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DATA INTEGRATION MODEL MANAGEMENT FOR COMPUTER VISION SYSTEM APPLIED IN AGRICULTURAL MACHINES

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Abstract. *Computer vision systems, when used in open and unstructured environments as in the inspection of crops, requires the use of specific acquiring algorithms prepared for such situations. These algorithms work mainly with images composed of complex objects. Likewise, recent lines of research intend to define the standards for the development of electronic systems and applications to facilitate integration and interoperability between agricultural systems, for example, the standard ISO11783 for agricultural machines with computer vision systems. The present project aims to apply merging techniques as un-supervised homogeneous segmentation algorithm and statistical classification for mobile robot inspection in agricultural orange crops for quantization of fruits, associating a hierarchical architecture of the systems involved in the process for precision agriculture, and development of algorithms for interoperability between agricultural robotic control systems and decision making support system.*

Keywords: *Computer vision, precision agriculture, systems integration, natural scenes, agricultural mobile robots.*

1. INTRODUCTION

Fruit recognition from images taken in an unstructured environment for fruit-harvesting robotic applications is a challenging task mainly due to the variable illumination, partial occlusion of the fruit area, shadow effect due to sunlight incident angle, merging of backgrounds (foliage), uncertainties due to shape of the fruits and the real-time restriction, just to mention some issues. According to [1], citrus are typical trees with a dense foliage and quite often 70-80% of the fruits have half or more of their surface obscured.

Despite these difficulties, several approaches based on image processing algorithms have been proposed to segment fruit from natural images [2], [3], [4], [5], [1], [6], and [7]. Other methods have also been proposed, such as those based on laser range-finder [8], the concept of chaos and neural networks [9], Support Vector Machine [10], and machine vision and ultrasonic sensors integration [11].

Comparative experiments involving Dynamic threshold segmentation method, extended Otsu, improved Otsu combined with genetic arithmetic, and adaptive segmentation method based on Learning Vector Quantization network was conducted by [12]. Tests using images of apple, tomato, strawberry, persimmon and orange demonstrated that Dynamic Thresh-old method has better performance and least cost time than extended Otsu method, improved Otsu combined with genetic arithmetic and adaptive segmentation method based on LVQ network. Besides, it has satisfactory effect upon fruit image under natural illumination condition. Adaptive segmentation method based on LQV network can only be applied into balanced colour instance of particular fruit, and it is not adapt to be applied into real-time occasion because of high cost time [12].

The development of robotic systems which work mainly with those algorithms, as the high degree of interdisciplinary, the difficulty of integration between the various robotic control systems and lack of standardization in the definition of electronics and control systems that will be used to build the robots, intend to define the standards for the development of electronic systems and applications to facilitate integration and interoperability between agricultural systems, for example, the standard ISO11783 [13] for agricultural machines. It implies the same needs and is also expected to provide integration with geographic information systems, due to its wide potential application in agriculture.

Thus, this project presents a hierarchical architecture of the systems involved in the process for precision agriculture, and development of algorithms for interoperability between robotic control systems and decision making support system – for pattern recognition of fruits. Based on the results of integrations, such systems can generate specific robotic missions to be inserted in an autonomous agricultural robot, designed according to the ISO11783 standard applied in computer vision

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2. METODOLOGY

2.1 Unsupervised homogeneous regions segmentation

Color images with homogeneous regions are segmented with an algorithm to generate clusters in the color space/class (different measures classes in spectral distribution, with distinct intensity of visible electromagnetic radiation at many discrete wavelengths) [14].

One way to segment images with textures is to consider the spatial arrangement of pixels using a region-growing technique whereby a homogeneity mode is defined with pixels grouped in the segmented region.

Furthermore, in order to segment texture images one must consider different scales of images. An unsupervised color-texture regions segmentation algorithm is ideal for this purpose, since it tests the homogeneity of a given color-texture pattern, which is computationally more feasible than model parameter estimation. It deals with the following assumptions for the acquired image:

- Image containing homogeneous color-texture regions;
- Color information is represented by quantized colors;
- Colors between two neighboring regions are distinguishable.

The JSEG algorithm segments images of natural scenes properly, without manual parameter adjustment for each image and simplifies texture and color.

Segmentation with this algorithm passes through two major stages, namely color space quantization (number reduction process of distinct colors in a given image), and hit rate regions with similar color regions merging, as secondary stage.

In the first stage, the color space is quantized with little perceptual degradation by using a quantization algorithm [15] [16] with minimum coloring. In this context, each color is associated with a class and the original image pixels are replaced by classes to form the class maps (texture composition) for the next stage.

Before performing the hit rate regions, the J-image – a class map for each windowed color region, whose positive and negative values represent the edges and textures of the processing image - must be created with pixel values used as a similarity algorithm for the hit rate region. These values are called ~~J~~-values" and are calculated from a window placed on the quantized image, where the J-value belongs. Therefore, the two-stage division is justified through the difficult analysis of the colors similarity withal their distributions.

The decoupling of these features (color similarity and spatial distribution) allows tractable algorithms development for each of the two processing stages (Figure 1).

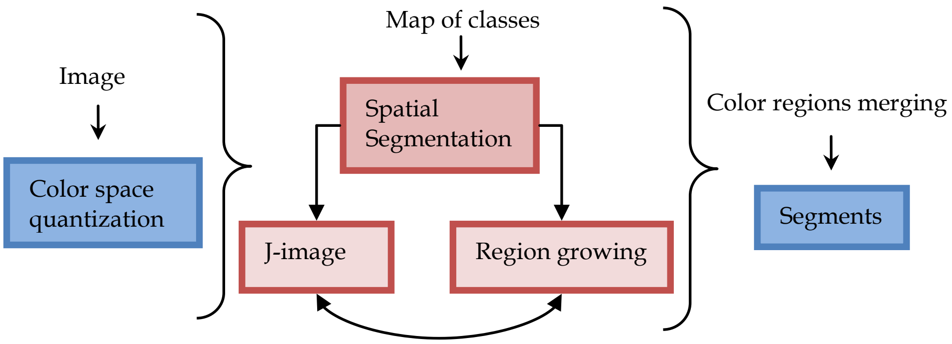

Figure 1. JSEG image segmentation steps [14].

2.2 Hierarchical architecture of a robotic system agricultural

Each agricultural operation, which can be called "mission" to be performed by a robot farm is the result of a series of processing and analysis of agronomic data spatial-temporal. After processing the data (geographic and agronomic), is defined a map of recommendation containing information about the mission, which is embedded in agricultural mobile robot with an autonomous navigation system, and used as reference for the implementation. The operating cycle of the robot is divided into five steps:

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1. Support System for decision making / GIS: Manage information about field operations, such as productivity, costs, machine maintenance, among other information, has generated research opportunities. The integration proposal envisages the creation of an algorithm that can export the geographic databases in default XML file maps of ISO 11783. That way can use GIS market with integrated farming systems that use the standard ISOBUS [13].

2. Missions: Maps containing information about the operations to perform on the field. These maps contain geographical information such as: boundary area to be used, known obstacles (trees, buildings), planting rows that need to be followed by the navigation system of the robot, and agronomic information specific about the "mission" that will be performed, such as: sequence of operations (capturing an image of the area, collect soil samples), sampling rates, the speed that operation must be performed, among others.

3. Autonomous agricultural robot: the robot agricultural has a series of devices (sensors and actuators), and motors, GPS and other electronic equipment. All these facilities are managed by autonomous systems of navigation, guidance and responsible for the tasks execution in the field. The robot has an electronic system that is in accordance with ISO 11783, which provides a standard for interconnecting electronic devices embedded and agricultural implements through a control network and serial communication [13].

4. Field: Areas planted with various crops (perennial and/or non-perennial), including: citrus and grains.

5. Results of mission: After execution of the tasks in the field, all operational data are exported agricultural machinery, imported and analyzed by Geographic Information System. The data must be exported in standard ISO 11783 has conversion algorithms for reading through Geographic Information Systems (GIS) market available.

Using the architecture presented above it becomes possible integration between the management systems and geographic information systems (GIS) with the control systems and agricultural mobile robot navigation for execution of specific operations in the field.

2.3 Agricultural robot platform for integrating system management and computer vision

All components were developed by different manufacturers, are controlled by software developed in different programming languages. To reduce the complexity of integration between the various control modules and communication with the bus ISOBUS, designed a software architecture that uses a middleware between the layers of perception and action, as the following Figure 2:

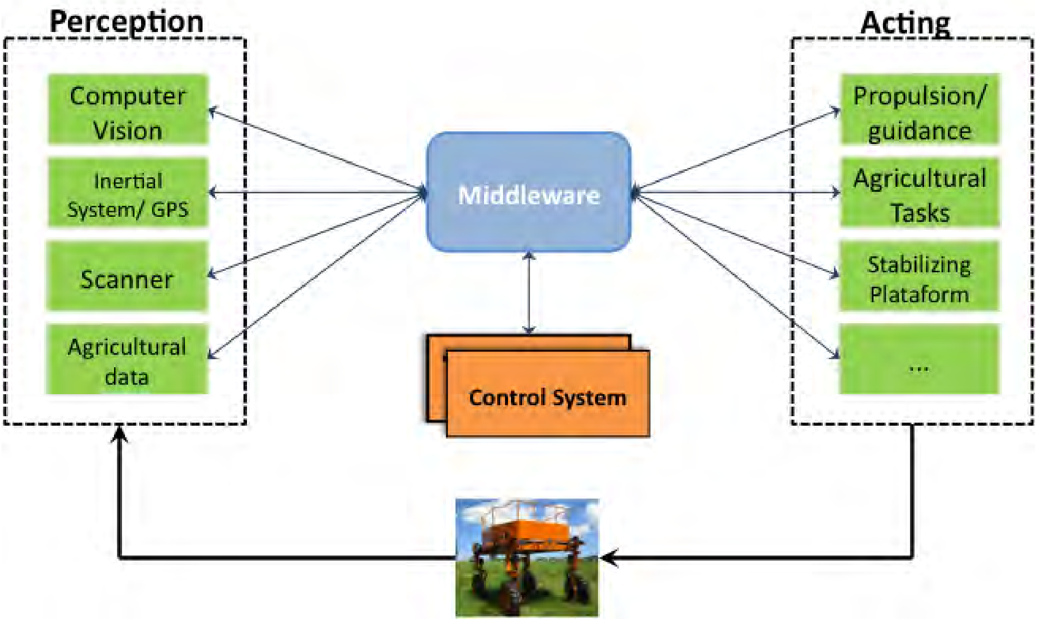

Figure 2. Integration of robotic architecture systems using middleware.

The Table 1 below shows the module embedded in the robot and its associated programming language that was used in development.

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Embedded Systems	Development Environment
Computer Vision	Matlab
Inertial System and GPS	C/C++
Scanner laser	C++
Robotic Arm	C/C++
Propulsion and Guidance	Labview
Stabilizing Platform	Labview

Table1. Embedded Systems and their development environments.

Within this context, the middleware layer is used to exchange information and data between programs developed in different communication protocols, operating systems and platforms. All software modules, regardless of programming language were developed, using an API to perform messaging with data from sensors and control and performance.

The integration of embedded systems can increase the efficiency of the control system because it allows exchanges of messages between modules of perception, generating redundant information. An example is the possibility of the Computer Vision System to receive information from laser scanner module to check a reading done. If the camera's computer vision systems make an data acquisition and identify an obstacle, can used the information generated by the scanner to confirm or discard this information. Thus information was restricted only to specific systems are available for use by other modules of the robot.

Figure 3 below shows the architecture of an exchange of messages between the modules loaded by the middleware.

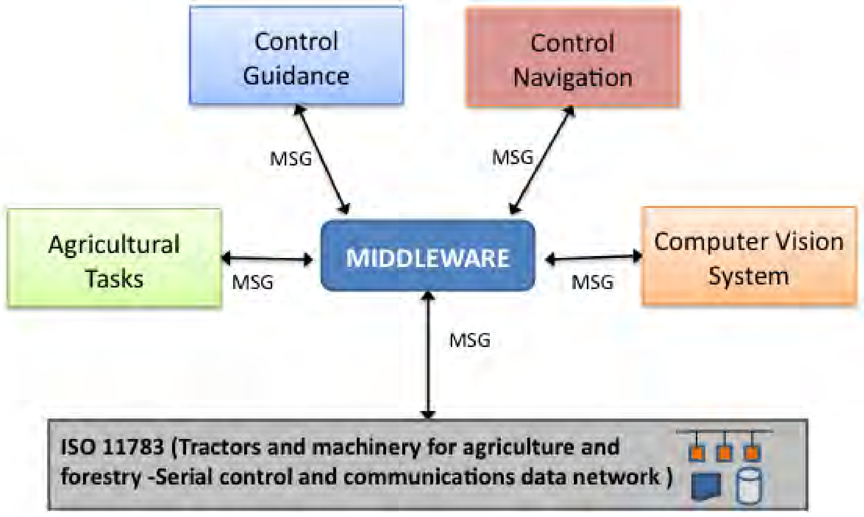

Figure 3. integration of embedded systems and messaging with middleware.

As can be seen, all messaging (MSG) on the CAN bus of the robot are sent to the middleware and are available for embedded modules, as well as the messages generated by these modules are sent to the bus. In the validation tests of the proposed architecture was used middleware OpenMQ.

3. RESULTS

In order to calculate the J-value, Z is defined as the set of all points of quantized image, then $z = (x, y)$ with $z \in Z$ and being m the average in all Z elements. C is the number of classes obtained in the quantization. Then Z is classified into C classes, Z_i are the elements of Z belonging to class i, where $i=1,\ldots,C$, and m_i are the element averages in Z_i. The J-value is as follows:

$$J = \frac{S_B}{S_W} = \frac{(S_T - S_W)}{S_W} \qquad (1)$$

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$$S_T = \sum_{z \in Z} \|z - m\|^2 \tag{2}$$

$$S_W = \sum_{i=1}^{C} \sum_{z \in Z} \|z - m_i\|^2 \tag{3}$$

Several window sizes are used by J-values: the largest detects the region boundaries by referring to texture parameters; the lowest detects changes in color and/or intensity of light. Each window size is associated with a scale image analysis. The concept of J-image, together with different scales, allows the segmentation of regions by referring to texture parameters.

Regions with the lowest values of J-image are called valleys. The lowest values are applied with a heuristic algorithm. Thus, it is possible to determine the starting point of efficient growth, which depends on the addition of similar valleys. The algorithm ends when there are spare pixels to be added to those regions.

Figure 4 shows three categories of orchards scenes. The first one identifies the most part of the tree, also evidencing the soil. In this category, the quantization threshold was adjusted to higher values in order to avoid the fusion of regions with the same color tonalities, e.g. stems, branches, twigs and soil. The second category represents details in given sets in the orchards scenes, excluding darker regions from the remaining scene.

Besides the irregularities of each leaf the abnormalities of tones of the fruit are segmented, allowing *posteriori* analysis of characteristic diseases in oranges. The third category identifies, like the first, most of the trees, but with a higher incidence of crown and regions of the sky

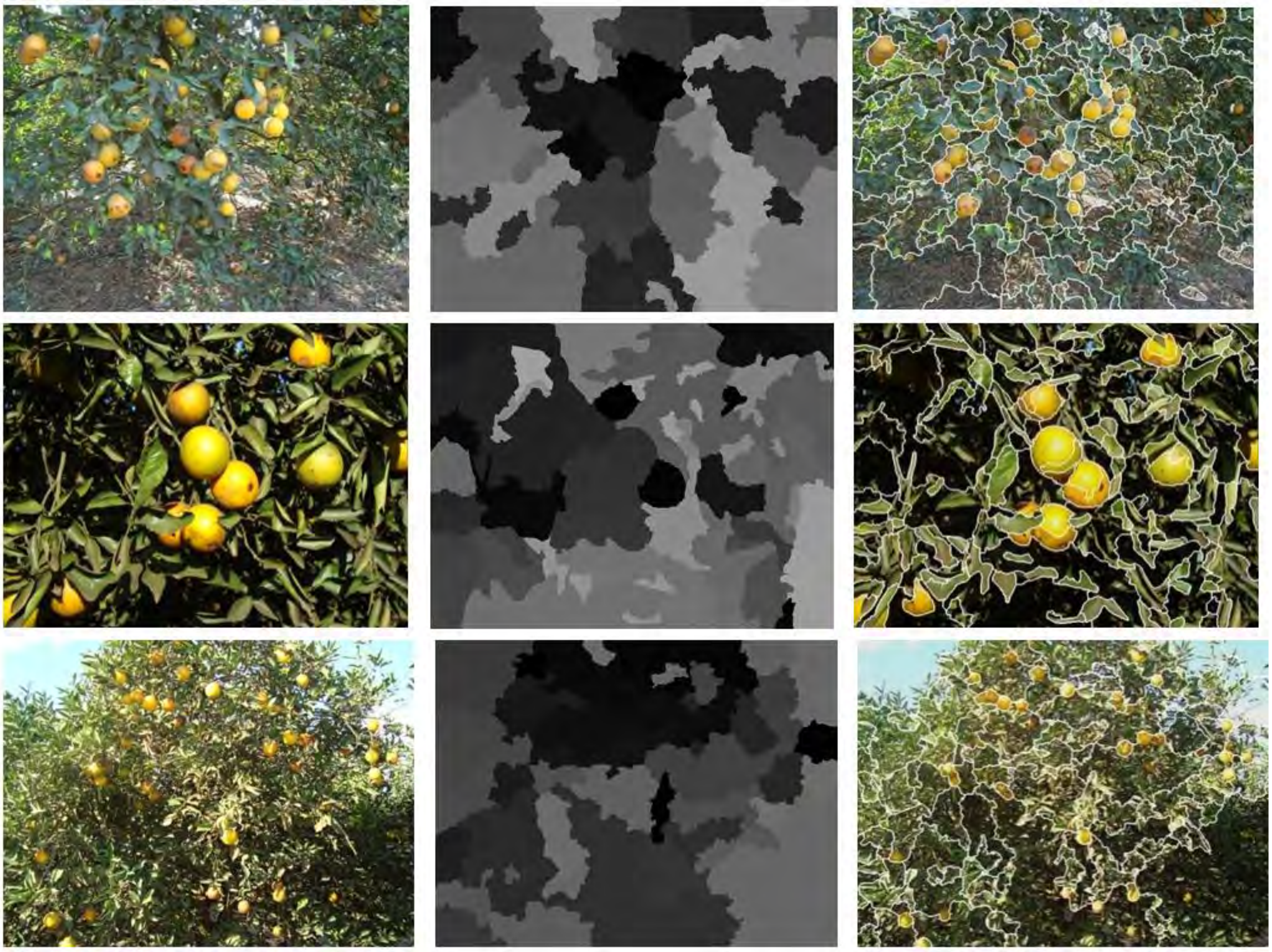

Figure 4. Fruit orchards original scenes (column 1); quantized color images (column 2); segmented images (column 3).

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In Figure 5 and Figure 6, for the location of fruits in the RGB case, the discrimination of the classes fruit, sky and leaves, twigs and branches, attends constant amounts proportional to the increasing of the training sets. This amount, for HSV case, is reduced for the fruit class, as the dispersion of pixels is greater in this color space.

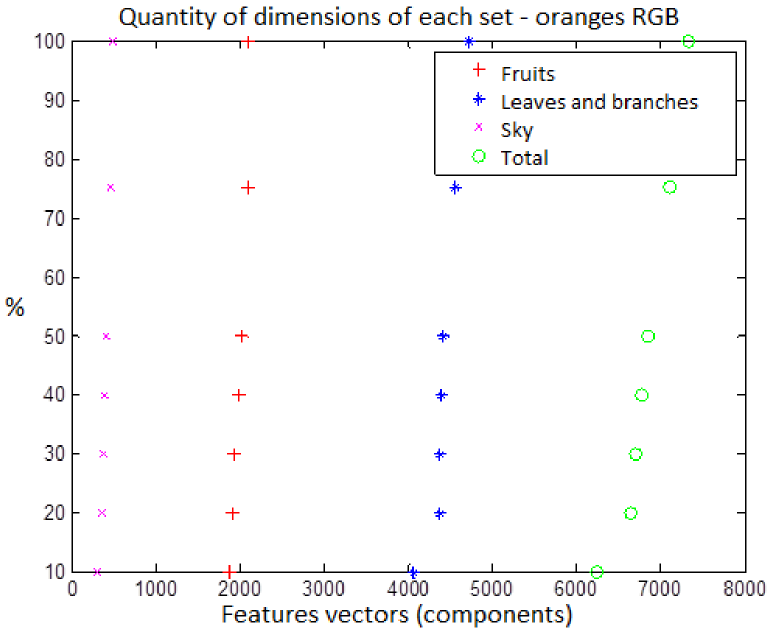

Figure 5. Quantity of dimensions of each set (orange RGB).

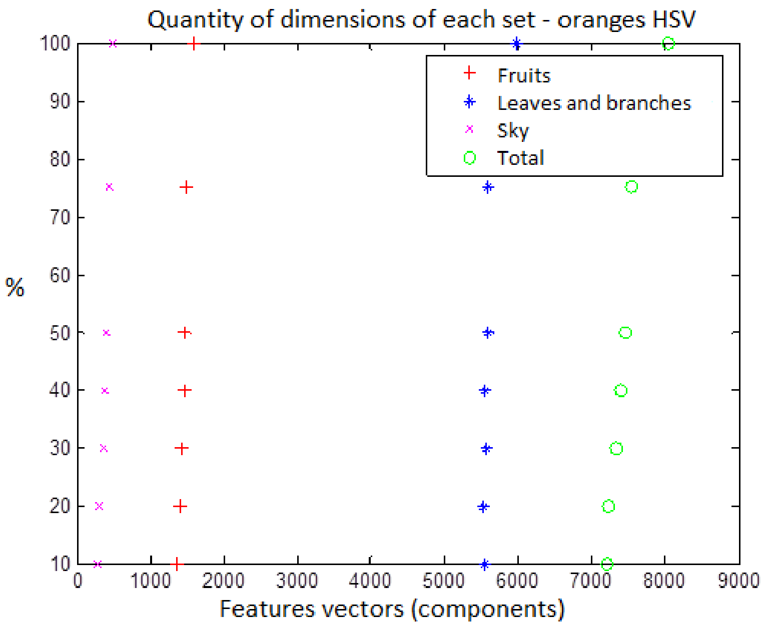

Figure 5. Quantity of dimensions of each set (orange HSV).

4. CONCLUSIONS

All tasks related to this project were implemented and well solved for the problem about the inspection of crops, using computer vision, when used in open and unstructured environments. These algorithms worked with images composed of complex objects. Similarly, the standards for the development of electronic systems and applications to facilitate integration and interoperability between agricultural systems (standard ISO11783) for agricultural machines was explained and integrated to computer vision systems, as the need of interoperability between agricultural robotic control systems and decision making support system, is present.

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7. RESPONSIBILITY NOTICE

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