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REVIEW ARTICLE

Artificial Vision in Mexican Agriculture for Identification of Diseases, Pests and Invasive Plants

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Abstract

According to the FAO the population will increase from 7000000 today to reach 9000000 by 2050. In contrast, the arable land decreases more and more which complicates the production of food for a population in constant increase. Mexico also has the same problem of producing for a population that in 2050 will be 2050 will be 150,837,517 (CONAPO 2017). Diseases and pests in the agricultural sector cause various types and amounts of losses, according to the plants or products that are obtained from them, as well as the causes of the disease. At present, agricultural production, and particularly plant health, is they focus more and more on management strategies based on information technologies, which have proven to be very useful to increase crop productivity and reduce pollution and environmental impact SIAP (2018). Sufficient reasons above to explore any new technology such as Agricultural Mechatronics, Precision Agriculture, Precision Beekeeping, Precision Livestock, Automatization of agriculture with Arduino and Artificial Neural Network, in which artificial vision plays an important role for its application in the Mexican agriculture. In México, the application of the artificial vision to agriculture for Identification of diseases, pests, invasive plants is low. It does not have the dynamism that it is taking in other countries, it is necessary to promote it.

Keywords: Agriculture; Mexico; Artificial Vision; Agricultural Technology; Diseases; Pests and Invasive Plants.

Introduction

At present there are around 7,000 million human beings in the world and the World Bank estimate is that we will reach some 9,000 million people by 2050. The FAO assures that the arable lands will not increase and that, due to the shortage of water and desertification will even decrease. Therefore, the two main challenges facing agriculture are: a) feed this growing population with less arable land and b) achieve this production with fewer resources [1,2]. Mexico is not exempt from the previous situation because it is estimated that the population of our country for 2050 will be 150,837,517 CONAPO (2017) [3]. World food security is determined by the production methods of poor farmers and by the purchasing power of low-income consumers.

Sufficient reasons above to explore any new technology for Mexican conditions such as those Agricultural Mechatronics, Precision Agriculture, Precision Beekeeping, Precision Livestock, Automatization of agricultura, with Arduino and Artificial Neural Network, Intenet of things in agricultura, in which artificial vision plays an important role for its application in the Mexican agriculture, increasing its productivity and to feed the population thus increasing the food security of our country [4-12].

Materials and Methods

A revision was made on the topics of artificial vision in agriculture on the Internet, in databases of libraries, magazines, journal, etc.

Artificial vision definition

Artificial intelligence opens a wide range of objects of study, one of them is artificial vision: You can define the “Artificial Vision” as a field of “Artificial Intelligence” that, through the use of appropriate techniques, allows obtaining, processing and analysis of any type of special information obtained through digital images. Artificial vision is made up of a set of processes used to perform image analysis. These processes are: capturing images, memorizing information, processing and interpreting the results. As you can see, the artificial vision seeks to imitate one of the 5 senses of man, a physiological sensor that we have capable of converting photons that travel in the space in the form of electromagnetic spectrum that lie between 400nm-700nm, range where we can witness the rainbow of colors that our eyes can see, this electromagnetic spectrum at the moment that affects our eyes, are automatically converted into electrical signals that they are interpreted by our brain to offer us the images with which we see the world. Artificial vision seeks to interpret the images through sensors that capture electromagnetic spectra, obtain images, and that systems are able to method, recognize the images, artificially giving them the quality of being able to see the reality, as our eyes and brains.

Artificial vision (also known as computer vision or computer vision) is an optical, clean, safe and very versatile acquisition technique. The analysis of the obtained images allows detecting in an object physical characteristic invisible to the human eye or establishing or checking some predetermined property or measurement [13].

Artificial vision in the agriculture of the world for Identification of diseases, pests, invasive plants.

Machine vision in agrobotic systems (henceforth, agrovision) is yet to reach its full potential, many applications have been developed for various tasks in the fields, orchards, and greenhouses. Among these are autonomous navigation and obstacles avoidance, precision and selective spraying; weeds detection, yield estimation, seedling planting and ripeness and quality evaluation [14].

Author and year	Description	Country
[15]	Reviews recent developments in image analysis systems for the plant growth and health evaluation	
[16]	Realized the design of an expert system based on computer vision for real-time crop rows and weeds identification in maize fields	Spain
[17]	Proposed testing and validating the accuracy of four image processing algorithms (wavelet transforms and Gabor filtering) for crop/weed discrimination in synthetic and real images.	
[18]	Studied a High-resolution images from digital cameras support of plant characteristics.	
[19]	Present a system consists of two independent subsystems, a fast image processing delivering results in real-time (Fast Image Processing, FIP), and a slower and more accurate processing (Robust Crop Row Detection, RCRD) that is used to correct the first subsystem's mistakes	Spain
[20]	Developed several computer-vision-based methods for the estimation of percentages of weed, crop and soil present in an image showing a region of interest of the crop field.	Spain
[21]	Used a method to provide real-time positional information of crop plants for a mechanical intra-row weeding robot.	China
[22]	Pproposed an automatic crop disease recognition method , which combined the statistical features of leaf images and meteorological data	China
[23]	Present a machine vision system for the identification of the visual symptoms of plant diseases, from coloured images.	UK
[24]	Present image-processing based method that identifies the visual symptoms of plant diseases, from an analysis of coloured images.	UK
[25]	Present an Autonomous spraying in vineyards and four machine vision algorithms that facilitate selective spraying.	Israel
[26]	Developing an easy and proficient automatic method for finding nitrogen and chlorophyll content in a plant based on leaf color and image processing	India
[27]	Design avision guidance system for automated weed detection robot	Pakistan
[28]	detect and recognize the plant stress caused by disease in the field conditions by combining hyperspectral reflection information between 450 and 900nm and fluorescence imaging.	Belgium
[29]	Detection of unhealthy region of plant leaves and classification of plant leaf diseases using texture features	India
[30]	Development of a pattern recognition system that recognizes weeds and gives the occupation percentage of wide and narrow leaves in an agricultural production system,with digital image processing techniques.	Brazil
[31]	Methods of vision-based row detection for lentil field	Iran
[32, 33]	Surveing methods that use digital image processing techniques to detect, quantify and classify plant diseases from digital images in the visible spectrum.	
[34, 35, 36]	Developed automatic computer vision method for detecting Avena sterilis, a noxious weed growing in cereal crops, and differential spraying to control the weed	Spain
[37]	Evaluate the discrimination among three nutritional levels in wheat crop using digital images and a portable chlorophyll meter.	Brazil
[26]	Reviewed an automatic method for finding nitrogen and chlorophyll content in a plant based on leaf colour and image processing	India
[38]	Present a method based in computer vision for the construction of maps of application of variable rate herbicide dedicated to broad-leaved and narrow-leaf invasive plants of maize.	Brazil
[17]	Developed a machine vision system for a real time precision sprayer. From a monochrome CCD camera located in front of the tractor, the discrimination between crop and weeds is obtained with image processing based on spatial information using a Gabor filter.	France
[39-41]	Develop a machine vision system for a real-time precisión sprayer	France
[42]	Develop autonomous agricultural mobile robot for mechanical weed control in outdoor environments.	Sweden

Author and year	Description	Country
[43]	Developed a moldy tobacco online detection system based on machine vision to realize automatic screening of mildew tobacco leaves .	China
[44]	Design and development of a camera-vision guided unmanned mover sprayer for the purpose of automatic weed control.	Malasya
[22]	Proposes an aerial images processing solution to be capable of identify exposed soil areas in large areas of plantations and can be embedded in a small computer and low power	
	Brazil	
[21]	Developed an automatic counting system for urediospores of wheat stripe rust pathogen based on image processing using MATLAB GUIDE platform in combination with Local C Compiler (LCC)	China
[16]	Design of an expert system based on computer vision for real-time crop rows and weeds identification in maize fields. Furthermore, the proposed system controls the guidance of the tractor and the overlapping of the areas of treatment in order to apply a site-specific treatment	Spain
[45]	Developed a novelty system for obtaining the crop cover with easy, unattended and automated procedures from a digital photography ,the crop water needs are calculated from this photography combined with a mathematical algorithm.	Spain
[46]	Propose a new approach for automatic classification of weeds and crop digital images.	Brazil
[47]	Designed a sprayed to detect between the trees in orchrads using a machine vision system to stop the spraying on places where no tree exists.	Iran
[46]	Develop and evaluate the performance of an image processing system to identify weeds in sugarcane and estimate their level of infestation, since the existence of a computer tool to recognize plants species should give a great support to decision-making about the management of weed communities.	Brazil
[48]	Proposed a method to detect and count the number of white-flies using image processing on Simulink and Matlab software.	India
[49]	Discussed existing segmentation method along with classifiers for detection of plant leaves. A Survey On Detection Of Unhealthy Region Of Plant Leaves By Using Image Processing	India
[50]	Propose a system that performs vegetation detection, local as well as object-based feature extraction, random forest classification, and smoothing through a Markov random field to obtain an accurate estimate of the crops and weeds.	Germany
[51]	Propose a system that performs vegetation detection, plant-tailored feature extraction, and classification to obtain an estimate of the distribution of crops and weeds in the field. We implemented and evaluated our system using UAVs	Germany
[37]	Develop and evaluate an algorithm for identifying damaged corn plants by the fall armyworm (Spodoptera frugiperda) using digital color images	Brazil
[52]	Implement a methodology through the generation of a supervised classifier based on the Mahalanobis distance to characterize the grapevine canopy and assess leaf area and yield using RGB images.	Spain
[34]	Developed an automatic image processing technique to detect rice Crop height based on images taken by a digital camera attached to a field server.	Thailand
[53]	Presents a technique using computer vision to detect disease stress in wheat.	USA
[54]	Develop and evaluate a weeds and corn identification system,using color and monochomatics digital images	Brazil
[55]	Design and evaluate a novel dual camera sensor for use in an accurate single leaf level plant detection and classification system for weed control purposes.	UK
[56]	Developed a novel computer vision-based approach for automatically identifying crop diseases based on marker-controlled watershed segmentation, superpixel based feature analysis and classification	China
[44]	Used a digital camera to take pictures of the canopies of 3 rice (Oryza sativa L.) cultivars with 6 different nitrogen (N) application rates.	China
[57-59]	Implemented image processing using MATLAB to detect the weed areas in an image we took from the fields.	India
[60]	Proposes a new method, oriented to crop row detection in images from maize fields with high weed pressure. The vision system is designed to be installed onboard a mobile agricultural vehicle	Spain
[61]	Presents a low-cost computer vision system with the use of stereoscopic imaging and computational model dedicated to the recognition of small their variability, with particular application to those that present geometric primitives based on circular patterns.	Brazil
[62]	Proposed a fuzzy classification system using the attributes described to infer about the infestation risks of crop regions by weed plants. Simulation results of the proposed risk classification system are presented to illustrate its use in the site-specific herbicide application.	Brazil
[63]	Proposed method for locating and identifying weeds, using cotton as the example crop. The system used a digital video camera for capturing images along the crop seedline while simultaneously capturing data from a global positioning system (GPS) receiver	USA
[64-66]	Proposes a system for weed identification based on pattern recognition in imagery taken from a Remotely Piloted Aircraft (RPA).	Brazil

Table 1: Literarature Review about Artificial Vision in World Agriculture for Identification of diseases, pests, invasive plants

Artificial vision for Identification of diseases, pests, invasive plants in Mexican agriculture [67]. Proposes the use of an artificial vision system to identify the fusarium fungus on corn crops by integrating the technology in a smartphone and an implementation of java CV to identify color patterns in the corn and be able to identify any anomaly. Artificial vision systems aim at mathematically modeling the visual perception systems of living beings and create programs that will allow the simulation of such capabilities by means of a computer system. The current frameworks that run on mobile devices allow both monochromatic and color image processing. The structure and properties of the 3D world that they try to describe aim at not just geometrical properties but also at properties such as material, light intensity/absorption on surfaces in an automated way. In Mexico, the implementation of such technologies in corn crops is almost nonexistent. However, by developing solutions the beneficial impact would boost the creation of technologies that may be able to detect plagues or diseases in crops.

Reports an FPGA-based Smart sensor able to perform non-destructive, real-time and in-situ analysis of leaf images to quantify multiple symptoms presented by diseased and malnourished plants; this system can serve as indicator of the health and nutrition in plants [68]. The effectiveness of the proposed smart-sensor was successfully tested by analyzing diseased and malnourished plants.

Develop an information system that works as a database tool for nutritional (nitrogen, phosphorous, potassium) deficiency and water stress characterizations of alfalfa crops, integrating all parameters mentioned before [18]. The database utilizes images captured by a CCD camera, and results of extraction techniques and recognition of configured patterns in a machine vision system previously developed. Integration of the artificial vision module and human expert knowledge module are presented in a single information base, programmed in Visual Basic language.

Proposes a method for knowing and preventing the disease in chili peppers plant through a color image processing, using online system developed in Java applets [45]. This system gets results in real time and remotely (Internet). The images are converted to perceptual spaces [hue, saturation and lightness (HSL), hue, saturation, and intensity (HSI) and hue saturation and value (HSV)]. Sequence was applied to the proposed method. HSI color space was the best detected disease. The percentage of disease in the leaf is of 12.42%. HSL and HSV do not expose the exact area of the disease compared to the HSI color space. Finally, images were analyzed and the disease is known by the expert in plant pathology to take preventive or corrective actions.

Developed a methodology to detect Escherichia coli, using thermal imaging [69]. Escherichia coli grown on classical LEVINE agar were imaged using a thermal IR camera. A prototype was developed to avoid temperature changes on the surface due to air movement. The prototype which injected heat from the bottom was analyzed thermally to detect relative humidity and temperature changes. The images had to be taken 15 s after taking the Petri dish from the incubator. The thermal images were processed by counting the pixels per color. A RGB processing algorithm worked better than the grey scale algorithm as yellow and rose could not be discriminated properly. The value was introduced in three equations and a detection success rate of 100% was achieved.

Developed a detection system of powdery mildew (Sphaerotheca pannosa) on rose with Open CV [70-72]. Open CV is an open source computer vision library, which is written in C and C++ language. The detection was made according to the HSV space color. The source image was converted from the RGB to the HSV space color and the disease and the plant parts were extracted according to the H, S and V information. After that the noise (white objects) was removed. Finally the accuracy of the detection was evaluated. The developed disease detection system is able to detect the powdery mildew disease through the HSV space color with Open CV. Better results were obtained when using close pictures (10 cm). The miss-matched rate caused mostly by halation when using distant pictures could be successfully avoided using active sensing which allows for disease detection even when using distant pictures.

Describes a machine vision system able to detect whiteflies (Bemisia tabaci Genn.) in a greenhouse by sensing their presence using hunting traps [73]. The extracted features corresponding to the eccentricity and area of the whiteflies projections allow establishing differences among pests and other insects on both the trap surfaces and dust generated artifacts. Because of whiteflies geometrical characteristics, it was possible to design an efficient (related to manual counting) machine vision algorithm to scout and count units of this pest within a greenhouse environment. These algorithm results show high correlation indexes for both, sticky screens ($R2 = 0.97$) and plant leaf situations ($R2 = 1.0$). The machine vision algorithm reduces the scouting time and the associated human error for IPM-related activities.

Conclusion

From the literature review, the results are dominated predominantly by Asian authors (India and China) in Europe Spain predominates and in Latin America Brazil has promoted it in research centers. In México, the application of the artificial vision to agriculture is low. It does not have the dynamism that it is taking in other countries, it is necessary to promote, to increase productivity and reduce losses due to the early detection of plant pests or diseases and invasive plants.

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