density variations, which may cause an error rate of up to 15 percent [56].

The gamma ray attenuation method is a radioactive technique that can be used to determine soil moisture content. This method assumes that the scattering and absorption of gamma rays are related to the density of matter in their path and that the specific gravity of a soil remains relatively constant as the wet density changes with increases or decreases in moisture. Changes in wet density are measured by the gamma transmission technique and the moisture content is determined from this density change [57].

Soil moisture content may be determined via its effect on dielectric constant by measuring the capacitance between two electrodes implanted in the soil. Where soil moisture is predominantly in the form of free water (e.g., in sandy soils), the dielectric constant is directly proportional to the moisture content. The probe is normally given a frequency excitation to permit measurement of the dielectric constant. The readout from the probe is not linear with water content and is influenced by soil type and soil temperature. Therefore, careful calibration is required and long-term stability of the calibration is questionable [58].

Electromagnetic techniques include methods that depend upon the effect of moisture on the electrical properties of soil. Soil resistivity depends on moisture content; hence it can serve as the basis for a sensor. It is possible either to measure the resistivity between electrodes in a soil or to measure the resistivity of a material in equilibrium with the soil. The difficulty with resistive sensors is that the absolute value of soil resistivity depends on ion concentration as well as on moisture concentration. Therefore, careful calibration is required for these techniques [59].

Time-domain reflectometer (TDR) determinations involve measuring the propagation of electromagnetic (EM) waves or signals. Propagation constants for EM waves in soil, such as velocity and attenuation, depend on soil properties, especially water content and electrical conductivity. The propagation of electrical signals in soil is influenced by soil water content and electrical conductivity. The dielectric constant, measured by TDR, provides a good measurement of this soil water content. This water content determination is essentially independent of soil texture, temperature, and salt content [60].

The relationship between moisture content in porous materials and the relative humidity (RH) of the immediate atmosphere is reasonably well known. Since thermal inertia of a porous medium depends on moisture content, soil surface temperature can be used as an indication of moisture content. Electrical resistance hygrometers utilize chemical salts and acids, aluminium oxide, electrolysis, thermal principles, and white hydrosol to measure RH. The measured resistance of the resistive element is a function of RH. The main application for this technology seems to be in materials where RH is directly related to other properties [61].

Remote sensing method includes satellite, radar (microwaves), and other non-contact techniques. The remote sensing of soil moisture depends on the measurement of electromagnetic energy that has been either reflected or emitted from the soil surface. The intensity of this radiation with soil moisture may vary depending on dielectric properties, soil temperature, or some combination of both. For active radar, the attenuation of microwave energy may be used to indicate the moisture content of porous media because of the effect of moisture content on the dielectric constant. Thermal infrared wavelengths are commonly used for this measurement [62].

Conclusion

In this paper, sensors used in precision agriculture and its benefits towards addressing the challenges, such as improved yield and efficient use of such resources as water, fertilizer and pesticides stress is discussed. Different types of plant stresses such as organellar, ER, chloroplast, mitochondrion and peroxisome, cell-wall, ionic, osmotic, cold and heat stress can be addressed by considering colour, texture, size etc. of plant or fruit. Remote sensing technology has the potential of revolutionizing the detection and characterization of agricultural productivity based on biophysical attributes of crops and/or soils. Essentially, like other precision agriculture components, the information gained from remote sensing data is more meaningful when used in combination with ground data.

Although remote sensing cannot capture all types of agricultural information, it can reliably provide accurate and timely information to guide agronomic and economic decision-making.

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