An Integral Automation of Industrial Fruit and Vegetable Sorting by Machine Vision*

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Abstract - *Intensive fruit and vegetable sorting is a common task in productive regions. In order to meet the market standards, produce is classified according to quality levels that depend on maturity degree, weight, size, density, skin defects, etc. Probably the most important of these tasks involve automatic visual inspection. A distributed and scalable system for sorting automation is presented, that addresses all aspects of quality classification mentioned above. The main characteristics of the system are: it can control from 1 to 10 conveyor belts; its maximum performance is 15 fruits per second per belt; apart from weight sensors, it combines infrared, color and ultraviolet images; some fruit defect modules are available to take account of the presence of a given defect.*

1. INTRODUCTION

The fruit and vegetable market is getting highly selective, requiring their suppliers to distribute the goods according to high standards of quality and presentation. In the last years, a number of fruit sorting and grading systems have appeared to fulfil the needs of the fruit processing industry. Present sorting systems tend to include the development of an electronic weight system and a vision-based sorting and grading unit which also measures size, with a friendly user interface that enables definition of classification parameters, reconfiguration of the outputs and maintenance of production statistics.

Some commercially available systems are approaching this objective, but prices are becoming almost prohibitive for small and medium companies that try to maintain competitive levels. Most of the systems we can find in the market are based on special architectures, for instance, DSP-based processors boards, hardware implementation of special purpose algorithm, VME architectures, etc.

This is the case of many Spanish fruit packing companies, which are usually small, agriculture products are quite price-sensitive, and they suffer from a hard competitive market like the European Union. The work we are presenting in this paper is the result of a project partially funded by an agricultural machinery company, *Maxfrut* S.L., with the participation of an electronics designer and manufacturer company, *Dismuntel* S.A.L., the *Digital Signal Processing Group* at the University of Valencia and the *eVis – Enginyeria Visual* Group at University Jaume I, Castelló, Spain. Previous work done by the same team [1] was directed to integrate existing control and weight systems, but they were limited by the capabilities of that system, trying to reduce costs by using special purpose image acquisition devices [2] designed for the project.

Thus, the idea was to build a new system integrating in a flexible way all parts (mechanics, control, weight and vision) of a fruit sorter. From the very beginning there was the criterion that the system should be conceived as an open platform ready to evolve and incorporate, without major changes, new requirements from the customers or simply an upgrade of any of its modules to avoid the obsolescence of its design or components.

The knowledge in the computer vision field has made a significant progress in the last years [3] and hardware improves very fast, providing powerful electronics and low cost architectures due to its standardisation and use for many purposes. Therefore, one of the objectives of the project was to develop a system using standard hardware where possible, which is the basis of a low cost architecture, trying to meet the requirements of the system, mainly in speed and accuracy of measurements.

The result of this work has been a system that is able to control up to (but not limited to) 10 conveyor belts, classifying fruits according to their weight, size and color, and distributing the fruits in different outputs at a maximum speed of 15 fruits per second per belt approximately. The speed limitation of the system, in the case of the vision module, is imposed by the constraints of the standard image acquisition devices used, since we use two frame grabbers per module and NTSC video format, which gives 30 frames per second.

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Figure 1 shows the illumination chamber of the system, where the cameras are placed, and fruits coming in through the conveyor belts.

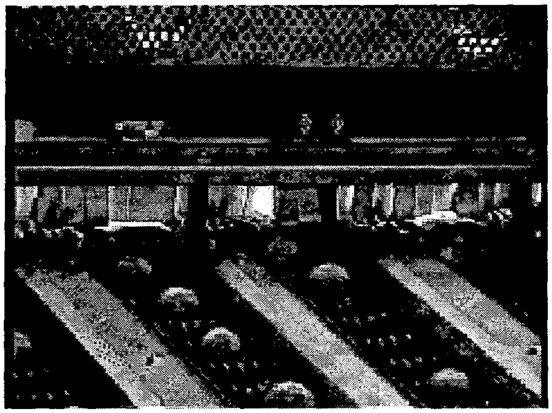

Figure 1. Illumination chamber and conveyor belts

2. SYSTEM OVERVIEW

As it has been pointed out in the previous section, the complete system is a flexible modular system consisting of:

1) a central control unit.
2) a user interface and storage unit.
3) a set of weight modules.
4) a set of vision modules.
5) a set of output control units.

The central control manages all the information about devices and sensors. It also manages the encoder and generates synchronization signals to the weight, vision and output modules. It controls the speed of the conveyor belts and gathers the information all the other modules send during the fruit sorting process, like weight measurements, colour and size estimations, error messages, configuration messages, etc.

The control unit is linked with all other modules through a CAN (Control Area Network) bus which allows real-time communication for control purposes. The CAN bus using a CAN protocol is able to manage short messages under real time requirements. All real-time information is sent across this bus, like synchronization signals, classification results, control orders to sensors and devices, etc. CAN interfaces for PC-based and embedded systems have been developed in the project by the electronics company.

The control unit is also connected via LAN (Local Area Network) to the user interface module and the vision modules. All messages that do not have to meet real time requirements are sent through the LAN using the ethernet/IPX protocol.

A scheme of the system showing its modules and connections can be seen in Figure 2.

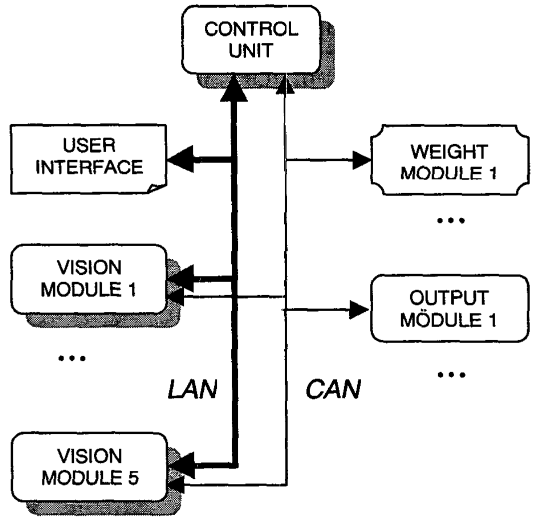

Figure 2. System modules and connections

3. MACHINE VISION MODULE

Each machine vision module is in charge of visually inspecting the fruits, estimating their size and classifying them according to their color properties. It is able to inspect two lines (conveyor belts) at the same time, and it is an embedded system based on a PC architecture without user interface and controlled through the CAN and LAN by the central control unit and the user interface module.

The vision module is composed of a PC-based motherboard with a commercial LAN and CAN controllers, and one or two image acquisition cards. Its application software runs under DOS operating system, using a DOS extender to work in 32 bits protected mode. At present we are using Pentium III processors at 500 MHz.

Each vision module can be equipped with a color and up to two monochrome cameras, one with an infrared filter to acquire only in the infrared, and the other with an ultraviolet filter to acquire in this band only. We use the facility that the CCD of most commercial monochrome cameras are sensible in the infrared and ultraviolet. We will call these cameras the color, IR and UV cameras.

If an IR camera is present in the system, it is used for fruit localization. It is more robust to segment the fruits from the background using an infrared image than doing it from a color image. But if the IR camera is not present (because one prefers a cheaper installation), this task is done from the color images. The UV camera is used for defect detection, although there is not a commercial use of it yet. Defect detection, and more important, defect singulation and classification, is our part of our current work at the time of writing this paper.

The combination of cameras present in a system can be: only color, only IR, color and IR. An UV camera can be also added to these combinations.

The color, IR and UV cameras are progressive scan commercial cameras providing non-interlaced video in NTSC format. Progressive scan is necessary to avoid image blurring due to the high-speed movement of objects.

Processing results are sent through the CAN bus to the control unit. While the vision system is in on-line state, the system is also listening to the LAN network and can receive messages from the user interface and control unit.

3. IMAGE ANALYSIS PROCESS.

3.1 Image acquisition

Fruits on the conveyor belts are singulated and rotated by transport rollers. When a new fruit enters the illumination chamber, a synchronization signal is generated from an incremental encoder, and sent through the CAN bus by this unit. If the vision modules are in on-line state (classifying), they capture images from their cameras.

The illumination chamber has been designed in order to provide diffuse illumination over the fruit surfaces, with the aim of avoiding highlights and specular reflections. This is achieved by illuminating indirectly the fruits, getting the light beams reflected on the chamber walls, coated with a mate white. The walls of the illumination chamber have a semi-circular shape in order to provide light beams on the fruit surfaces from as many directions as possible, simulating diffuse illumination (Figure 3).

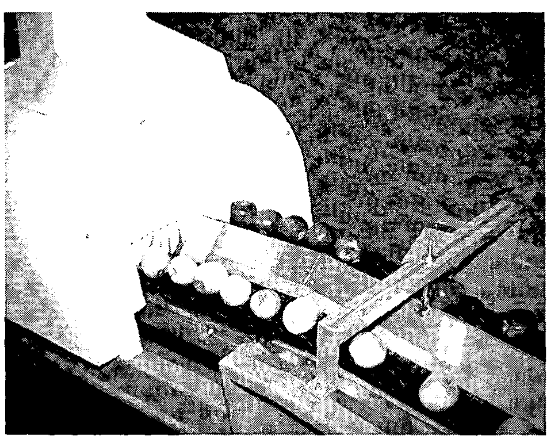

Figure 3. Illumination chamber

The lamps cover the range of visible light, near IR, and near UV spectrum. Halogen lamps are used for illuminating in the visible and the IR, and special UV tubes for providing light in the UV.

3.2 Fruit location

Because of the synchronized image acquisition process, in every image fruits are located approximately at the same place with respect to the image coordinates, but they have to be singulated, since they may touch each other and have different sizes. To identify and singulate every fruit, an algorithm based on projections is used.

After the image is segmented, a projection histogram is calculated on the abscisa axis, that is, along the movement direction. Due to the fact that most of fruits are approximately round shape, their projection usually shows a modal shape, and the projection of all fruits in the line appears as the intersection of several modal shapes with their corresponding maxima and minima. The algorithm developed looks for minima in the projection histogram which correspond to the fruit limits along the abscisa axis.

Once fruits are delimited along the abscisa axis, we can check for joint fruits reasoning on their size and location with respect to the rollers. If a fruit is mislocated it wont be weighted or it will false the weight of another fruit, so the classification is not performed for this fruit.

Similarly, a vertical projection histogram is worked out to find the vertical limits of the fruits. During this process we detect errors consisting of two fruits placed on the same cup, a double fruit. Fruits in this situation have also to be discarded.

3.3 Color processing

Image analysis begins with colour segmentation by means of a Look Up Table (LUT). The color LUT for image segmentation is built previously to the image processing step using a color map defined by the user. We have chosen the RGB representation, mainly because the camera provides images in this representation, although data is further processed and transformed in an adequate format to simplify its interpretation.

Although the illumination is controlled, changes on the illumination level at different points of the fruit surface arise from the geometry of the light reaching the imaging device [4]. One of the objectives in the segmentation step is to avoid the problems caused by highlights on the fruit surface. To avoid the information provided by highlights we would have to use either some color representation regardless of the illuminant [5] or any other representation that allows us to identify and characterize them. We adopted a scheme based on characterizing the highlights using a spherical coordinates representation of RGB space [6] assuming the dichromatic reflection model [7]. The user can either define clusters in this chromatic space or perform a clustering algorithm on a sample image providing the number of color clusters. The clustering, in this case, is done on the RGB space using a C-means algorithm [8].

In systems with color and IR cameras the intensity limits of the first color are used to segment the IR image in pixels of class fruit and no fruit. After that, only the pixels of class fruit have to be classified by color. The resulting segmented or labeled image does not differ in concept of a labeled image computed only from the color information, and it is used to locate the fruits as explained in the previous subsection.

A color and labeled image can be seen in Figure 4.

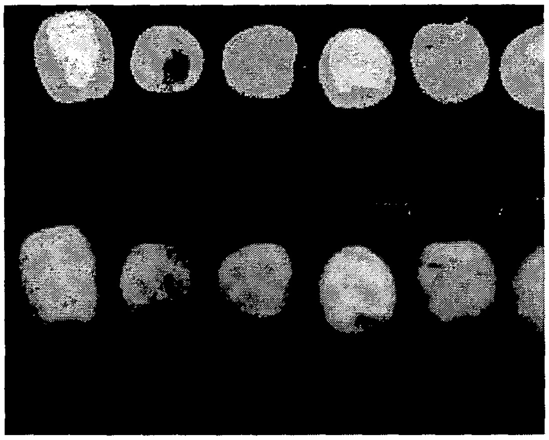

Figure 4. Labeled and color image

3.4 Size estimation

Size parameters for fruits are usually given in terms of their maximum, minimum or medium diameters. To calculate the maximum and minimum diameters of a fruit, they are approximated by the maximum diameters projected on the principal axes of the fruit image. The principal axes are the axes of maximum and minimum moment of inertia of the fruit outline. This method works for almost-round fruits as well as for elongated fruits like pears, regardless of its position.

Size in pixel units is transformed to millimeters through the calibration factors worked out in the calibration phase during the system configuration.

3.5 Size and color classification

Once fruits are singulated and located in the image, two types of information is used to classify them, their size and their color. The area of each color label defined by the user is calculated on the fruit surface, and ratios of every color label with respect to the total area of the fruit are also calculated. The information for each fruit is stored and, after processing up to four views for every fruit, a decision about its class is worked out and sent to the control unit via CAN interface.

In order to discard surface areas of the fruit which may have been regarded twice or more times, repeated views of the same surface patch are estimated by approximating the rotation undergone for each fruit. The repeated area of the surface of the fruits are calculated modelling the fruit as a sphere, taking its radius as the transversal radius calculated from the fruit image. Knowing the translation suffered by the conveyor from image to image, the angle rotated by fruit with respect to the previous view can be estimated.

To classify each fruit into the classes defined by the user, some classification rules are applied which are derived from an approximation of the classification rules provided by a binary decision tree. The decision tree uses the ratios of colors defined by the user as feature vectors. Decision trees are generated from a learning process using Quinlan's method [9]. Tree rules are simplified in the way of logical ands of rules for each color ratio c_i of the form $r_i<c_i<R_i$, being r_i and R_i the upper and lower bounding constants derived from the tree learning process.

4. USER INTERFACE

A graphical user interface with an icon-directed manipulation-based style allows the user to handle all the options of the system, such as the initial set up, monitoring statistics and classification parameters configuration. The simplicity and usability of the interface makes it easy enough to be used for non-technical operators. The parts of the user interface concerning the vision module are:

- Color map editor (Figure 5). Its purpose is to define the colour labels and the clusters assigned in the color space to each color label.

- Color class editor (Figure 6). To define the color classification rules.

- Color calibration (Figure 7). In order to make that color measurements of all vision modules in the system are the same for the same objects in the same conditions, the cameras of each vision module are calibrated and a set of color calibration parameters to correct the color measures of each camera are computed. These parameters correspond to a linear model of the color camera measurements.

- Camera position, process areas and size calibration (Figure 8). To calculate the ratio between pixels in the image and millimeters we use a calibration object of known size, that is located and segmented with a specified color map. We also use a calibration grid to help to set the image plane parallel to the object plane (Figure

9). The process automatically detects the grid and informs the user of how to move the camera to get a better positioning.

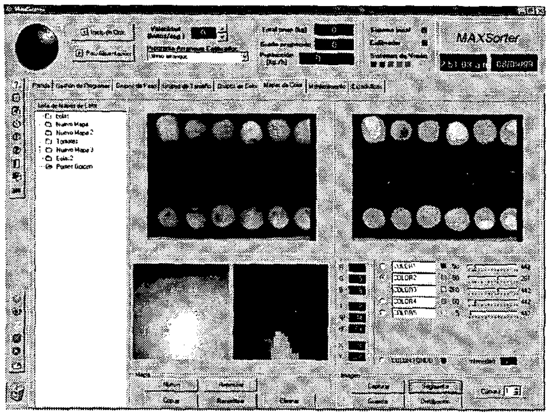

Figure 5. Color map editor of the user interface.

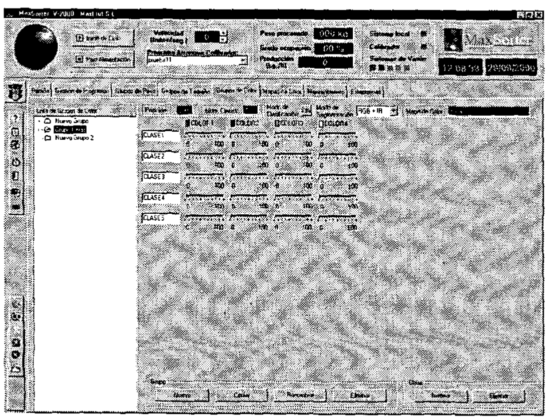

Figure 6. Color groups editor.

5. SYSTEM PERFORMANCE

The maximum number of color labels is at present fixed to eight, and the maximum color classes are 12, which covers most types of fruits and vegetables. The system performance has been compared with human criteria and no significant disagreement has been found between human and machine decisions in color classification. Noteworthy is the case of fruits that can be assigned to two different classes: human decisions often vary, nevertheless the machine vision rarely changes its decision.

Concerning the computation time required for the standard classification, and using a PC-based motherboard with a Pentium III at 450 MHz, the system can process up to 15 fruits/second and line, inspecting two lines at the same time. Image processing speed is limited to the image acquisition card and cameras used, due to video signal standard specifications. To increase image processing rate, non-standard color cameras or digital camera with high frame rate should be used, but present mechanical specifications of rolling chains and transport lines are not designed to support much higher speeds.

The machine vision module has been tested with satisfactory results in several facilities in Spain grading tomatoes, apples, pears, oranges, peaches, etc. Previous versions of the system [2] have been also working, with satisfactory results for long periods of time (several years).

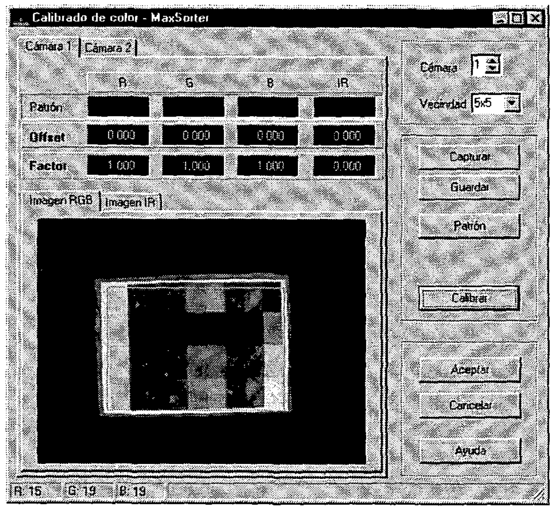

Figure 7. Color calibration window.

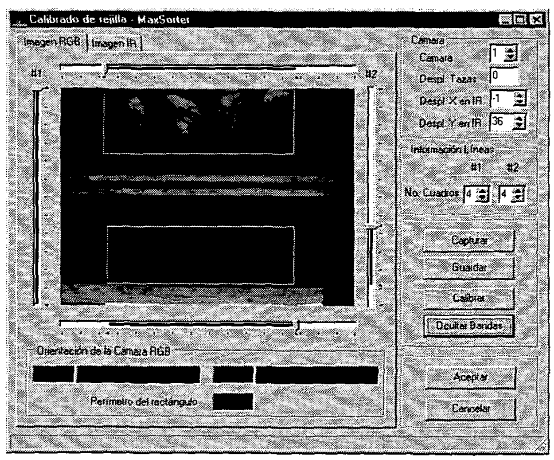

Figure 8. Processing areas, positioning, and size calibration window.

Size calculation accuracy depends on the camera set-up. Typical camera set-ups (6 mm focal length and 70 cm distance from the camera to the transport lines) in the fruit sorting system developed can provide 1 mm error approximately.

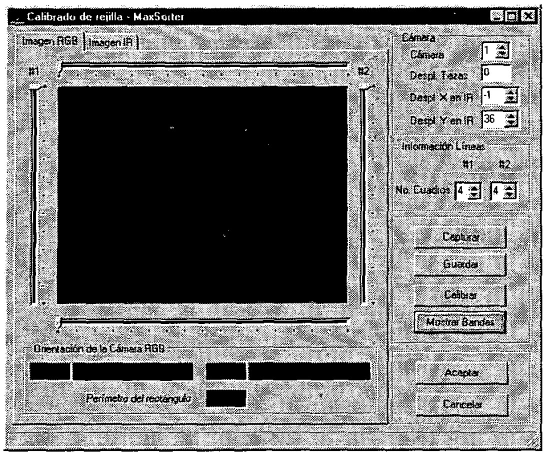

Figure 9. Positioning grid.

5. CONCLUSIONS AND FUTURE TRENDS

We have presented a fruit grading machine vision system for color and size classification which is being commercialized in Spain. The vision system is part of a modular fruit grading system that integrates mechanics, control unit, user interface, weight cells and output control units, all linked with a real time CAN based network and a LAN for non real-time communications. The system can process up to 15 fruits per second per line, and sort them according to its weight, size and color.

The vision module uses a low cost architecture, consisting of a PC-based embedded system with commercial image acquisition cards, making the cost of the system really competitive with respect to existing systems in the market.

The modularity and distributed nature of the approach makes the system easy to be upgraded in the future, although at present it covers most Spanish fruit-market requirements of the small and medium fruit packing plants.

Processing speed achieved is considered enough for the existing mechanics of the transport lines and present packing houses facilities. Future work is directed to add other fruit inspection capabilities, like detection of specific features on the fruit surface which need more specific image processing techniques, in order to increase quality standards.

In particular, at present we are working on identifying several defects in oranges, and quantifying them providing a few degrees of defect presence, apart from the defect type. Current systems can detect skin defects but not classify them. They detect defects by measuring the fruit area that does not correspond to any given color in the color map. Besides a general defect detection approach such as this one, our intention is to provide the machine with the possibility of installing, or activating, some defect-detection modules for specific defects.

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