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RESEARCH ARTICLE

THE APPLICATION OF IMAGE PROCESSING FOR HORTI-AGRICULTURAL EXPERIMENTS

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ABSTRACT

Horti-Agricultural industry is demanding techno-logical solutions focused on automating agricultural tasks in order to increase the production and benefits while reducing time and costs. Technological advances in precision agriculture have an essential role and enable the implementation of new techniques based on sensor technologies and image processing systems. The no. of application using machine vision and image processing techniques in the Horti-Agriculture structure is in-creasing rapidly day by day. The application include detection of diseases in plant, measuring the severity of diseases, counting fruits on-tree, classification of mature and immature fruits and pest detection. The quantification of the visual properties of Horti-Agricultural product and plants can play an important role to improve and designing automatic task management system. This paper describe various proto type of image processing for different task of Horti-Agricultural sector.

INTRODUCTION

A large number of the tasks conducted in the agricultural field are human-performed operations, highly time consuming and prone to produce stress and fatigue to their human opera-tors due to the nature of the conditions under which they take place. Thanks to the technological advances that have appeared over the last years, such as image processing procedures and sensor-based technologies, a considerable number of novel techniques have been implemented allowing the automation of many of these tasks and, thus, leading to big economic and efficiency gains. These technological solutions cover all phases of the industrial process; pre-harvest, harvest and post-harvest. The needs to be solved identified by farmers are focused on the following topics.

- Seeds, seedling, breeding, growing and state of health. Location and detection of crops and yield estimation.
- Weed control and machinery.
- Positioning, navigation and safety.
- Microorganisms and pest control.
- Crop quality.

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Seeds, seedling, breeding, growing and state of health

The control of crop seedling, breeding and growing as well as the identification of its different growth phases are some of the main challenges in precision agriculture. For example, in (Zhang *et al*., 2012), hyperspectral imaging techniques applied in the visible and near infrared region (VIS-NIR) were developed to dis-criminate varieties of maize seeds achieving a success rate of 98.89%. Techniques such as principal component analysis (PCA), kernel principal component analysis (KPCA), least squares-support vector machine (LS-SVM) and back propa-gation neural network (BPNN) were applied. A configurable growth chamber equipped with CCD cameras and artificial illumination was designed in (Navarro *et al*., 2012) to control the circadian rhythm in plants. In (Kim *et al*., 2013) a thermal imaging technique based on infrared sensors was evaluated to study lettuce seed viability. It was proved that aged lettuce seeds can be distinguished from the normal seeds by applying time-dependent thermal decay characterization in combination with decay amplitude and delay time images. In (You *et al*., 2012) a slim and small open-ended coaxial probe was used to detect moisture of rice grains. In (Giselsson *et al*., 2013) shape feature generation approaches based on the approximate distance distribution of an object were introduced to enhance the recognition of plant seedling. In addition, plant silhouettes were used as inputs for the classifier methods. In (Busemeyer *et al*., 2013) a mul-tisensory platform equipped with optical sensors (light curtain imaging, 3D time-of-flight cameras, laser distance sensors, hyperspectral imaging and color imaging) was developed with the aim of characterizing plants in cereals orchards, to measure plant moisture content, lodging, tiller density or biomass yield. In (Yao *et al*., 2013), three different ground sensors were used to measure canopy spectral reflectance and vegetation indices to monitor above-ground plant nitrogen uptake in winter wheat. In (Fernandez-Jaramillo *et al*., 2012)a review of the state of the art of chlorophyll fluorescence sensing systems was assessed to obtain information of the state of health of a photosynthetic tissue.

Detection of crops and yield estimation

Tasks focused on the detection, location and counting of elements are being automated considering different scenarios and set-up possibilities in order to reduce costs (Peacock *et al*., 2012) and to avoid errors produced by the fatigue and stress of human operators by the long working hours. Additionally, one of the biggest challenges in agricultural industry is to estimate yield with accuracy and to predict variations in its qual-ity, which are dependable on environmental variables (soil characteristics, weather conditions, pests and plant diseases), farming factors (addition of products such as water, pesticide or fertilizer), and agricultural operations (pruning, thinning). The uncertainties about how these factors affect crop quality make the management of orchards very complex. For this reason, crop yield estimation is a topic of relevant interest in precision agriculture. The automatic estimation of yield is based on counting the number of agricultural elements in images, such as trees (Recio *et al*., 2013), or vegetables and fruits (Stajnkoa *et al*., 2004; Chinchuluun, 2006; Wijethunga *et al*., 2008; Linker, 2012) by using algorithms based on image-processing techniques (Stajnkoa *et al*., 2004; Chinchuluun *et al*., 2006; Wijethunga *et al*., 2008; Linker *et al*., 2012, Payne *et al*., 2013; Teixid, 2012Teixid *et al*., 2012).These techniques can be more or less complex depending on the element (fruit, vegetables) to be counted and its particularities. For example, occlusions problems, color differences between the element and the background, lighting conditions or the dimensions of the objects are some of the main problems to overcome. The proposal of (Stajnkoa *et al*., 2004) was to count the number of apples in thermal images. The method showed good accuracy between the results from the manual and automatic procedure. In (Chinchuluun *et al*., 2006) a fruit counting method was presented taking into account illumination adjustments and removing the noise from the image. First, a segmentation procedure using the RGB and HSI color spaces was applied to the images. Then, a K-means clustering algorithm was used to classify elements into fruits in combination with a marker-controlled watershed function used to split connected fruits. Finally, a blob analysis was applied in order to count individual fruits. The development of two automatic counting methods to estimate the number of kiwi in the CIELab color space was addressed in (Wijethunga *et al*., 2008). In this work it was considered that the intensity of the pixels was higher at the center of the fruit and that the number of peaks in the image corresponded to the number of fruits. The automatic counting method used in the first technique was based on counting the peaks in a gray color image whereas the second technique used a binary image in order to compute the distance from a fruit pixel to the nearest background pixel. The results showed a counting success rate of 90% and 70% in case of gold and green varieties of kiwi, respectively. An alternative counting technique was presented in (Linker *et al*., 2012). The methodology applied was to identify the pixels belonging to the fruit in the image, connecting these pixels into sets, and use the information of the contours of these sets to define an apple model. Themethod was dependent on lighting conditions achieving a minimum and a maximum success rate of 85% and 95%, respectively. In (Payne *et al*., 2013) an automatic method to count mango fruit was presented based on identifying the fruit pixels in the image applying a combination of a color (in the RGB and YCbCr color spaces) and texture segmentation and then, using a blob analysis in order to count the fruits. The results showed a strong correlation, 0.91, when comparing the automatic with the manual counting data. Automatic location of red peaches in daylight images were assessed in (Teixid *et al*., 2012) by applying linear color models in the RGB color space.

Additionally, a procedure to estimate peach diameter based on an ellipsoidal fitting was proposed. Similarly, in (Teixid *et al*., 2012) red peaches were also detected by implementing algorithms based on linear color models and fruit histograms in combination with a look-up-tables (LUT) technique applied to the RGB color space. In (Nuske *et al*., 2011) the number of individual grapes from vineyard images were estimated by using a radial symmetry transform (Loy *et al*., 2003). The method consisted in identifying pixels with a high level of radial symmetry and in connecting the neighboring berries into clusters in order to predict yield. The results showed that the yield could be estimated with an error of 9.8%. More recently, in (Cubero *et al*., 2014) the size and weight of grapes were accurately estimate with values of 0.97 and 0.96, respectively. Other tasks focused on predicting yield are based on studying the effects of the use of agricultural machinery in fields (Valera *et al*., 2012) or characterizing fruits and plants (Valera *et al*., 2012; Rossi *et al*., 2013; 6,7, 29, 30). In the specific case of studying the effects of the use of machinery in fields it was proved that high values of sinkage and cone index produced a decrement in crop yield. In (Valera *et al*., 2012) variations in the dry bulk density, cone index and sinkage were measured over the same land but at five different passes of three tractors. Two different devices were designed and tested for this specific purpose; a laser microrelief profile and an electrical penetrometer. The results suggested that soil compaction should be avoided by ensuring that tractors always travel along the same tracks. In (Rossi *et al*., 2013), vegetative growth and yield were measured by means of soil electrical resistivity and ancillary topography. The proposal of (Lofton *et al*., 2012) was to estimate potential sugarcane yield using the in-season estimation of normalized difference vegetative index (NDVI) and a Green Seeker device. The results showed that in-season estimates of yield values, which were computed by diving NDVI by thermal variables, were suitable to predict sugarcane yield. The proposal of (30) was to use a smart one-chip camera adapted to pass red and near-infrared spectral bands in order to detect plants by estimating NDVI. In (Diago *et al*., 2012) a methodology based on a supervised classifier in combination with the Mahalanobis distance was implemented on the RGB color space and applied to daylight images in order to characterize grapevine canopy and evaluate leaf area and yield. The results showed good correlations when evaluating the leaf area of grapevines, 0.81, and when assessing yield, 0.73.

Weed Control and Machinery

Weed control is also an important step in the automation of agricultural tasks implying the design of effective machinery.The application of agrochemicals in orchards is very complex since canopies are spatially variable and specific doses may be required at different areas of the orchard. Machinery is being designed to spray at an adequate rate in order to use the adequate amount of agrochemicals. For example, in (Garca-Ramos *et al*., 2012) an assisted sprayer equipped with two axial fans and a 3D sonic anemometer was designed and implemented to apply the exact quantity of agrochemicals needed. In (Gil *et al*., 2013) the use of a scanning Light Detection and Ranging (LIDAR) system during pesticide tasks to control drift in vineyard spraying was described. In(Gil *et al*., 2013)a prototype of six-row mechanical weed control cultivator for inter-row areas and band spraying for intra-row areas was implemented.

The results showed a significant decrease in the herbicide application rate and consequently a reduction in the operating cost. In (Perez-Ruiz, 2013) the reduction of weed competition in wheat and barley was controlled using a harrow equipped with bi-spectral cameras, which detected crop leaf cover, weed cover and soil density. In (Rueda-Ayala *et al*., 2013) LIDAR sensors mounted on a tractor used to evaluate geometric and structural parameters of vines such as the height, the cross-sectional area, the canopy volume and the tree area index (TAI). These parameters were used to predict the leaf area index (LAI). The results showed that the TAI was the best estimation of the LAI achieving a strong correlation of 0.92. In (Arn *et al*., 2013) a sprayer prototype was designed and implemented to regulate the volume application rate to the canopy volume in orchards. The conclusions were that there were strong relationships between the intended and the sprayed flow rates (R2= 0.935) and between the canopy cross-sectional areas and the sprayed flow rates (R2= 0.926). Other tasks that require automation are fruit harvesting and classification. For example, in (Escol *et al*., 2013) a vision-based estimation and control system for robotic fruit harvesting was presented whereas in (Mehtaa *et al*., 2014) a multiarm robotic harvester was developed to harvest melons.

Positioning, Navigation and Safety

The automation of agricultural applications that involve land vehicles requires knowing global and local positions of specific elements in an orchard. In addition,safety while navigating is also essential. The two most commonly used methods to estimate global and local coordinates are the GPS system and crop rows detection systems, respectively. Nowadays, researchers focused their efforts to integrate the inertial navigation system (INS) with GPS to enhance positioning and navigation information for agricultural machinery. In (Ziona *et al*., 2014) a novel inertial sensor was developed to remove error components in order to enhance positioning and navigation for land vehicles by applying a fast orthogonal search modeling technique. In (Noureldin *et al*., 2012) a vehicle was guided inside greenhouses by means of a laser sensor. The vehicle integrated several tools for a wide range of applications such as a spray system for applying plant-protection product, a lifting platform to reach the top part of the plants to perform pruning and harvesting tasks, and a trailer to transport fruits, plants, and crop waste.

Microorganisms and pest control

Pests and microorganisms in plants and trees are a threat to production causing important losses. Agricultural resources are focused on controlling and monitoring them, which is a time- and cost-consuming operation since it must be performed periodically through the field and so, its automation implies benefits in all aspects. In (Snchez-Hermosilla *et al*., 2013) an autonomous system based on a low-cost image sensor was responsible of monitoring pests by capturing and sending images of trap contents, which were distributed through the field, to a control station. The images were processed in the control station in order to calculate the number of insects. In (Lpez *et al*., 2012) a development of an immunocapture real-time reverse transcription-polymerase chain reaction (RT-PCR) assay to detect the tobacco mosaic virus in the soil was presented. In (Yang *et al*., 2012) a system to detect root colonization by microorganism in potatoes was developed. A technique to excite material and produce fluorescence was applied for this purpose. In (Krzyzanowska *et al*., 2012) an ultrasonic distance sensor in combination with a camera was used to estimate plant height in cereal crops and to determine the weed and crop coverage The results showed a success of 92.8% when separating weed infested zones and non-infested zones. The acquisition of sounds through a bio-acoustic sensor was used to detect real palm weevil for pest control (Andjar *et al*., 2012). Finally, in (Rach *et al*., 2013), a non-destructive method based on the Raman spectroscopy in combination with a laser source in order to detect pesticide residues on apple skin surfaces was developed.

Crop Quality

The monitoring and control of quality indices in crops during the life cycle of the product is essential in order to assess crop grading and crop health. The estimation of quality parameters by using non-destructive techniques is of special interest in precision agriculture. For example, in (Dhakal *et al*., 2014) a system based on Vis/NIR spectroscopy and a polychromatic spectrometer was used in order to measure quality indices of Royal Gala apples such as color, starch pattern index, soluble solids content (SSC), firmness, quantitative starch, and titratable acidity (TA). The results showed a good estimation of the quality parameters studied and a dependency between the SSC and soluble carbohydrates. In (McGlone *et al*., 2002) 19 apple cultivars were analysed to find correlations between parameters extracted from non-destructive measurements (Vis/NIR spectroscopy) and by destructive measurements (penetrometer). The re-sults showed that the parameters obtained with destructive measurements were strong correlated with sensory textural parameters. Another proposal was to assess physicochemical properties of two apple varieties to assess correlations between biochemical markers and fruit sensory properties (McGlone *et al*., 2003). The results showed that the galacturonic acid had a positive cor-relation with mealiness but a negative one with crunchiness and firmness. Finally, the total neutral sugar content was correlated with apple texture properties. In (Zdunek *et al*., 2011) correlations between biospeckle activity (BA) and other quality-attributes parameters obtained with destructive methods (firmness, SSC, TA and starch content (SC)) were assessed in case of applefruits. The results showed a strong correlation between BA and SC. The assessment of crop health is based on estimating fruit damage.

For example, in (Lee *et al*., 2014) NIR hyperspectral imaging techniques were used to identify damages underneath fruit skin achieving a success rate of 92%. Another proposal was to use Vis/NIR spectroscopy but to identify internal defects in fruits (Takizawa *et al*., 2014). In this case, the method showed an accuracy of 97%. In (Zhang *et al*., 2014) two parameters (signal to noise ratio and area change rate) extracted from the application of Vis/NIR spectroscopic techniques were evaluated to measure internal defects. The conclusion obtained was that there was a strong correlation between these variables. Changes in fruit ripening usually involve changes in the skin color caused by synthesis of pigments (Bramley, 2002). This information is used to classify elements depending on their ripeness stage. For example, in (Fadilah *et al*., 2012) color vision techniques based on Artificial Neural Network (ANN) learning and PCA were applied for ripeness classification of oil palm fresh fruit bunches. In (Aroca *et al*., 2013) a glove-based system was designed to measure fruit attributes and as a tool for fruit grading. The glove system incorporates several sensors such as touch pressure, imaging, inertial measurements localization and a Radio Frequency Identification (RFID) reader. Alter-natively, in (Mendoza *et al*., 2014) an approach based on the measurement of internal quality parameters (firmness and SSC) and skin Color components was developed to grade three apples cultivars by evaluating two different methods; Vis/NIR spectroscopy and spectral scattering. The conclusions obtained were that the results from the Vis/NIR technique were better achieving grading successes of 97% in the case of firmness and 92% for the SSC quality index. In (Zhang *et al*., 2014) another method for grading fruits automatically was presented. The method was based on computing skin histograms of the fruits processed to correlate the evolution of these values with the fruit ripeness.

Conclusion

The development of new systems based on image processing techniques is realiable and efficient enough to do the automat-ing agricultural tasks in different phases:pre-harvest, harvest and post-harvest.

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