Universitat de Lleida

Application of image processing methodologies for fruit detection and analysis

Davínia Font Calafell

Dipòsit Legal: L.1695-2014
http://hdl.handle.net/10803/284652

Universitat de Lleida

PhD Thesis
Engineering and Information Technologies

Application of image processing methodologies for fruit detection and analysis

Author

Davínia Font Calafell
Department of Computer Science and Industrial Engineering
University of Lleida
dfont@diei.udl.cat

Director of the PhD Thesis

Dr. Jorge Palacín Roca

Lleida, 30th of July of 2014

Departament d'Informàtica i Enginyeria Industrial
Escola Politècnica Superior
Universitat de Lleida

Application of image processing methodologies for fruit detection and analysis

Memòria presentada per optar al grau de Doctor per la Universitat de Lleida redactada segons els criteris establerts en l'Acord núm. 19/2002 de la Junta de Govern del 26 de febrer de 2002 per la presentació de la tesis doctoral en format d'articles i menció international.

Programa de doctorat: Enginyeria i Tecnologies de la Informació

Director de la Tesis: Dr. Jordí Palacin Roca

El Dr. Jordi Palacín Roca, professor titular de l'Escola Politècnica Superior de la Universitat de Lleida

CERTIFICA:

Que la memòria "Application of image processing methodologies for fruit detection and analysis" presentada per Davínia Font Calafell per optar al grau de Doctor s'ha realitzat sota la seva supervisió.

Lleida, 30 de Juliol de 2014

Acknowledgements

First of all, I would like to thank Dr. Jordi Palacín for the tasks performed as the supervisor of this thesis. All the knowledge he shared with me, his encouragement, guidance, and persistence during the evolution of this PhD Thesis has been essential for my development as a researcher.

I would like to thank the University of Lleida, the UdL-IMPULS project (reference: X10020), the Government of Catalonia (Comisionat per a Universitats i Recerca, Departament d'Innovació, Universitats i Empresa) and the European Social Fund with references 2012FI_B 00301, 2013FI_B1 00010 and 2014FI_B2 00118 for funding this PhD Thesis.

Thanks to my family, especially to my grandparents, parents, siblings and partner: Benjamí, Magina, Josep, Teresa, Edgard, Jessica and Samuel for their immense support, patience and understanding. They have always transmitted great values and principles making me to fight with perseverance, and giving me the motivation I needed at every specific moment. They have always given me courage and support being my strength in difficult moments and the people with whom I wanted to share all the successes.

Thanks to all my department colleagues: Mercè, Tomàs, Marcel, Javier, and Dani for their help and friendship, they have been essential on the development of this PhD Thesis. Also thanks to my colleagues from CMU (Carnegie Mellon University) and especially to Dr. Stephen Nuske, who guided me during the research stays I performed in this institution.

Finally, I would thank to all who directly or indirectly participated in the realization of this thesis, thank you to everyone!

Resum

En aquesta memòria es presenten diversos treballs d'investigació centrats en l'automatització d'operacions agrícoles mitjançant l'aplicació de diverses tècniques de processament d'imatge.

La indústria de l'agricultura està exigint solucions tecnològiques basades en l'automatització de les tasques agrícoles amb l'objectiu d'incrementar la producció i beneficis reduint al mateix temps el temps i els costos. Els avenços tecnològics en l'agricultura tenen un factor rellevant i fan possible la implementació de noves tècniques basades en les tecnologies de sensors i de processament d'imatges. Tot i això, encara hi ha molts reptes a resoldre.

En la memòria es presenta, en primer lloc, un nou mètode de processament d'imatge desenvolupat per detectar i comptar raïms vermells mitjançant la localització de pics d'intensitat en superfícies esfèriques. En la mateixa línia de treball es proposa una segona aplicació en la qual es desenvolupa un sistema de recol·lecció automàtica de fruita mitjançant la combinació d'una càmera estereoscòpica de baix cost i un braç robòtic. Tècniques de processament d'imatges aplicades a les imatges extretes de la càmera de visió estereoscòpica s'utilitzen per estimar la mida, la distància i la posició de la fruita mentre que el braç robòtic s'utilitza per a la recol·lecció automàtica de fruita. En tercer lloc es proposa una aplicació en què es desenvolupa un mètode de processament d'imatge basat en l'ús de la informació de color per a la verificació d'una varietat de nectarines de forma automàtica i individual en una línia d'embalatge de fruita. En quart lloc s'han estudiat les correlacions entre els paràmetres de qualitat de la fruita i el espectre visible de la seva pell amb l'objectiu de controlar la seva qualitat de forma no destructiva durant el seu emmagatzematge. Els resultats obtinguts en les diverses aplicacions propostes han demostrat la utilitat i versatilitat dels sistemes de processat d'imatges utilitzats.

Resumen

En esta memoria se presentan diversos trabajos de investigación centrados en la automatización de operaciones agrícolas mediante la aplicación de distintas técnicas de procesado de imágenes.

La industria de la agricultura está exigiendo soluciones tecnológicas centradas en la automatización de las tareas agrícolas con el fin de aumentar la producción y los beneficios reduciendo al mismo tiempo el tiempo y los costes. Los avances tecnológicos en la agricultura de precisión tienen un papel relevante y hacen posible la implementación de nuevas técnicas basadas en las tecnologías de sensores y en procesado de imágenes. Sin embargo, todavía hay muchos desafíos a resolver.

En la memoria se presenta, en primer lugar, un nuevo método de procesado de imágenes desarrollado para detectar y contar uvas rojas mediante la identificación de picos de intensidad en las superficies esféricas. En la misma línea de trabajo se propone una segunda aplicación en la que se desarrolla un sistema de recolección automática de fruta mediante la combinación de una cámara estereoscópica de bajo coste y un brazo robótico. Técnicas de procesado de imágenes aplicadas en las imágenes extraídas de la cámara de visión estereoscópica se utilizan para estimar el tamaño, la distancia y la posición de la fruta mientras que el brazo robótico se utiliza para la recolección automática de fruta. En tercer lugar se propone una aplicación en la que se desarrolla un método de procesamiento de imágenes basado en el uso de la información de color para la verificación de una variedad de nectarinas de forma automática e individual en una línea de envasado de fruta. En cuarto lugar se han estudiado las correlaciones entre los parámetros de calidad de la fruta y el espectro visible de su piel con el fin de controlar su calidad de forma no destructiva durante el almacenamiento. Los resultados obtenidos en las diversas aplicaciones propuestas han demostrado la utilidad y versatilidad de los sistemas de procesado de imágenes utilizados.

Summary

This memory introduces several research works developed to automate agricultural tasks by applying image processing techniques.

Agricultural industry is demanding technological 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. However, there are still many challenges and problems to be solved.

This PhD Thesis presents the results of four automated agricultural tasks. In the first place a new image processing method is proposed for detecting and counting red grapes by identifying specular reflection peaks from spherical surfaces. The proposal of the second application is to develop an automatic fruit harvesting system by combining a low cost stereovision camera and a robotic arm. Image processing techniques applied to the images from the stereovision camera were used to estimate the size, distance and position of the fruits whereas the robotic arm was used for the automatic fruit harvesting. The third application proposed is to develop a novel image processing method based on the use of color information to verify an in-line automatic and individual nectarine variety verification in a fruit-packing line. In the fourth place a study focused on assessing correlations between post-storage fruit quality indices and the visible spectra of the skin of the fruit is proposed in order to control fruit quality in a non-destructive way during the storage. The results obtained in the proposed applications have proved the suitability and versatility of the image processing techniques used.

Contents

List of Figures

Counting red grapes in vineyards by detecting specular spherical reflection peaks in RGB images obtained at night with artificial illumination

A proposal for automatic fruit harvesting by combining a low cost stereovision camera and a robotic arm

An image processing method for in-line nectarine variety verification based on the comparison of skin feature histogram vectors

Assessment of the correlation between post-storage fruit quality parameters and visible spectra of the skin for 'Golden Smoothee' apple

List of Tables

Chapter 1

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 operators 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. However, there are still many challenges and problems to be solved.

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: 1.1) Soil analysis, 1.2) Seeds, seedling, breeding, growing and state of health, 1.3) Location and detection of crops, and yield estimation, 1.4) Weed control and machinery, 1.5) Positioning, navigation and safety, 1.6) Microorganisms and pest control, and 1.7) Crop quality.

1.1. Soil analysis

Soil is a critical element in agriculture being essential for crop growth, yield production and products quality. In this direction, the proposal of [1] was to use a spectroradiometer sensor to perform a hyperspectral analysis based on regression trees in order to characterize soil contents such as nitrogen, carbon and organic matter. The results showed the suitability of the method for assessing soil attributes within the electromagnetic ranges of 400 to 1,000 nm. In [2] a frequency-domain reflectometry sensor was used for soil salinity assessment of sandy mineral soils and bulk electrical conductivity. In [3] a time domain reflectometry system was applied to analyze soil moisture, electrical conductivity and temperature. In [4] image processing techniques applied to splashed particles were designed to evaluate the impact of water drop in order to characterize soil detachment. In [5] a low-cost capacitance-resistance probe was used to monitor soil volumetric water content and salinity. In [6], new devices based on an electrical penetrometer and a laser microrelief profile meter were designed to study the effects that the transit of the tractors cause on the fields. Variations in the dry bulk density, cone index of clayey soil and sinkage (rut depth) of the running gear were measured. In [7] an automatic resistivity profiler (ARP) sensor in combination with a GPS system (see Fig. 1.1-a) was used to evaluate spatial variability patterns of vegetative growth and yield in a vineyard based on electrical resistivity (ER) and ancillary topographic attributes. In addition, regression and cluster analysis were performed to evaluate soil resistivity data, landscape attributes and grapevine variables. The results showed that the ER obtained good correlations with trunk circumference spatial pattern and yield. In [8] a prototype soil strength sensor equipped with Real Time Kinematic- Global Positioning Systems technology (RTK-GPS) (see Fig. 1.1-b) was designed to measure soil cutting resistance at various depths of a field. The results showed that under the conditions established there was a quadratic relationship between the soil strength profile sensor cutting force and the soil cone index values.

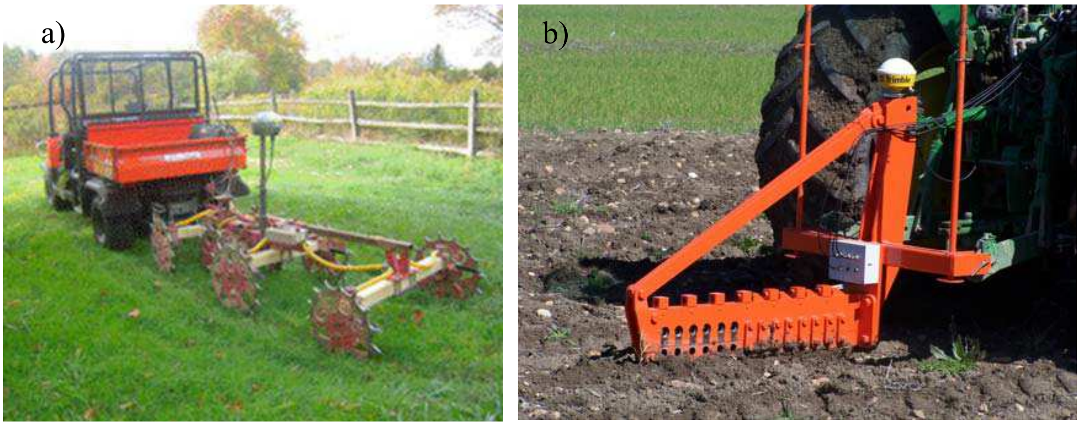

Fig. 1.1. (**a**) ARP system [7]; (**b**) Prototype soil strength sensor [8].

1.2. 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 [9] hyperspectral imaging techniques applied in the visible and near infrared region (VIS-NIR) were developed to discriminate 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 propagation neural network (BPNN) were applied. A configurable growth chamber equipped with CCD cameras and artificial illumination was designed in [10] to control the circadian rhythm in plants. In [11] 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 [12] a slim and small open-ended coaxial probe was used to detect moisture of rice grains. In [13] 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 [14] a multisensory 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. Fig. 1.2 shows the multisensory platform when performing measurements outdoors. In [15], 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 [16] 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.

Fig. 1.2. Multisensory platform [14].

1.3. 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 [17] 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 quality, 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 [18], or vegetables and fruits [19-22] by using algorithms based on image-processing techniques [19-22, 23-25]. 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 [19] 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 [20] 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 [21]. 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 [22]. 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. The method was dependent on lighting conditions achieving a minimum and a maximum success rate of 85% and 95%, respectively. In [23] 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 [24] 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 [25] 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 [26] the number of individual grapes from vineyard images were estimated by using a radial symmetry transform [27]. 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 [28] 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 [6] or characterizing fruits and plants [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 [6] 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 [7], vegetative growth and yield were measured by means of soil electrical resistivity and ancillary topography. The proposal of [29] was to estimate potential sugarcane yield using the in-season estimation of normalized difference vegetative index (NDVI) and a GreenSeeker® 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 [31] 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.

1.4. 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 [32] 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 [33] the use of a scanning Light Detection and Ranging (LIDAR) system during pesticide tasks to control drift in vineyard spraying was described. In [34] a prototype of six-row mechanical weed control cultivator for inter-row areas and band spraying for intra-row areas was implemented (see Fig. 1.3-a). The results showed a significant decrease in the herbicide application rate and consequently a reduction in the operating cost. In [35] 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 [36] LIDAR sensors mounted on a tractor (see Fig. 1.3-b) were 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 [37] 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 (R^2= 0.935) and between the canopy cross-sectional areas and the sprayed flow rates (R^2= 0.926).

Other tasks that require automation are fruit harvesting and classification. For example, in [38] a vision-based estimation and control system for robotic fruit harvesting was presented whereas in [39] a multiarm robotic harvester was developed to harvest melons.

Fig. 1.3. (**a**) Weed control prototype [34]; (**b**) LAI prediction by using LIDAR sensors mounted on a tractor [36].

1.5. 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 [40] 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 [41] 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.

1.6. 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 [42] 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 [43] 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 [44] 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 [45] 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 (see Fig. 1.4). 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 [46]. Finally, in [47], 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. The results showed that the system was able to detect pesticide residues up to 6.69 mg/kg in less than 4 s.

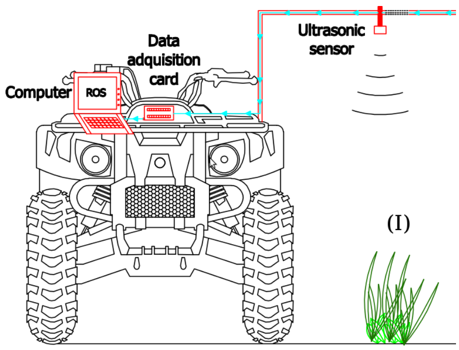

Fig. 1.4. Ground-based ultrasonic system [45].

1.7. 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 [48] 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 [49] 19 apple cultivars were analyzed to find correlations between parameters extracted from non-destructive measurements (Vis/NIR spectroscopy) and by destructive measurements (penetrometer). The results 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 [50]. The results showed that the galacturonic acid had a positive correlation with mealiness but a negative one with crunchiness and firmness. Finally, the total neutral sugar content was correlated with apple texture properties. In [51] 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 apple fruits. The results showed a strong correlation between BA and SC.

The assessment of crop health is based on estimating fruit damage. For example, in [52] 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 [53]. In this case, the method showed an accuracy of 97%. In [54] 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 [55]. This information is used to classify elements depending on their ripeness stage. For example, in [56] color vision techniques based on Artificial Neural Network (ANN) learning and PCA were applied for ripeness classification of oil palm fresh fruit bunches. In [57] 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 (Fig. 1.5). Alternatively, in [58] 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 [59] 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. The results showed good correlation between these parameters.

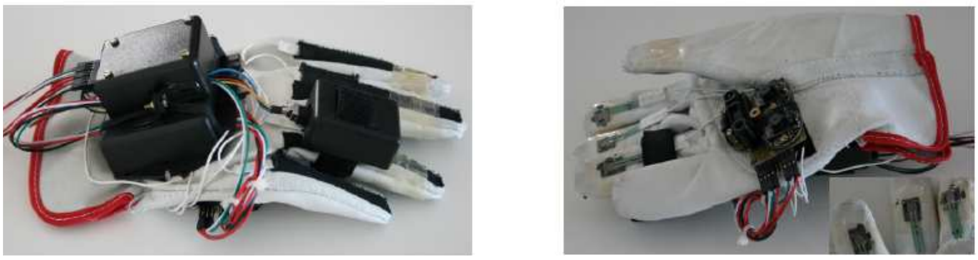

Fig. 1.5. Glove-based system prototype for measuring fruit attributes [57].

1.8. References

[1] Gmur, S.; Vogt, D.; Zabowski, D.; Moskal, L.M. Hyperspectral Analysis of Soil Nitrogen, Carbon, Carbonate, and Organic Matter Using Regression Trees. *Sensors* **2012**, *12*, 10639–10658.

[2] Wilczek, A.; Szypłowska, A.; Skierucha, W.; Cieśla, J.; Pichler, V.; Janik, G. Determination of Soil Pore Water Salinity Using an FDR Sensor Working at Various Frequencies up to 500 MHz. *Sensors* **2012**, 12, 10890–10905.

[3] Skierucha, W.; Wilczek, A.; Szypłowska, A.; Sławiński, C.; Lamorski, K. A TDR-Based Soil Moisture Monitoring System with Simultaneous

Measurement of Soil Temperature and Electrical Conductivity. *Sensors* **2012**, 12, 13545–13566.

[4] Ryżak, M.; Bieganowski, A. Using the Image Analysis Method for Describing Soil Detachment by a Single Water Drop Impact. *Sensors* **2012**, 12, 11527–11543.

[5] Scudiero, E.; Berti, A.; Teatini, P.; Morari, F. Simultaneous Monitoring of Soil Water Content and Salinity with a Low-Cost Capacitance-Resistance Probe. *Sensors* **2012**, 12, 17588–17607.

[6] Valera, D.L.; Gil, J.; Agüera, J. Design of a New Sensor for Determination of the Effects of Tractor Field Usage in Southern Spain: Soil Sinkage and Alterations in the Cone Index and Dry Bulk Density. *Sensors* **2012**, 12, 13480–13490.

[7] Rossi, R.; Pollice, A.; Diago, M.-P.; Oliveira, M.; Millan, B.; Bitella, G.; Amato, M.; Tardaguila, J. Using an Automatic Resistivity Profiler Soil Sensor On-The-Go in Precision Viticulture. *Sensors* **2013**, 13, 1121–1136

[8] Agüera, J.; Carballido, J.; Gil, J.; Gliever, C.J.; Perez-Ruiz, M. Design of a Soil Cutting Resistance Sensor for Application in Site-Specific Tillage. *Sensors* **2013**, 13, 5945–5957.

[9] Zhang, X.; Liu, F.; He, Y.; Li, X. Application of Hyperspectral Imaging and Chemometric Calibrations for Variety Discrimination of Maize Seeds. *Sensors* **2012**, 12, 17234–17246.

[10] Navarro, P.J.; Fernández, C.; Weiss, J.; Egea-Cortines, M. Development of a Configurable Growth Chamber with a Computer Vision System to Study Circadian Rhythm in Plants. *Sensors* **2012**, 12, 15356–15375.

[11] Kim, G.; Kim, G.H.; Ahn, C.-K.; Yoo, Y.; Cho, B.-K. Mid-Infrared Lifetime Imaging for Viability Evaluation of Lettuce Seeds Based on Time-Dependent Thermal Decay Characterization. *Sensors* **2013**, 13, 2986–2996.

[12] You, K.Y.; Mun, H.K.; You, L.L.; Salleh, J.; Abbas, Z. A Small and Slim Coaxial Probe for Single Rice Grain Moisture Sensing. *Sensors* **2013**, 13, 3652–3663.

[13] Giselsson, T.M.; Midtiby, H.S.; Jørgensen, R.N. Seedling Discrimination with Shape Features Derived from a Distance Transform. *Sensors* **2013**, 13, 5585–5602.

[14] Busemeyer, L.; Mentrup, D.; Möller, K.; Wunder, E.; Alheit, K.; Hahn, V.; Maurer, H.P.; Reif, J.C.; Würschum, T.; Müller, J.; Rahe, F.; Ruckelshausen, A. BreedVision - A Multi-Sensor Platform for Non-Destructive Field-Based Phenotyping in Plant Breeding. *Sensors* **2013**, 13, 2830–2847.

[15] Yao, X.; Yao, X.; Jia, W.; Tian, Y.; Ni, J.; Cao, W.; Zhu, Y. Comparison and Intercalibration of Vegetation Indices from Different Sensors for Monitoring Above-Ground Plant Nitrogen Uptake in Winter Wheat. *Sensors* **2013**, 13, 3109–3130.

[16] Fernandez-Jaramillo, A.A.; Duarte-Galvan, C.; Contreras-Medina, L.M.; Torres-Pacheco, I.; Romero-Troncoso, R.J.; Guevara-Gonzalez, R.G.; Millan-Almaraz, J.R. Instrumentation in Developing Chlorophyll Fluorescence Biosensing: A Review. *Sensors* **2012**, 12, 11853–11869.

[17] Peacock, W.L.; Vasquez, S.J.; Hashim-Buckey, J.M.; Klonsky, K.M.; De Moura, R. L. Sample costs to establish and produce table grapes. Crimson Seedless. University of California, Cooperative Extension, GR-VS-07-2, 2007.

[18] Recio, J.A.; Hermosilla, T.; Ruiz, L.A.; Palomar, J. Automated extraction of tree and plot-based parameters in citrus orchards from aerial images. *Computers and Electronics in Agriculture* **2013**, 90, 24–34.

[19] Stajnkoa, D.; Lakotaa, M.; Hocevar, M. Estimation of number and diameter of apple fruits in an orchard during the growing season by thermal imaging. *Computers and Electronics in Agriculture* **2004**, 42, 31–42.

[20] Chinchuluun, R.; Lee, W.S. Citrus yield mapping system in natural outdoor scene using the watershed transform. ASAE, Paper No. 063010, 2006.

[21] Wijethunga, P.; Samarasinghe, S.; Kulasiri, D.; Woodhead, I. Digital Image Analysis Based Automated Kiwifruit Counting Technique. 23rd International Conference Image and Vision Computing New Zealand, Christchurch, pp. 1-6, 2008.

[22] Linker, R.; Cohen, O.; Naor, A. Determination of the number of green apples in RGB images recorded in orchards. *Computers and Electronics in Agriculture* **2012**, 81, 45–57.

[23] Payne, A.B.; Walsh, K.B.; Subedi, P.P.; Jarvis, D. Estimation of mango crop yield using image analysis – Segmentation method. *Computers and Electronics in Agriculture* **2013**, 91, 57–64.

[24] Teixidó, M.; Font, D.; Pallejà, T.; Tresanchez, M.; Nogués, M.; Palacín, J. Definition of Linear Color Models in the RGB Vector Color Space to Detect Red Peaches in Orchard Images Taken under Natural Illumination. *Sensors* **2012**, 12, 7701–7718.

[25] Teixidó, M.; Font, D.; Pallejà, T.; Tresanchez, M.; Nogués, M.; Palacín, J. An Embedded Real-Time Red Peach Detection System Based on an OV7670 Camera, ARM Cortex-M4 Processor and 3D Look-Up Tables. *Sensors* **2012**, 12, 14129–14143.

[26] Nuske, S.; Achar, S.; Bates, T.; Narasimhan, S.; Singh, S. Yield Estimation in Vineyards by Visual Grape Detection. IEEE/RSJ International Conference on Intelligent Robots and Systems. San Francisco, CA, USA, 2011.

[27] Loy, G., Zelinsky, A. Fast Radial Symmetry for Detecting Points of Interest. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **2003**, 25, 959 – 973.

[28] Cubero, S.; Diago, M.P.; Blasco, J.; Tardáguila, J.; Millán, B.; Aleixos, N. A new method for pedicel/peduncle detection and size assessment of grapevine berries and other fruits by image analysis. *Biosystems Engineering* **2014**, 117, 62-72.

[29] Lofton, J.; Tubana, B.S.; Kanke, Y.; Teboh, J.; Viator, H.; Dalen, M. Estimating Sugarcane Yield Potential Using an In-Season Determination of Normalized Difference Vegetative Index. *Sensors* **2012**, 12, 7529–7547.

[30] Dworak, V.; Selbeck, J.; Dammer, K.-H.; Hoffmann, M.; Zarezadeh, A.A.; Bobda, C. Strategy for the Development of a Smart NDVI Camera System for Outdoor Plant Detection and Agricultural Embedded Systems. *Sensors* **2013**, 13, 1523–1538.

[31] Diago, M.-P.; Correa, C.; Millán, B.; Barreiro, P.; Valero, C.; Tardaguila, J. Grapevine Yield and Leaf Area Estimation Using Supervised Classification Methodology on RGB Images Taken under Field Conditions. *Sensors* **2012**, 12, 16988–17006.

[32] García-Ramos, F.J.; Vidal, M.; Boné, A.; Malón, H.; Aguirre, J. Analysis of the Air Flow Generated by an Air-Assisted Sprayer Equipped with Two Axial Fans Using a 3D Sonic Anemometer. *Sensors* **2012**, 12, 7598–7613.

[33] Gil, E.; Llorens, J.; Llop, J.; Fàbregas, X.; Gallart, M. Use of a Terrestrial LIDAR Sensor for Drift Detection in Vineyard Spraying. *Sensors* **2013**, 13, 516–534.

[34] Perez-Ruiz, M.; Carballido, J.; Agüera, J.; Rodríguez-Lizana, A. Development and Evaluation of a Combined Cultivator and Band Sprayer with a Row-Centering RTK-GPS Guidance System. *Sensors* **2013**, 13, 3313–3330.

[35] Rueda-Ayala, V.; Weis, M.; Keller, M.; Andújar, D.; Gerhards, R. Development and Testing of a Decision Making Based Method to Adjust Automatically the Harrowing Intensity. *Sensors* **2013**, 13, 6254–6271.

[36] Arnó, J.; Escolà, A.; Vallès, J.M.; Llorens, J.; Sanz, R.; Masip, J.; Palacín, J.; Rosell-Polo, J.R. Leaf area index estimation in vineyards using a ground-based LiDAR scanner. *Precision Agriculture* **2013**, 14, 290–306.

[37] Escolà, A.; Rosell-Polo, J.R.; Planas, S.; Gil, E.; Pomar, J.; Camp, F.; Llorens, J.; Solanelles, F. Variable rate sprayer. Part 1 – Orchard prototype: Design, implementation and validation. *Computers and Electronics in Agriculture* **2013**, 95, 122–135.

[38] Mehtaa, S.S.; Burks, T.F. Vision-based control of robotic manipulator for citrus harvesting. *Computers and Electronics in Agriculture* **2014**, 102, 146-158.

[39] Ziona, B.; Mann M.; Levina, D.; Shilo, A.; Rubinstein, D.; Shmulevich, I. Harvest-order planning for a multiarm robotic harvester. *Computers and Electronics in Agriculture* **2014**, 103, 75–81

[40] Noureldin, A.; Armstrong, J.; El-Shafie, A.; Karamat, T.; McGaughey, D.; Korenberg, M.; Hussain, A. Accuracy Enhancement of Inertial Sensors

Utilizing High Resolution Spectral Analysis. *Sensors* **2012**, 12, 11638–11660.

[41] Sánchez-Hermosilla, J.; González, R.; Rodríguez, F.; Donaire, J.G. Mechatronic Description of a Laser Autoguided Vehicle for Greenhouse Operations. *Sensors* **2013**, 13, 769–784.

[42] López, O.; Rach, M.M.; Migallon, H.; Malumbres, M.P.; Bonastre, A.; Serrano, J.J. Monitoring Pest Insect Traps by Means of Low-Power Image Sensor Technologies. *Sensors* **2012**, 12, 15801–15819.

[43] Yang, J.-G.; Wang, F.-L.; Chen, D.-X.; Shen, L.-L.; Qian, Y.-M.; Liang, Z.-Y.; Zhou, W.-C.; Yan, T.-H. Development of a One-Step Immunocapture Real-Time RT-PCR Assay for Detection of Tobacco Mosaic Virus in Soil. *Sensors* **2012**, 12, 16685–16694.

[44] Krzyzanowska, D.; Obuchowski, M.; Bikowski, M.; Rychlowski, M.; Jafra, S. Colonization of Potato Rhizosphere by GFP-Tagged Bacillus subtilis MB73/2, Pseudomonas sp. P482 and Ochrobactrum sp. A44 Shown on Large Sections of Roots Using Enrichment Sample Preparation and Confocal Laser Scanning Microscopy. *Sensors* **2012**, 12, 17608–17619.

[45] Andújar, D.; Weis, M.; Gerhards, R. An Ultrasonic System for Weed Detection in Cereal Crops. *Sensors* **2012**, 12, 17343–17357.

[46] Rach, M.M.; Gomis, H.M.; Granado, O.L.; Malumbres, M.P.; Campoy, A.M.; Martín, J.J.S. On the Design of a Bioacoustic Sensor for the Early Detection of the Red Palm Weevil. *Sensors* **2013**, 13, 1706–1729.

[47] Dhakal, S., Li, Y., Peng, Y., Chao, K., Qin, J., Guo, L., 2014. Prototype instrument development for non-destructive detection of pesticide residue in apple surface using Raman technology. *Journal of Food Engineering* **2014**, 123, 94–103.

[48] McGlone, V.A.; Jordan, R.; Martinsen, P. Vis/NIR estimation at harvest of pre- and post-storage quality indices for 'Royal Gala' apple. Postharvest *Biology and Technology* **2002**, 25, 135–144.

[49] Mehinagic, E.; Royer, G.; Bertrand, D.; Symoneaux, R.; Laurens, F.; Jourjon, F. Relationship between sensory analysis, penetrometry and visible–

NIR spectroscopy of apples belonging to different cultivars. *Food Quality and Preference* **2003**, 14, 473–484.

[50] Billy, L.; Mehinagic, E.; Royer, G.; Renard, C.; Arvisenet, G.; Prost, C.; Jourjon, F. Relationship between texture and pectin composition of two apple cultivars during storage. *Postharvest Biology and Technology* **2008**, 47, 315–324.

[51] Zdunek, A. and Cybulska, J. Relation of Biospeckle Activity with Quality Attributes of Apples. *Sensors* **2011**, 11, 6317-6327.

[52] Lee, W.; Kim, M.; Lee, H.; Delwiche, S.R.; Bae, H.; Kim, D.; Cho, B. Hyperspectral near-infrared imaging for the detection of physical damages of pear. *Journal of Food Engineering* **2014**, 130, 1–7.

[53] Takizawa, K.; Nakano, K.; Ohashi, S.; Yoshizawa, H.; Wang, J.; Sasaki, Y. Development of nondestructive technique for detecting internal defects in Japanese radishes. *Journal of Food Engineering* **2014**, 126, 43–47.

[54] Zhang, B.; Huang, W.; Li, J.; Zhao, C.; Fan, S.; Wu, J.; Liu, C. Principles, developments and applications of computer vision for external quality inspection of fruits and vegetables: A review. *Food Research International* **2014**, 62, 326–343.

[55] Bramley, P., 2002. Regulation of carotenoid formation during tomato fruit ripening and development. Journal of Experimental Botany 53, 2107-2113.

[56] Fadilah, N.; Mohamad-Saleh, J.; Abdul Halim, Z.; Ibrahim, H.; Syed Ali, S.S. Intelligent Color Vision System for Ripeness Classification of Oil Palm Fresh Fruit Bunch. *Sensors* **2012**, 12, 14179–14195.

[57] Aroca, R.V.; Gomes, R.B.; Dantas, R.R.; Calbo, A.G.; Gonçalves, L.M.G. A Wearable Mobile Sensor Platform to Assist Fruit Grading. *Sensors* **2013**, 13, 6109–6140.

[58] Mendoza, F.; Lu, R.; Cen, H. Grading of apples based on firmness and soluble solids content using Vis/SWNIR spectroscopy and spectral scattering techniques. *Journal of Food Engineering* **2014**, 125, 59–68.

[59] Zhang, D.; Lee, D.; Tippetts, B.J.; Lillywhite, K.D. Date maturity and quality evaluation using color distribution analysis and back projection. *Journal of Food Engineering* **2014**, 131, 161–169.

Chapter 2

Objectives

The main objective of this thesis is the development of new systems based on image processing techniques focused on automating agricultural tasks in all the phases of the industrial process; pre-harvest, harvest and post-harvest.

It is intended that the developed systems can be used, in the future, in agricultural platforms as part of more complex applications with industrial interest that may contribute to the improvement of management techniques in orchards incrementing benefits and product quality while reducing time and costs.

The specific objectives of this PhD Thesis are:

- To develop new image processing methods in order to detect and count objects at a pre-harvest stage based on the identification of specular reflection peaks from spherical surfaces. The application proposed was an automatic method for counting red grapes from high-resolution images of vineyards taken under artificial lighting at night.

- To design an image processing method based on the use of stereovision systems in order to estimate the location and position of objects at harvest stage. The application proposed was the development of an automatic fruit harvesting system by combining a low cost stereovision camera and a robotic arm. The stereovision camera was used to estimate the size, distance and position of the fruits whereas the robotic arm was used for the automatic fruit harvesting.

- To develop novel image processing methods based on the use of color information in order to verify objects and improve fruit quality at post-harvest stage. The application proposed was to develop an in-line automatic and individual nectarine variety verification in a fruit-packing line by comparing a feature histogram vector computed from the central part of the skin of the nectarines processed.
- To develop novel image processing methods based on the use of color information to establish relations between post-storage fruit quality attributes, which are obtained by performing contact non-destructive and contact destructive experiments, and the visible spectra of the skin of the fruit. In this work, the fruit quality parameters studied were fruit diameter, fruit mass, skin color, fruit firmness, SSC, and TA whereas the visible spectra of the skin of the fruit was defined with the RGB, Grey, HSV, and CIELAB color layers.

Chapter 3

PhD Thesis structure

The development of this PhD Thesis has been performed in the Research Line of Signal Processing and Robotics of the INSPIRES UdL group (Institut Politècnic d'Innovació i Recerca en Sostenibilitat, centre de recerca de la Universitat de Lleida) and under the UdL-IMPULS project.

This thesis proposes the use of image processing techniques that contribute to the development of new technologies to automate agricultural applications, leading to an improvement of management operations in all phases of the agricultural industry. Four different agricultural applications were developed and proposed as the basis of this work according to the needs or problems to be solved identified by farmers.

This PhD Thesis is structured in four chapters and four SCI papers; three of them were already published in SCI/Q1 journals and the last paper is currently under revision in a SCI/Q1 journal. Figure 3.1 shows the structure of the PhD Thesis. The referenced papers are:

- Font, D.; Pallejà, T.; Tresanchez, M.; Teixidó, M.; Martinez, D.; Moreno, J.; Palacín, J. Counting red grapes in vineyards by detecting specular spherical reflection peaks in RGB images obtained at night with artificial illumination. Computers and Electronics in Agriculture (journal indexed as Q1) 2014, 108, 105-111.

- Font, D.; Pallejà, T.; Tresanchez, M.; Runcan, D.; Moreno, J.; Martínez, D.; Teixidó, M.; Palacín, J. A proposal for automatic fruit harvesting by combining a low cost stereovision camera and a robotic arm. Sensors (journal indexed as Q1) 2014, 14, 11557-11579.

- Font, D.; Tresanchez, M.; Pallejà, T.; Teixidó, M.; Martinez, D.; Moreno, J.; Palacín, J. An image processing method for in-line nectarine variety verification based on the comparison of skin feature histogram vectors. Computers and Electronics in Agriculture (journal indexed as Q1) 2014, 102, 112–119.
- Font, D.; Teixidó, M.; Tresanchez, M.; Martínez, D.; Moreno J.; Graell J.; Lara, I.; Palacín, J. Assessment of the correlation between post-storage fruit quality parameters and visible spectra of the skin for ‘Golden Smoothee’ apple. Submitted to Journal of Food Engineering (journal indexed as Q1), July 2014.

The chapters represent the different stages of the agricultural industrial process; pre-harvest, harvest and post-harvest. The first paper, presented in Chapter 4, is focused on counting red grapes in vineyards by detecting specular spherical reflection peaks in RGB images obtained at night with artificial illumination. The counting of agricultural element is essential for yield estimate at pre-harvest stage. The proposal of the second paper, presented in Chapter 5, is the development of an automatic fruit harvesting system by combining a low cost stereovision camera and a robotic arm. This operation is crucial at harvest stage. The third and fourth papers, presented in Chapter 6 and 7 respectively, are focused on solving problems at post-harvest stage with the aim of enhancing fruit quality, which can affect consumer acceptance. In Chapter 6 an image processing method for in-line nectarine variety verification based on the comparison of skin feature histogram vectors is presented, whereas in Chapter 7 the correlation between post-storage fruit quality attributes and the visible spectra of the skin of the ‘Golden Smoothee’ apple was studied.

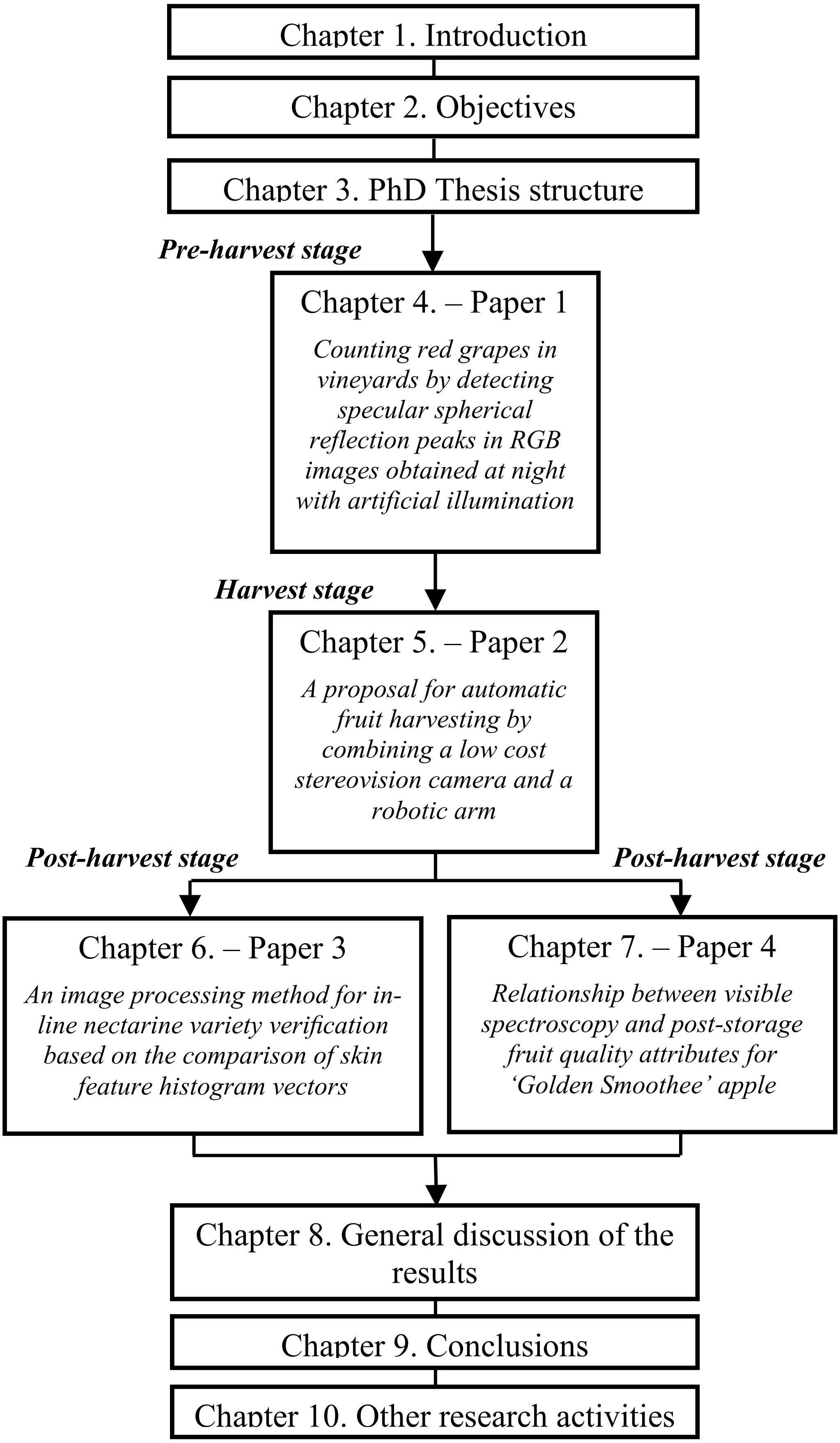

Fig. 3.1. PhD Thesis structure.

Chapter 4

Image processing method applied to locate agricultural elements at pre-harvest stage: counting red grapes

---

4.1. Introduction

This chapter proposes an image processing method based on detecting intensity peaks from spherical objects. The paper presented in this chapter proposed the design of a new procedure used at pre-harvest stage in order to count the number of grapes in vineyard images obtained at night under artificial lighting. The new contribution of this paper was to use the artificial lighting to detect the specular reflection peaks originated in the spherical surface of the grapes. Fig. 4.1 shows the specular reflection peaks detection. Fig. 4.1-a shows a detail of an original vineyard image whereas Fig. 4.1-b shows a representation of the normalized grayscale image, where the hot spots originated by the specular spherical reflection on the grapes are highlighted.

Yield prediction is a topic of special interest in precision agriculture because it leads to an improvement of management operations in orchards. Currently yield prediction is an inaccurate, time-consuming and expensive operation since it is performed manually by counting the number of individual fruits. Tasks focused on counting elements in agriculture are being automated due to the application of image-processing techniques. These automatic methods have been demonstrated to be more efficient, faster, and less prone to inconsistencies. However, there are factors such as environmental conditions, crop properties, occlusions and lighting that affect the automatic counting task.

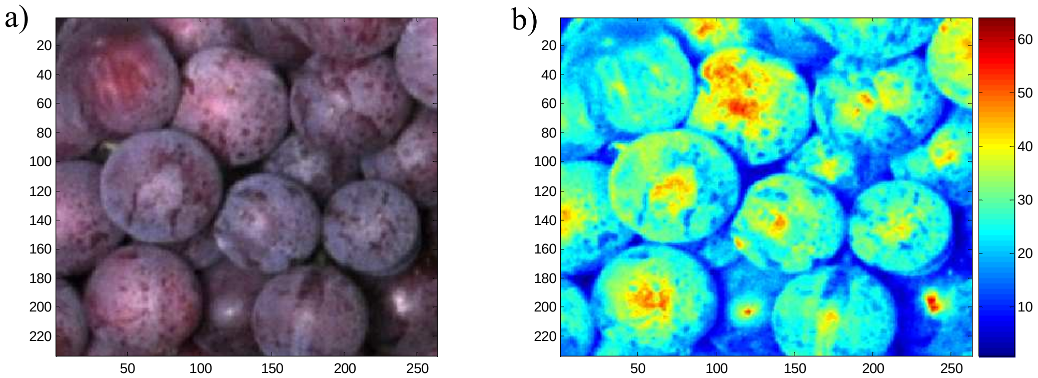

Fig 4.1. Sample of specular reflection: (**a**) original vineyard image; (**b**) normalized grayscale image.

4.2. Contributions to the state of the art

Precision agriculture is a broad and promising area demanding technological solutions with the aim of increasing production in orchards. One of the topics addressed by precision agriculture is the counting of different agricultural elements in images which can be very challenging depending on the scenario and type of element.

Agricultural research has been focusing on developing algorithms to count agricultural elements, mainly vegetables and fruits [1-7] in order to estimate the production. The easiest scenario to automatically count fruits and vegetables in situ is when they are isolated elements of considerable dimensions. The proposal of [1] was to count kiwifruit using the CIELab color space by finding the peaks originated on the surface of the elements. Two automatic algorithms were proposed to identify the peaks on the surface of the fruit. The first used a gray color image whereas the second was based on a transformed image used to estimate the distance from each pixel belonging to the fruit to the nearest background pixel. The results showed good accuracies for gold (90%) and green (70%) varieties of kiwi. Alternatively, in [2] a counting method based on identifying fruit pixels in images was proposed. The methodology used was to connect fruit pixels into sets, then the contours of these sets were segmented and finally, an apple model was created by using the definition of the contours. The conclusion obtained was that the technique proposed was not robust to lighting changes but it achieved a success rate from 85% up to 95%. In [3] mango fruit from orchard images were counted. The technique applied was to segment the pixels of the images into two groups, fruit and background, by means of color and texture information. Then, the resultant blobs were identified to count the number of fruits in the image. The automatic results were correlated with a manual counting achieving a strong correlation of 0.91. More recently, in [4] another mango counting approach was proposed. The mango counting procedure was based on combining an altered color matching with a Hessian filtering applied to images taken at night under controlled lighting. Alternatively, in [5] a method for identifying and counting fruits from images acquired in cluttered greenhouses was presented. The automatic method was based on applying bag-of-words model and statistical approaches. The results showed a strong correlation, 94.6%, between the automatic and manual counting data.

The automatic counting in the case of grapes is a challenging task due to the difficulty of distinguishing the grapes from the background as a consequence of occlusions and the similarities in color. In addition, the grapes belonging to different clusters have different scales, and the changes in lighting can also affect the visibility of the fruit since it produces reflections and shadows. For example, in [6] a method for counting grapes based on the application of a radial symmetry transform was used in order to estimate yield. The results showed a good yield accuracy estimation with only an error of 9.8%. The proposal of [7] was to design a counting method based on the computation of the correlation between the Gaussian profile and the neighborhood of each pixel to obtain a correlation map, which was segmented and filtered.

4.3. References

[1] Wijethunga, P.; Samarasinghe, S.; Kulasiri, D.; Woodhead, I. Digital Image Analysis Based Automated Kiwifruit Counting Technique. *23rd International*

Conference Image and Vision Computing **2008**, New Zealand, Christchurch, pp. 1-6.

[2] Linker, R.; Cohen, O.; Naor, A. Determination of the number of green apples in RGB images recorded in orchards. *Computers and Electronics in Agriculture* **2012**, 81, 45–57.

[3] Payne, A.B.; Walsh, K.B.; Subedi, P.P.; Jarvis, D. Estimation of mango crop yield using image analysis – Segmentation method. *Computers and Electronics in Agriculture* **2013**, 91, 57–64.

[4] Payne, A.; Walsh, K.; Subedi, P.; Jarvis, D. Estimating mango crop yield using image analysis using fruit at 'stone hardening' stage and night time imaging. *Computers and Electronics in Agriculture* **2014**, 100, 160–167.

[5] Song, Y.; Glasbey, C.A.; Horgan, G.W.; Polder, G.; Dieleman, J.A.; van der Heijden, G.W.A.M. Automatic fruit recognition and counting from multiple images. *Biosystems Engineering* **2014**, 118, 203-215.

[6] Nuske, S.; Achar, S.; Bates, T.; Narasimhan, S.; Singh, S. Yield Estimation in Vineyards by Visual Grape Detection. *IEEE/RSJ International Conference on Intelligent Robots and Systems* **2011**, San Francisco, CA, USA.

[7] Grossetête, M.; Berthoumieu, Y.; Da Costa, J.P.; Germain, C.; Lavialle, O.; Grenier, G. Early estimation of vineyard field: site specific counting of berries by using a smartphone. *International Conference of Agricultural Engineering* **2012**. Abstract number C1915. Valencia.

Pages from 41 to 52 contain the following paper:

D. Font, T. Pallejà, M. Tresanchez, M. Teixidó, D. Martinez, J. Moreno, J. Palacín. "Counting red grapes in vineyards by detecting specular spherical reflection peaks in RGB images obtained at night with artificial illumination," *Computers and Electronics in Agriculture* 108 (2014) 105–111.

http://dx.doi.org/10.1016/j.compag.2014.07.006
ISSN: 0168-1699

Chapter 5

Image processing method applied to estimate size, distance and position of fruits at harvest stage: automatic fruit harvesting

5.1. Introduction

This chapter proposes the development of an automatic fruit harvesting system by combining a low cost stereovision camera and a robotic arm. The stereovision camera was placed in the gripper tool of the robotic arm and had two functionalities: 1) to estimate the size, distance and position of the fruits and 2) to guide the automatic pickup of specific targets. The robotic arm was used as a mechanic device to perform the pickup of the fruits. Fig. 5.1 shows a fruit pickup performed in laboratory conditions using a pear as a target.

Agricultural industry is investing on automating agricultural tasks and the automation of harvesting operations is crucial at harvest stage. The development of a harvesting system is a complicated task that requires the accomplishment of smaller operations such as the automatic detection and localization of fruits, the estimation of fruit parameters (size, relative location and orientation) [1-3], and finally the control of the mechanic device by considering a non-stressing pickup methodology [4, 5].

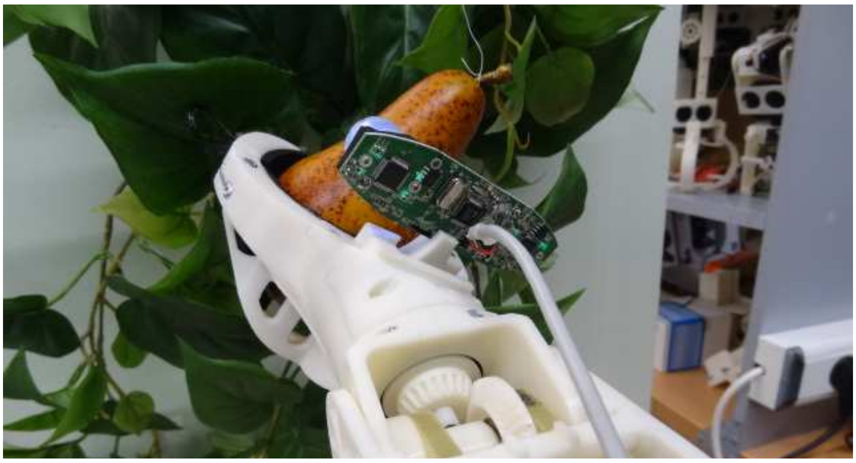

Fig. 5.1. Stereovision camera placed in the gripper of the robotic arm.

5.2. Contributions to the state of the art

The accurate detection of fruits in trees is an essential step for automating harvest operations. This task can be approached with different strategies such as the use of a monocular camera attached to a gripper tool [6] or the use of a monocular camera and a stepper motor [7] in order to control a mechanical pickup. In [6], the distance between the camera and the fruit was estimated by measuring the dimensions of the fruit when locating the camera at different positions with a known distance between the two objects. The next step was to match the center of the fruit with the center of the image in order to align the gripper tool with the fruit. In [7] a monocular camera in combination with a stepper motor, which was used as a displacement device, were used to generate depth maps with the aim of reconstructing 3D natural scenes.

Another alternative is the use of stereovision systems [8]. The main problem is to correlate the same information in two different images taken from different perspectives but over the same region or element. In most cases, this is solved by identifying the targets on the images and then, computing their centroids to compute the distance of the element. However, this methodology is dependent on geometric camera nonlinearities that can be removed or decreased by performing camera calibrations. The proposal of [9] was to implement a real-time stereovision system. The methodology used was to identify an object in both images, to segment the object and then, to apply a connected component analysis and a blob extraction technique with the final objective of estimating the distance and size of the object. In [10], two different stereovision techniques applied to apple-picking robots were compared. The first technique was based on attaching a target to the apples (manual operation) and the second system consisted of computing the centroid of the segmented fruit (automatic operation) in order to estimate the distance. The results showed an error in the distance estimate of 0.63% and 3.54% in the first and the second techniques, respectively.

Stereovision systems are also applied to control robotized systems such as robotic arms. However, in the literature there are very few works focused on applying stereovision systems to develop fruit harvest operations. Some of these examples are described in [11, 12]. In [11] a stereovision system was implemented as part of a robotized platform in order to locate fruits and to correct the trajectory of the robotic arm when harvesting fruits. The approach was studied in laboratory conditions with simulated scenarios. In [12] the combination of a fixed camera and a camera placed in the gripper tool of the robotic arm was proposed for automatic harvest of citrus. A vision-based estimation and control system was developed for robotic fruit harvesting whereas keeping the stability and performances of the closed-loop system.

5.3. References

[1] Teixidó, M.; Font, D.; Pallejà, T.; Tresanchez, M.; Nogués, M.; Palacín, J. An Embedded Real-Time Red Peach Detection System Based on an OV7670 Camera, ARM Cortex-M4 Processor and 3D Look-Up Tables. *Sensors* **2012**, 12, 14129–14143.

[2] Teixidó, M.; Font, D.; Pallejà, T.; Tresanchez, M.; Nogués, M.; Palacín, J. Definition of Linear Color Models in the RGB Vector Color Space to Detect Red Peaches in Orchard Images Taken under Natural Illumination. *Sensors* **2012**, 12, 7701–7718.

[3] Aroca, R.V.; Gomes, R.B.; Dantas, R.R.; Calbo A.G.; Gonçalves, L.M.G. A Wearable Mobile Sensor Platform to Assist Fruit Grading. *Sensors* **2013**, 13, 6109–6140.

[4] Zion, B.; Mann, M.; Levin, D.; Shilo, A.; Rubinstein, D.; Shmulevich. I. Harvest-order planning for a multiarm robotic harvester. *Computers and Electronics in Agriculture* **2014**, 103, 75-81.

[5] Mehtaa, S.S.; Burks, T.F. Vision-based control of robotic manipulator for citrus harvesting. *Computers and Electronics in Agriculture* **2014**, 102, 146–158.

[6] Lv, J.; Zhao, D-A.; Ji, W.; Chen, Y.; Shen, H. Design and Research on Vision System of Apple Harvesting Robot. *International Conference on Intelligent Human-Machine Systems and Cybernetics* **2011**, vol.1, pp.177-180.

[7] Billiot, B.; Cointault, F.; Journaux, L.; Simon, J-C.; Gouton, P. 3D Image Acquisition System Based on Shape from Focus Technique. *Sensors* **2013**, 13, 5040-5053.

[8] Brown, M.Z.; Burschka, D.; Hager, G.D. Advances in computational stereo. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **2003**, vol.25, no.8, pp.993-1008.

[9] Mustafah, Y.M.; Noor, R.; Hasbi, H.; Azma, A.W. Stereo vision images processing for real-time object distance and size measurements. *International Conference on Computer and Communication Engineering* **2012**, Kuala Lumpur, pp. 659-663.

[10] Jian, L.; Shujuan, C.; Chengyan, Z.; Haifeng, C. Research on Localization of Apples Based on Binocular Stereo Vision Marked by Cancroids Matching. *3rd International Conference on Digital Manufacturing and Automation* **2012**, GuiLin, pp.683-686.

[11] Zou, X.; Zou, H.; Lu, J. Virtual manipulator-based binocular stereo vision positioning system and errors modeling. *Machine Vision and Applications* **2012**, 23, 43–63.

[12] Mehtaa, S.S.; Burks, T.F. Vision-based control of robotic manipulator for citrus harvesting. *Computers and Electronics in Agriculture* **2014**, 102, 146–158.

Pages from 57 to 84 contain the following paper:

D. Font, T. Pallejà, M. Tresanchez, D. Runcan, J. Moreno, D. Martínez, M. Teixidó, J. Palacín. "A proposal for automatic fruit harvesting by combining a low cost stereovision camera and a robotic arm," *Sensors* 14 (2014) 11557-11579.

http://dx.doi.org/10.3390/s140711557
ISSN: 1424-8220

Chapter 6

Image processing method applied as a fruit quality control tool at post-harvest stage: nectarine variety verification

6.1. Introduction

This chapter proposes an image processing method based on the use of fruit color information for quality control in post-harvest stages. The proposal was to develop an in-line nectarine variety verification system based on computing a histogram vector from the surface of the analyzed fruit. The histogram vector can be generated by a mixture of several intensity color layers from different color spaces (Fig. 6.1). The idea of this proposal was based on the knowledge that the comparison of two histograms from the skin of nectarine samples in the RGB color space shows similarities when the nectarines are from the same variety and differences when they are from different varieties.

The experimental part of this study was performed in the province of Lleida, Spain which produces the 36% of the total Spanish nectarine production. Moreover, the province of Lleida has mostly small orchards, less than 1ha, used to cultivate a unique fruit variety. Another factor is that there is a broad agronomical research based on creating new nectarine varieties optimized for specific weather conditions and soil characteristics of a particular region, resulting in a wide range of novel nectarine varieties with different demand [1] and market value. All these factors can contribute to accidentally mixing nectarine varieties during the post-harvesting process that can have a severe effect on the agricultural industry leading to the consumer rejection of the processed fruit.

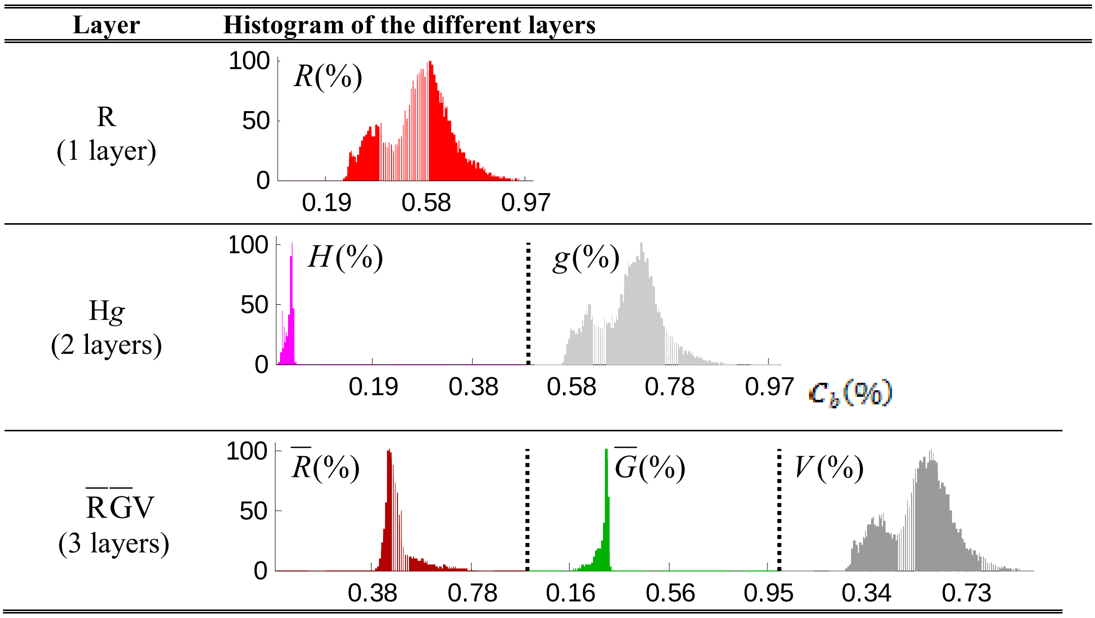

Fig. 6.1: Examples of nectarine skin histograms concatenating several intensity color layers from different color spaces.

6.2. Contributions to the state of the art

In the literature there are several works focused on using color histogram information in order to classify objects. In the same research line, this work used the color histogram information from the skin of a fruit to verify a fruit variety. The proposal of [3] was to detect external defects on oranges by analyzing the histograms of the fruit in the RGB color space. The skin defects were detected by studying images taken from six orthogonal directions at the same fruit and applying a neural network classifier. The conclusions showed that the proposed method had a minimum error of 2.06% whereas the maximum error was 13.73%. In [4] skin color histograms in the RGB and HSI color spaces were analyzed in the case of apples in order to sort and grade fruits. The methodology used achieved a success rate of 98%. Another proposal was to simplify the HSI color histogram into sub-ranges and to use a trained neural network through a particle swarm optimization algorithm [5]. The method reached an accuracy of 94%. In [6] the analysis of HSI color histograms of the skin of the fruit was proposed to classify fruit in a system that combined a conveyor belt with a vision system. In [7] the Mahalanobis distance algorithm was used as a method to perform statistical analysis in order to grade oil palm fruit bunches. The technique proposed showed a success rate of 93.53%. In [8] the HSI skin color histogram was also applied to grade apples according to quality parameters. Similarly, in [9], the HSI color histogram of the skin of nectarines was analyzed. The results showed a low average classification success rate of 43%. This result showed the difficulties when classifying and grading nectarine varieties.

6.3. References

[1] Bonany, J.; Buehler, A.; Carbó, J.; Codarin, S.; Donati, F.; Echeverria, G.; Egger, S.; Guerra, W.; Hilaire, C.; Höller, I.; Iglesias, I.; Jesionkowska, K.; Konopacka, D.; Kruczynska, D.; Martinelli, A.; Pitiot, C.; Sansavini, S.; Stehr, R.; Schoorl, F. Consumer eating quality acceptance of new apple varieties in different European countries. Food Quality and Preference **2013**, 30, 250–259.

[2] IRTA: Institut de Recerca i Tecnologia Agroalimentaries, Technical report on nectarine production. Available online: http://www.irta.cat. Accessed 11 July 2014.

[3] Recce, M.; Taylor, J.; Piebe, A.; Tropiano, G. High speed vision-based quality grading of oranges. *Proceedings on International Workshop on Neural Networks for Identification, Control, Robotics, and Signal/Image Processing* **1996**, Venice, pp. 136–144.

[4] Sudhakara, P.; Gopal, A.; Revathy, R.; Meenakshi, K. Color analysis of fruits using machine vision system for automatic sorting and grading. *Journal of Instrument Society of India* **1999**, 34, 284–291.

[5] Ji, H.; Yuan, J. The application study of apple color grading by particle swarm optimization neural networks. *6th World Congress on Intelligent Control and Automation* **2006**, Dalian, pp. 2651–2654.

[6] Buzera, M.; Groza, V.; Prostean, G.; Prostean, O. Techniques of analyzing the colour of produces for automatic classification. *International Conference on Intelligent Engineering Systems* **2008**, Miami, FL., pp. 209–214.

[7] Makky, M.; Soni, P. Development of an automatic grading machine for oil palm fresh fruits bunches (FFBs) based on machine vision. *Computers and Electronics in Agriculture* **2013**, 93, 129–139.

[8] D'Amato, J.P., García, C., Boroni, G., 2011. Color based fruits classification using GPU. *IEEE Latin America Transactions* **2011**, 3, 346–350.

[9] Font, D. ; Palleja, T.; Tresanchez, M.; Teixidó, M.; Palacin, J. Preliminary study on color based nectarine variety classification. *IEEE International and Measurement Technology Conference* **2012**, Graz, pp. 2187–2190.

Pages from 89 to 103 contain the following paper:

D. Font, M. Tresanchez, T. Pallejà, M. Teixidó, D. Martinez, J. Moreno, J. Palacín. "An image processing method for in-line nectarine variety verification based on the comparison of skin feature histogram vectors," *Computers and Electronics in Agriculture* 102 (2014) 112–119.

http://dx.doi.org/10.1016/j.compag.2014.01.013
ISSN: 0168-1699

Chapter 7

Image processing method applied as a fruit quality monitoring tool at post-harvest stage: correlation between quality indices and visible spectra of the skin of the fruit

7.1. Introduction

This chapter proposes a new image processing method applied to the visible spectra of the skin of the fruit in order to analyze the correlation between the fruit skin color and different fruit quality attributes. The fruit quality indices, which were measured by performing contact and even destructive experiments, assessed in this work were: diameter, weight, skin color, flesh firmness, soluble solids content (SSC) and titratable acidity (TA). Conversely, the visible spectra of the skin, which was measured by performing non-contact analysis, was defined by using the RGB, Grey, HSV, and CIELab color spaces. The fruit evaluated was the 'Golden Smoothee' apple, which is a typical cultivar widely produced in Spain (Fig. 7.1). Especially, the region of Lleida, where the experimental part of this work was developed, represented the 38% of the total Spanish production of apples in 2013-2014.

Fruit quality estimation is essential in fresh-market fruit production in order to assure the best fruit appearance [1] and physicochemical properties [2]. At post-harvest stages and during the storage of the fruit some procedures to monitor the quality of the fruit are required. Mostly, these procedures are based on destructive experiments leading to important production losses. The new contribution of this work is to develop a non-destructive technique to estimate quality indices of apples from their skin color.

Fig. 7.1. 'Golden Smoothee' apple.

7.2. Contributions to the state of the art

Fruit quality attributes can be estimated by performing contact non-destructive and contact destructive experiments. For example in [3] a system that combined Vis/NIR spectroscopy with a polychromatic spectrometer was proposed in order to measure quality parameters of 'Royal Gala' apples such as color, starch pattern index, soluble solids content (SSC), firmness, quantitative starch, and titratable acidity (TA). The results showed that the SSC quality attribute was related to soluble carbohydrates. The proposal of [4] was to assess correlations between parameters measured with a penetrometer (destructive measurement) and with visible and near infrared spectroscopy (non-destructive measurement) analyzing nineteen varieties of apple. The results showed that sensory textural parameters were strong correlated with the parameters obtained by performing destructive experiments. In [5] physicochemical characteristics of two apple cultivars were evaluated with the aim of finding relationships between biochemical markers and fruit sensory attributes. The result obtained was that apple texture attributes were correlated with the total neutral sugar content. In [6] a non-destructive analysis was presented to assess the relationships between biospeckle activity (BA) and quality indices measured with destructive tests such as firmness, SSC, TA and starch content (SC) was developed. The results showed a strong correlation between BA and SC. Additionally, it was observed that the values of the quality indices change considerably during fruit ripeness.

7.3. References

[1] Abbott, J.A. Quality measurement of fruits and vegetables. *Postharvest Biology and Technology* **1999**, 15, 207-225.

[2] Wu, C.; Gao, Q.; Guo, X.; Yu, J.; Wang, M. Effect of ripening stage on physicochemical properties and antioxidant profiles of a promising table fruit 'pear-jujube' (Zizyphus jujuba Mill.). *Scientia Horticulturae* **2012**, 148, 177-184.

[3] McGlone, V.A.; Jordan, R.; Martinsen, P. Vis/NIR estimation at harvest of pre- and post-storage quality indices for 'Royal Gala' apple. *Postharvest Biology and Technology* **2002**, 25, 135–144.

[4] Mehinagic, E.; Royer, G.; Bertrand, D.; Symoneaux, R.; Laurens, F.; Jourjon, F. Relationship between sensory analysis, penetrometry and visible–NIR spectroscopy of apples belonging to different cultivars. *Food Quality and Preference* **2003**, 14, 473–484.

[5] Billy, L.; Mehinagic, E.; Royer, G.; Renard, C.; Arvisenet, G.; Prost, C.; Jourjon, F. Relationship between texture and pectin composition of two apple cultivars during storage. *Postharvest Biology and Technology* **2008**, 47, 315–324.

[6] Zdunek, A; Cybulska, J. Relation of Biospeckle Activity with Quality Attributes of Apples. *Sensors* **2011**, 11, 6317-6327.

Pages from 108 to 124 contain the following paper:

D. Font, M. Teixidó, M. Tresanchez, D. Martínez, J. Moreno, J. Graell, I. Lara, J. Palacín. "Assessment of the correlation between post-storage fruit quality parameters and visible spectra of the skin for 'Golden Smoothee' apple," Submitted to Journal of Food Engineering, July 2014.

ISSN: 0260-8774

Chapter 8

General discussion of the results

This section summarizes the general discussion of the results obtained in each of the chapters presented in this PhD Thesis.

8.1. Image processing method applied to locate agricultural elements at pre-harvest stage: counting red grapes

The general discussion and main conclusions extracted from the analysis performed in chapter 4 are explained in this section.

The automatic counting system based on the identification of specular reflection peaks on the spherical surface of the grapes followed a three-step methodology: segmentation, image filtering, and peak detection and counting. First, a segmentation procedure deeply studied in a previous work [1] was applied in order to remove the background from the fruit. This procedure consisted in obtaining the Hue intensity color layer from the original RGB image to apply a threshold value before the application of morphological operations used to eliminate the small objects in the segmented image. The second step of the automatic counting method was to apply a smoothing procedure to the segmented grapes image in order to reduce their color intensity variability with the practical effects of improving the identification of detecting only one intensity peak per fruit. The third step was to apply a morphological filter to detect the intensity peaks in grapes. This morphological peak detector was defined with one central point and several radial points with the condition that the central point must have higher intensity than the radial points. The morphological filter was optimized by analyzing empirically two critical parameters: the number of radial points equidistantly distributed along an external radius and the value of this external radius. The analysis was performed by considering that the intensity peaks have always a lower radius than the grapes (a preliminary study proved that the most frequent radius for grapes was 75 pixels). Therefore, the range of the values of the external radius considered was from 10 to 50 pixels being analyzed in steps of 10 pixels. Similarly, the number of radial points selected was from 5 to 35 points being analyzed in steps of 5 points. Finally, the selected parameter combination for the morphological filter was a radius of 30 pixels and 15 radial points equidistantly distributed along the external radius. Moreover, the morphological detector was applied to the R intensity color layer of the segmented and filtered images due to the reddish nature of the grapes. The results showed that this configuration provided a good agreement between time-performances and the success achieved; the morphological detector was very fast achieving a success rate of 85% when counting clusters of grapes identifying even highly occluded grapes with a low percentage of false positives (10%).

The results of the automatic method were validated with a manual labeling procedure, which consisted in classifying individual grapes into three categories: totally visible grapes, grapes with an occlusion of less than 75% of their surface, and grapes with an occlusion between 75% and 99% of their surface. The results from the manual test showed that for the analyzed images the average number of totally visible grapes was 18%, the average number of grapes with an occlusion of less than 75% of their surface was 49%, and the number grapes with an occlusion between 75% and 99% of their surface was 33%. The conclusions when comparing both procedures were that on average the counting detection method underestimated the number of grapes with an error of -14%. This can be considered a good result since the 33% of the grapes in the processed images were highly occluded (with more than the 75% of its surface occluded), being their detection almost impossible by means of other conventional shape methods. Moreover, on average the method provided a number of false positives of only 7%

whereas the number of false negatives reached 21%. This means that the proposed method can identify the non-occluded grapes and the ones with an occlusion inferior to 75% of their surface with high accuracy, whereas the highly occluded grapes can also be distinguished but with a lower percentage. These results confirm that this method can count even highly occluded grapes showing the suitability of the proposed automatic method.

Future work will be focused on implementing this automatic procedure to other grape varieties and fruits with the final aim of predicting yield production in orchards. Additionally, it will be studied the correlation between the automatic grape counting results and the degree of fruit ripeness.

8.2. Image processing method applied to estimate size, distance and position of fruits at harvest stage: automatic fruit harvesting

The general discussion and main conclusions extracted from the analysis performed in chapter 5 are explained in this section.

The proposed automatic fruit harvesting system combined a low cost stereovision camera with a robotic arm. The stereovision camera was used to estimate the size, distance and position of fruits whereas the robotic arm was used to automatically harvest the selected fruits.

The image acquisition equipment used in this work was the Minoru 3D USB Webcam, which used two cameras placed at the same plane with a distance of 60 mm from each other. In addition, a red cross laser was also used in combination with the image acquisition device in order to accurately locate the targets. The targets tested in this work were a blue pushpin (used as a reference element), and two fruit targets: a green apple and a brown pear. The robotic arm was created with a 3D rapid prototyping printer in ABS plastic material including six DC gear motors used to control the five linked members. Additionally, the robotic arm was equipped with an interchangeable gripper.

To automatically control the robotic arm when performing the fruit harvesting operation it is required to estimate the fruit distances, positions and sizes. In this work these estimations were performed with a stereovision system. The detection accuracy of the proposed stereovision system was tested in laboratory conditions in the cases of correcting and not correcting geometric camera distortions. A total of 1,470 images were analyzed corresponding to the three targets located in 49 positions of a relative grid and in 10 different distances from the camera. The methodology used was to estimate the inclination, the centroid and the diameter of all the targets by applying a fruit segmentation procedure. Two different alternatives to perform the segmentation procedure were analyzed; color intensity threshold and Linear Color Models. Then, the relative distance of the targets to the camera, its relative position and its absolute diameter were computed by using the advantages of the stereovision systems; which allows having two images of the same object from different but known point of views. The results achieved were that the average distance error was in a range from 4% to 5%, and that the average diameter error was from 2% to 6% in the case of the fruit targets. These results validated the use of the proposed low cost stereovision system as a tool to estimate fruit distance and fruit size.

In this work the stereovision system was attached to the gripper element not only to estimate the relative distance, orientation and size of the fruit but also to provide information of the actions executed by the robotic arm. After the initial fruit location, the automatic fruit harvesting procedure required the computation of the inverse kinematics of the robotic arm in order to guide the gripper close to the fruit, and then the position of the gripper was iteratively adjusted until the fruit was harvested. The inverse kinematics computation was simplified by considering a two-joint robotic arm. Moreover, the guidance and control of the robotic arm was simulated and validated by using the definition of the Denavit-Hartenberg parametric model. The complete harvest system was tested in laboratory conditions using controlled and uniform lighting. Finally, the time-performances of the complete harvesting cycle were analyzed resulting that the proposed automatic system required on average 16 s to detect and pickup a pear, taking into account that the 95% of this time was conditioned by the mechanical limitations of the robotic arm.

Future work will be focused on optimizing the automatic fruit harvesting prototype in real farming operations.

8.3. Image processing method applied as a fruit quality control tool at post-harvest stage: nectarine variety verification

The general discussion and main conclusions extracted from the analysis performed in chapter 6 are explained in this section.

The in-line automatic and individual nectarine variety verification in a fruit-packing line was performed by comparing a feature histogram vector computed from the skin of a nectarine processed with the feature histogram vectors resulting from analyzing representative nectarines from the target variety saved in a dataset. The designed system was able to confirm that each piece of fruit analyzed in the fruit-packing line belongs to the current fruit variety so as to avoid consumer rejection of fruits as a consequence of accidental mixes with other varieties.

The nectarine cultivars selected for the study were varieties with similar harvesting times because they can be picked simultaneously: Honey BlazePVC, ASF 08.21, ASF 08.05, Queen Gem®, NectareinePVC, NectarrevePVCR. The Nectarreve variety was selected as the representative cultivar for the industrial production simulation because it was the variety with the most overlapped harvesting time. The image acquisition device working under controlled artificial lighting took non-interpolated RGB color images from each nectarine processed. Then, the images were analyzed following a 4-step image-processing algorithm. First, the images were segmented by applying the Otsu method fixing the threshold at 51 in order to optimize time performances. The second step was to compute the bounding box and the center of the segmented nectarine. The third step consisted in defining the region of interest of the fruit, which was established as a smaller circular area (80 pixels) of the skin of the fruit having the center at the center of the fruit, so as to avoid the illumination changes at the edge of the fruit. Finally, the histograms of the skin of the nectarine analyzed were computed and created by concatenating histogram values corresponding to different intensity color layers such as the RGB, HSV, YCbCr, and $\overline{R}\overline{G}\overline{B}$. Additionally, these feature histograms can be tuned by applying a zero-phase digital average filter used to modify the shape, and by changing the weight distribution to remove noise.

The validation of the proposed method was based on comparing different skin feature histogram vectors; one identifying the current variety and the others representing the target variety that are saved in a dataset. Two different methods were used to assess this comparison: the application of Pearson's correlation coefficient and the application of the cumulative absolute subtraction. The critical step of the experimental procedure was the estimation of a variety classification threshold, which represents the minimum similarity used to decide whether a current nectarine can be accepted as a member of the processed variety. The automatic estimate of this parameter was performed by doing a cross comparison with all the feature histograms vectors included in the dataset.

The experimental procedure was based on analyzing 10 nectarines from each one of the 6 varieties selected, which were placed randomly on the conveyor belt, and analyzing all the possible color layer combinations for the creation of the skin feature histogram vectors. All the combinations represented 268 results obtained with Pearson correlation and 268 results obtained with the cumulative subtraction technique. The best results obtained (achieving a success ratio of 100%) in the case of comparing the feature histogram vectors using the Pearson correlation were the vectors created from the Rg histograms (non-filtered and non-normalized) and from the $Y\overline{R}$ (non-filtered and normalized) histograms. Surprisingly, both of them were a 2-layer histogram without filtering. Considering histograms with different number of layers, the maximum success ratio obtained when using 1 layer was 83% in case of the Y intensity color layer and 90% when using 3 layers in case of the RGB color components. These results proved that the Pearson correlation method can be used to verify nectarines with high accuracy. Conversely, the best results obtained with the cumulative subtraction were 90% in case of using a 3-layer histogram created from the HSV color layers (filtered and non-normalized), and 88% when using the same layers but without filtering. So, the best results were achieved when not normalizing the shape of the histogram.

Considering histograms with different number of layers, the maximum success ratio obtained when using 1 layer was 70% in case of the R, H, and V color layers and 87% using a 2-layer histogram created from the HCr case. These results showed that the cumulative subtraction method is also a suitable method to use for verifying nectarines with high accuracy. Additionally, the comparison using the cumulative subtraction was faster than the Pearson correlation and could be a more suitable alternative for a real implementation.

In all the tests performed, the nectarine varieties incorrectly accepted as the Nectarreve variety were the ASF 08.21 and the ASF 08.05 varieties due to the skin similarities, which were also the varieties with the most time overlapping.

Finally, the automatic method was compared with a manual experiment, where an expert human operator classified nectarines reaching a success ratio of 87%. The conclusion obtained was that the two automatic classification methods proposed in this work improved the success rate of a manual classification.

Future research will be focused on optimizing the industrial application proposed and on defining additional quality attributes for creating the feature histogram vectors of the nectarines processed.

8.4. Image processing method applied as a fruit quality monitoring tool at post-harvest stage: correlation between quality indices and visible spectra of the skin of the fruit

The general discussion and main conclusions extracted from the analysis performed in chapter 7 are explained in this section.

The fruit quality indices, which were measured by performing contact and even destructive experiments, assessed were: diameter, weight, skin color, flesh firmness, soluble solids content (SSC) and titratable acidity (TA). Conversely, the visible spectra of the skin, which was measured by performing non-contact analysis, was defined by using the RGB, Grey, HSV, and CIELab color spaces. The fruit variety analyzed was the ‘Golden Smoothee’ apple and the quality parameters were measured with specific devices. For example, the size was measured with a digital caliper, the weight with a digital balance (model GF-2000), the skin color with a Chroma Meter CR-300 colorimeter, the flesh firmness with a manual FT327 penetrometer, the SSC with a digital refractometer (PR32 model), and the TA following a specific procedure by mixing 10 mL of apple juice, 10 mL of distilled water, and 3-4 drops of phenolphthalein. Conversely, the visible spectra of the skin of the fruit was measured by applying a methodology for image acquisition and analysis. The image acquisition device used was a high-resolution IS Pro FUJIFILM camera in combination with commercial fluorescent lighting kit SDI-70 Studio Light SDI 2 used to generate artificial illumination.

The procedure used for the automatic analysis of the visible spectra of the skin of the apples followed four steps. First, the image of the apple was converted into gray intensity level. Then, an adaptive segmentation, which used default values of rectangular window and local threshold, was applied to obtain the contour of the apple. The third step was to remove the noisy pixels from the binary image by applying morphological operations; object labeling and size filtering (values were obtained by trial and error procedure). The last operation was to create a bounding box containing the contour of the apple used to automatically define two circular regions; a central circular area and a centre-right area. These two areas will be used as representative regions of the apple in order to compute the average visible spectral. Finally, the central area defined was seen not to be suitable for the analyses because of specular reflections whereas the centre-right area perceive more changes during the experiments and, consequently, represented better the evolution of the parameters.

The values of the parameters used to perform the analyses were measured over 165 ‘Golden Smoothee’ apples selected from a commercial cold storage unit and they were repeated 11 times every 4 days in order to obtain an accurate evolution. The assessment of the correlation between each fruit parameter obtained from contact based measurements and the visible spectra of the skin of the apples were studied. The best results of these correlations are listed below:

- The maximum correlation achieved for the L parameter (from the colorimeter) was with the S color layer with a value of 0.98, and it was strongly correlated with the L (from the RGB image), R, B, H, V, b, a, and Gray intensity color layers.

- The maximum correlation achieved for a parameter (from the colorimeter) was with the a and H color layers (from the RGB image) both with a value of 0.99, and it was strongly correlated with the R, B, S, V, b, and Gray intensity color layers.
- The maximum correlation achieved for the b parameter (from the colorimeter) was with the R, B, H, S and V color layers with a value of 0.99, and it was strongly correlated with the b, a, L, and Gray intensity color layers.
- The maximum correlation achieved for the size parameter with the a color layer (from the RGB image) achieving a value of 0.93, and it was strongly correlated with the H, B, S, R, V, and b intensity color layers.
- The maximum correlation achieved for the weight parameter was with the a color layer (from the RGB image) obtaining a value of 0.99, and it was strongly correlated with the H, B, R, S, and V intensity color layers.
- The TA parameter was maximally correlated with the b and S intensity color layers (from the RGB image) reaching a value of 0.94, and it was strongly correlated with the B, R, V, and H color components.
- The flesh firmness parameter was maximally correlated with the a color layer (from the RGB image) achieving a value 0.92, and it was strongly correlated with the H, B, R, V, and S intensity color layers.
- The SSC parameter was maximally correlated with the G color layer achieving a weak correlation of 0.50. The G color layer was one of the worst alternatives in the other cases studied.

The final conclusion is that most post-storage apple quality parameters obtained from contact and even destructive measurements were strongly correlated with the visible skin spectra of the fruits. The results showed that the parameters obtained from contact-based measurements were on average strongly correlated with the intensity color layers from the RGB color space of the apples analyzed. However, the best correlation results were achieved when using the CIELab color components. Therefore, most of these fruit quality attributes can be estimated by using techniques based on image processing analyses, which are faster and more efficient.

Future work will be focused on the development of novel image processing techniques for the estimation of new post-storage fruit quality parameters.

8.5. References

[1] Font, D.; Tresanchez, M.; Teixidó, M.; Pallejà, T.; Moreno, J.; Palacín, J. Assessment of pixel-based grape detection methods in color orchard images taken under artificial illumination at night. Submitted to *Biosystems Engineering*, June **2014**.

Chapter 9

Conclusions

This PhD Thesis is focused on the automation of agricultural tasks considering all the stages of the industrial process.

The major achievements of this PhD are the following:

- **<u>At pre-harvest stage.</u>**
  The results from the red-grape image-processing counting method indicated the suitability of the proposed system to detect grapes with different degree of occlusion. The automatic technique presented detected not only totally visible grapes but also grapes with an occlusion inferior to 75% with high accuracy. Additionally, the method was able to count grapes highly occluded but with a lower success rate. The conclusions obtained where that the proposed automatic method had on average a counting detection error of -14% and a low percentage of false positives (7%).

- **<u>At harvest stage.</u>**
  The results from the automatic fruit harvesting system have validated the use of the proposed low cost stereovision system for fruit size, distance and position estimation. Moreover, the complete harvesting prototype based on a robotic arm was tested in laboratory conditions, being able to pickup a pear target in 16 s.

- **At post-harvest stage.**

  The conclusions from the nectarine variety verification system were that the automatic system presented performed the classification better (100%) than an experienced human operator (87%). The best results from the automatic method were obtained with the Pearson correlation comparison achieving a success ratio of 100% whereas the cumulative subtraction technique obtained a 90%. However, the cumulative subtraction comparison was faster and could be a more suitable alternative for a real implementation.

  The results from the assessment of the correlation between post-storage fruit quality indices and visible spectra of the skin of the fruit were that most apple quality parameters (size, weight, skin color, flesh firmness, soluble solids contents and titratable acidity), which were obtained by performing contact and even destructive measurements, could be estimated by means of less time-consuming technique based on image processing analyses (non-contact based measurement). The conclusion was that the best correlation was achieved with the components of the CIELab color space even though the R and B intensity color layers from the RGB color space also offered strong correlations. However, the worst relationship was obtained in the case of the SSC parameter, which had a plain evolution along the fruit ripening.

Chapter 10

Other research activities

10.1 Contribution to publications

The other research activities performed during the development of this PhD Thesis were focused mainly on the development of agricultural applications and control systems:

- Font, D.; Tresanchez, M.; Teixidó, M.; Pallejà, T.; Moreno, J.; Palacín, J. Assessment of pixel-based grape detection methods in color orchard images taken under artificial illumination at night. Submitted to Biosystems Engineering, June 2014.

- Palleja, T.; Teixido, M.; Font, D.; Tresanchez, M.; Palacin, J. Desarrollo de un Caso Practico de Aprendizaje Combinando Vision Artificial y un Brazo Robot. VAEP-RITA **2013**, 1, 61-68.

- Teixidó, M.; Font, D.; Pallejà, T.; Tresanchez, M.; Nogués, M.; Palacín, J. Definition of Linear Color Models in the RGB Vector Color Space to Detect Red Peaches in Orchard Images Taken under Natural Illumination. *Sensors* **2012**, *12*, 7701-7718.

- Teixidó, M.; Font, D.; Pallejà, T.; Tresanchez, M.; Nogués, M.; Palacín, J. An embedded real-time red peach detection system based on OV7670 camera, ARM Cortex-M4 processor and 3D Look-Up Tables. *Sensors* **2012**, *12*, 14129-14143.

- Font, D.; Palleja, T.; Teixido, M.; Tresanchez, M.; Palacin, J. Development of a Virtual Humanoid Model Using the Denavit-

Hartenberg Parameters as a Base for Visual Feedback Applications. Lecture Notes in Electrical Engineering 122: Advances in Automation and Robotics 2011, 1, 639-646.

10.2 Contribution to conferences

The research activities performed have been also presented in several national and international conferences related to precision agriculture and control systems:

- Moreno, J.; Tresanchez, M.; Palleja, T.; Teixido, M.; Font, D.; Palacin, J. Desarrollo de un robot cartesiano de uso docente con 5 grados de libertad y una camara en la pinza. Annual seminary of Automatic, Industrial Electronic and Instrumentation (SAAEI 2013), Madrid, Spain, 10-12 July, 2013.

- Font, D.; Moreno, J.; Tresanchez, M.; Teixido, M.; Palleja, T.; Palacin, J. Compact and low cost embedded vision system for fruit detection and tracking. 9th European Conference on Precision Agriculture (ECPA 2013), Lleida, Spain, July 8-11, 2013. ISBN: 978-84-695-8176-6.

- Font, D.; Palleja, T.; Tresanchez, M.; Teixido, M.; Palacin, J. Preliminary study on color based nectarine variety classification. Proceedings of the 2012 IEEE International Instrumentation and Measurement Technology Conference (2012 IEEE I2MTC), 2187-2190, Graz, Austria, May 13-16, 2012. ISBN: 978-1-4577-1771-0.

- Teixido, M.; Font, D.; Palleja, T.; Tresanchez, M.; Palacin, J. Ejemplo de caso práctico de aprendizaje combinando visión artificial y un brazo robot. Annual seminary of Automatic, Industrial Electronic and Instrumentation (SAAEI 2012), 835-839, Guimaraes, Portugal, 11-13 July, 2012.

- Tresanchez, M.; Teixido, M.; Font, D.; Palleja, T.; Palacin, J. Embedded Vision System for Real-Time Fruit Detection and Tracking. First International Conference on Robotics and Associated High-Techonologies and Equipment for Agriculture (RHEA 2012), 331-336, Pisa, Italy, September 19-21, 2012.

- Font, D.; Palleja, T.; Teixido, M.; Tresanchez, M.; Palacin, J. Development of a Virtual Humanoid Model Using the Denavit-Hartenberg Parameters as a Base for Visual Feedback Applications, 2011 International Conference on Automation and Robotics (ICAR2011), Dubai, UAE, December 1-2, 2011. ISBN: 978-3-642-25552-6.

10.3 Scientific foreign exchange

The scientific foreign exchange performed during the development of this PhD Thesis was in the Field Robotics Center (FRC), a department of the Robotics Institute (RI) at Carnegie Mellon University (CMU), in Pittsburgh, PA, USA. This exchange was performed in two consecutive years, in 2012 and 2013, in a 3 + 3 month research stay under the supervision of Dr. Stephen T. Nuske.

The research carried out in this exchange was also related with the study of the use of robotics in agriculture. The work was focused on the automation applied to table-grape vineyards for automatically evaluating the fruit in situ close to harvest. The study compared different methods applied to collect and process images for the purpose of evaluating the fruit hanging on the vines and comprised data collection, experiment setup development and the application of different image processing methods to process the images in order to distinguish ripe harvestable clusters from non-harvestable clusters. Finally, the results obtained with the automatic procedures developed were compared with manual data.

Nomenclature

ARP	Automatic Resistivity Profiler
ER	Electrical Resistivity
RTK	Real Time Kinematic
GPS	Global Positioning System
VIS-NIR	Visible-Near-Infrared
PCA	Principal Component Analysis
KPCA	Kernel Principal Component Analysis
LS-SVM	Least Squares-Support Vector Machine
BPNN	Back Propagation Neural Network
CCD	Charge Coupled Device
PIXEL	Picture Element
RGB	Red, Green, Blue
HSI	Hue, Saturation, Intensity
CIELab	L is the luminance, a is the red-green axis, and b is the blue-yellow axis
YCbCr	Y is the luminance, Cb is the blue-difference chroma component, and Cr is the red-difference chroma component
LUT	Look up Tables
NDVI	Normalized Difference Vegetative Index
LIDAR	Light Detection and Ranging system
TAI	Tree Area Index
LAI	Leaf Area Index
INS	Inertial Navigation System
RT-PCR	Reverse Transcription-Polymerase Chain Reaction
SSC	Soluble Solids Content
TA	Titratable Acidity
BA	Biospeckle Activity
SC	Starch Content
ANN	Artificial Neural Network
RFID	Radio Frequency Identification