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Olive Fruits Recognition Using Neural Networks

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Abstract

A new method for olive fruit recognition is presented. Olive fruits size and weight are used for estimating the best harvesting moment of olive trees. Olive fruit recognition is performed by analyzing RGB images taken from olive trees. The harvesting decision comprehends two stages, the first stage focused on deciding whether or not the candidate identified in the picture corresponds to an olive fruit, and the second stage focused on olives overlapping in the pictures. The analyses required in these two stages are performed by implementing a neural networks solution approach.

Keywords: Image processing; pattern recognition; RGB model; CIELAB color space; neural networks; olive harvesting

1. Introduction

One of the key aspects of olive cultivation is the ability to estimate the moment when the harvest should take place, to obtain the best yielding from the plantation. The better the estimation of the harvesting moment is, results in better financial and agricultural condition for the owner of the olive plantation. The problem of obtaining the optimal plantation yield consists on determining the largest fruit size based on its equatorial and polar diameters.

Literature review for the past 30 years shows that there are no publications regarding the actual count of olives fruits, focusing mostly on olive tree identification. Reference [1] used a method of classification of eggplants by using neural networks in the RGB color model and color space CIELAB. In [2] compare different types of classifiers for the recognition of defective blocks. SVM (Support Vector Machine) algorithm achieved the best results, increasing by around 90% of correct classification. Object recognition can be achieved by correlating the shape and contours of each shape [3]. In many cases, it achieves satisfactory results. In reference [4] color and texture properties for the recognition of red and green apples is used. This analysis proved successful by including the properties of the co-occurrence matrix jointly with the levels of red, performing segmentation using clustering analysis. In [5], proposed a technique for counting kiwis, based on the

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segmentation of images using the CIELAB color model and the “Watershed” transformation to count the number of fruits in each image. A simpler method for the tomatoes identification is presented, achieving 75% of correct classification [6].

According to [7], by taking a greater amount of information with the physical and color parameters of the RGB color model, a k-Nearest Neighbors (k-NN) based on Euclidean distance classifier can be obtained for fruit classification. Classification results showed 90% correct classification using the method. In classification of mature fruits and vegetables, based on a neuro-fuzzy classification, classification is performed by taking intensity of the red, green, and blue as a parameter, showing an accuracy level of 73.3% when classifying ripe fruits and vegetables [8]. Reference [9] presents a comparison between Artificial Neural Networks (ANN) and Support Vector Machines (SVP) for apples classification. SVP presented a better result in classification of apples, yielding almost 90% of correct classification for estimating the apple harvest moment. Authors of this paper have previous works in fruits recognition and classification [10].

The main difference between the objectives of the works cited and the work presented here, is concerned primarily with the identification of specific fruits, leaving a large margin of slack when developing classification models.

In this paper, a new method for olive fruit recognition is presented. A model is used to characterize and recognize olive fruits in the tree and measuring the caliber of each specimen as they appear in pictures taken to the olive tree [11]. The approach proposed is close to the correlation with an idealized model. A model for the recognition of the diameter of olives has been developed. The recognition is performed by analyzing the RGB images obtained from olive tree. This information could be useful for estimating the best harvesting time.

2. Background Extraction

Histogram analysis from an olive tree picture is used to verify the possibility of separation of strata and check the data set under analysis for normality. The strata chosen for analysis are: 1) Olive, 2) Leaf type 1 (dark green), 3) Leaf type 2 (light green), and 4) Stem. Figure 1 shows the layers corresponding to each stratum with the background turned white for improved perception. Stratification of the data is improved due to the color reference standard. Figure 2 shows data sets used in the statistical analysis. Top left is olive fruit, top right is leaf type 1, bottom left is leaf type 2, and bottom right is stem. By visual inspection, it could be inferred that in some images there is some overlap of color in the layers, i.e., some olives (or a part of them) have very similar color to that found in strata relating to leaves types 1 and 2 respectively. Analyzing the spectral behavior of all 4 layers for the channels red, green, and blue color of RGB model, hue, saturation, value color of model HSV, L, a, b, a/b of CIELAB color space, respectively.

Figure 3 shows the spectrum analysis of channel data to the color space for the four strata (olives, leaves types 1 and 2, and stem). After the analysis for each channel within the models of the RGB and HSV models, and including the Lab color space, layer segmentation opportunity for olives is more likely in matrix a. Then, a
statistical analysis verifies the normality of the data in each stratum, considered random variables under a normal distribution of data. The probability density function of a normal distributed variable \( x_k \) is defined as

\[
\varphi_{\mu_i, \sigma_i}(x) = \frac{1}{\sigma_i \sqrt{2\pi}} e^{-\frac{1}{2} \left(\frac{x - \mu_i}{\sigma_i}\right)^2}, \quad x \in \mathbb{R},
\]

where \( \varphi \) is the probability density function of the \( i \)-th stratum, \( \mu \) the arithmetic mean of the \( i \)-th stratum, \( \sigma \), the standard deviation of the \( i \)-th stratum, and \( x_k \) the discrete random variable. The data relationship with respect to a normal distribution curve, the random variable is plotted against the probability density curve. In this case, the curves have a correlation coefficient \( R^2 \) between 0.972 and 0.994. The distribution function of normal distribution is defined by

\[
\Phi_{\mu_i, \sigma_i}(x) = \int_{-\infty}^{x} \varphi_{\mu_i, \sigma_i}(t) dt = \int_{-\infty}^{x} \frac{1}{\sigma_i \sqrt{2\pi}} e^{-\frac{1}{2} \left(\frac{t - \mu_i}{\sigma_i}\right)^2} dt, \quad x \in \mathbb{R}.
\]

Table 1 shows the results. Based on this results, cutoff value is made equal to 112, because layers of leaf type 1, leaf type 2, and stem together do not exceed 3% incidence, while the stratum corresponding to olives has an incidence of over 85%, with an average cut equal to the mean plus 1.0441 standard deviations. To represent the ideal olive shape, the Principal Components Analysis (PCA) is used for finding the best projection representing our goal (olives ready for harvesting) by least squares statistical representation. The idea is to find the eigenvectors of the data sets characterizing all possible combinations of olives.

### Table 1 Distribution functions of four strata for closed interval 112 to 116

<table>
<thead>
<tr>
<th>Cutoff</th>
<th>Value</th>
<th>Distribution</th>
<th>Functions</th>
</tr>
</thead>
<tbody>
<tr>
<td>( x_c )</td>
<td>( x_c = \mu_i + \sigma_i )</td>
<td>Olive</td>
<td>Leaf 1</td>
</tr>
<tr>
<td>112</td>
<td>( \mu_1 + 1.0441\sigma_1 )</td>
<td>85.1771</td>
<td>2.4738</td>
</tr>
<tr>
<td>113</td>
<td>( \mu_1 + 1.3176\sigma_1 )</td>
<td>90.6169</td>
<td>4.2190</td>
</tr>
<tr>
<td>114</td>
<td>( \mu_1 + 1.3176\sigma_1 )</td>
<td>94.4198</td>
<td>6.8484</td>
</tr>
<tr>
<td>115</td>
<td>( \mu_1 + 1.8645\sigma_1 )</td>
<td>96.8873</td>
<td>10.5917</td>
</tr>
<tr>
<td>116</td>
<td>( \mu_1 + 2.1380\sigma_1 )</td>
<td>98.3739</td>
<td>15.6276</td>
</tr>
</tbody>
</table>

This evaluation minimizes the amount of probability of occurrence of data for the layers leaf type 1 and type 2 stem leaves, and getting as much information as possible for the olives. That it is possible to find a good theoretical cutting height, but the data are discrete integer random variables. To resolve this limitation, all distribution functions are evaluated to a closed interval 112 and 116 to verifying their occurrence probability. Table 1 shows the results. Based on this results, cutoff value is made equal to 112, because layers of leaf type 1, leaf type 2, and stem together do not exceed 3% incidence, while the stratum corresponding to olives has an incidence of over 85%, with an average cut equal to the mean plus 1.0441 standard deviations. To represent the ideal olive shape, the Principal Components Analysis (PCA) is used for finding the best projection representing our goal (olives ready for harvesting) by least squares statistical representation. The idea is to find the eigenvectors of the data sets characterizing all possible combinations of olives.

### 3. The Model

The proposed solution model consists in creating three matrices RGB respectively, containing the factors described and the data of the stratum for olives. With the fundamental matrices linearly independent, it is possible to build any olive on the basis of the linear combination of the factors represented in the fundamental matrices, obtained by using the PCA method. This method finds a set of uncorrelated variables to describe the set of observations. In this case, a combination of those uncorrelated variables is taken, to generate one Eigen
matrix for each RGB channel. In order to achieve representativeness and also to include variability, samples of various sizes, colors, brightness, contrast, a number of 50 replications of the random data sets are gathered.

Figure 4 shows the data set chosen for analysis of principal components. Because olives are of different sizes and their pictures are at different angles of inclination, a routine is devised to find its rotation angle with respect to a reference point considering the polar and equatorial diameters of the olives. Once found these angles, data normalization of the median longitudinal and equatorial diameters is applied. Note, in Figure 5, the median is independent of presence of extreme data. Figure 6 shows the Eigen image gotten with PCA.

The cross-correlation index can be used for identifying patterns or correlation between two data sets. An advantage of this index is its ability to consider both discrete as continuous data. Within the CIELAB color space segments of olives, leaves, and stem are markedly distinct and well defined, as well as with the Eigen image obtained after the PCA process. These two sets of data can also be correlated, and it is defined by

\[
(f * g)_i = \sum_j f_j^* g_{i-j}.
\]

Figure 7 shows the cross-correlation results for a test image. Regarding olive counting, the need to estimate olives size makes the process not yet complete (contour estimation). Estimation can be achieved by using centroids of figures with greater correlation to an olive’s shape. However the olive shapes are variable and not complete. Problems arise when two or more olives overlap. This problem is solved with an iterative expansion of the object, starting from the centroid to a boundary that minimizes the energy function. Then, splitting separates contiguous specimens by Euclidean distance transformations, for eliminating possible random seams.

By minimizing the Euclidean distance between the candidate’s contours, it is possible to reformulate the problem using the Active Contours Chan-Vese method. This it makes possible to vary the image and allows computing the gradient. The gradient gives a significant value where variations occur and it is very helpful to finding the contours. Centroids of the potential candidates were identified by the cross-correlation function. However, the difficulty is the extent to which adjacent olives overlap among them. According to the Stokes theorem [12], the value of this integral corresponds to the dot product of the vector field with respect to a
differential arc length. The solution proposed by Chan and Vese [13], is to minimize the energy function required to form a region. This solution is described a paradigm [12], [14], resulting in an active solution that iteratively finds the point when the energy function phi is zero (Equation 4). This situation implies that for region \( a \) and region \( b \), the energy is the same for both of them, as described also by the Continuity theorem.

\[
\phi = \int_{\Omega_a} (I - \overline{X}_a)^2 dA + \int_{\Omega_b} (I - \overline{X}_b)^2 dA.
\]

Figure 8 show the mask generated using the contour search algorithm. Important is the starting point of the process of energy minimization. The initial mask of active contours is the centroids obtained by the correlation.

4. Olive Recognition

In the process of edge detection and selection of candidates, there may be a latent error, especially if the process is automated. It is necessary to have two stages of decision, one focused on discerning if the candidate is an olive and the other to determine the number of olives, considering overlap of them, in function of geometric and morphological properties of the specimens overlapping. To meet these requirements a feedforward neural network is used, with a backpropagation learning algorithm.

In this paper, a neural network model with stages as a framework process is proposed. The main idea is separate the requirements in two steps, utilizing two neural networks: one for classification and other for selection of non-overlapping olives. In the first stage of decision, the configuration with lower training error, a sigmoidal activation function is used because it has hidden layers generalization and thereby increases the discernment of atypical cases. The neural network must be trained to learn the characteristics of the eccentricity, color in the RGB and HSV models, in filter lab space, size, area, etc. In the second decision stage, a hyperbolic arc tangent activation function is used due to it is increasing, differentiable, and it has higher output interval. This neural network has one less layer, but a greater number of neurons, meaning that the network has the selectivity required, the three possible answers. The super elliptical model of an olive is used, taking into account the existence of two or three digitally overlapping olives, which is the most common situation.

Before the learning starts, it is needed to decide what input data will be fed to the network. This process is not trivial when data has a high level of correlation and do not contribute to training. In this particular case, the patterns are divided into two groups. The first group corresponds to the morphological patterns of the area, the eccentricity, the extent, and average correlation. The second group corresponds to average values of the R, G, B, H, S, V, L, a, b/b, for each candidate. There are 14 patterns, 4 morphological, and 10 corresponding to color.

In neural networks stages, each one has a corresponding number of neurons and number of layers obtained through a trial and error tests. On the other hand, a testing process is computed based on a testing dataset due to validate the training process. Furthermore, the results are based on the average of 4 cross-validations of data to reduce the variability of results.
In the first decision stage, the back-propagation algorithm is programmed in MATLAB, using a neural network, with 14 neurons in the input layer, three hidden layers of 14 neurons each and one neuron in the output layer, with a sigmoidal activation function in each layer. Results show a percentage correct classification of 96.551724% and a percentage incorrect classification 3.448276%.

For the second stage of decision, a neural network with 14 neurons in the input layer, 14 in a hidden layer and one neuron in the output, with an activation function hyperbolic arc tangent is chosen. Network shows the best network performance, with a 12.93% classification error during training.

To estimate the performance, confusion matrix and cumulative scores are used. The confusion matrix is an array indicating how well the algorithm achieves classification. For the first neural network, gives 97.41% of recognition and adding the complement of the diagonal, error is 2.59%. This error indicates that the neural network classifies 2.59% of the data, or failing in only 3 occasions. The latter error is called false positive and it is a mistake that benefits the system. For the second neural network, the correct classification performance rises to 88.8%, and 11.2% classification error, which is subdivided into five error contributions (complements of the diagonal). Within the classification error contributions, the largest contributor is the false negative 2-1 with a 6.9% error and 8 incidents, representing a 61.6% classification error. This means stability and reliability.

Using cumulative score to estimate performance, the graphs indicate the absolute maximum error for a certain percentage of accumulated data. The cumulative score for the first network without correction on the output, for 90% of the data, there is an absolute error close to 0.22. With output correction, after rounding, for both networks decreases the classification error, improving the accumulated error.

5. Evaluations

To evaluate the proposed system, pictures are compared with empirical data obtained for the weight in grams, polar and equatorial diameter (longitudinal), with 0.01 millimeters of resolution. The projected area density, bulk density, and the surface are not calculated given the difficulty of implementation in the super-elliptical model. Empirical measurements were made during the month of January 2010, in Rapel, O'Higgins Region, Chile, for specific quarters referenced by Geographic Information System (GIS). The empirical data is analyzed to establish trends and to determine what variables influence to different types of densities of the olives: volumetric density, projected area and linear, for elliptical and super elliptical models. To calculate the function that better describes the weight of the olives, olives with the same weight are grouped, to see if there is a distribution that relates the diameter and weight of the olives. The analysis of the probability density function is applied to the study of the polar and equatorial diameters. Pictures from the captured images are selected by taking olives estimates of equatorial and polar diameters, eccentricity, volume, weight, and average color properties. One software limitation is the over and under exposure of the image captured by the camera. To eliminate the problem of exposure, a routine discards images with problems. The program is designed to work in batch mode, delivering a report summarizing each quarter statistical analysis, in an MS-Excel file. The program takes about 90 seconds per picture (5.0 megapixels) in a Laptop with AMD Athlon X2 Dual Core QL-66, 2.20 GHz, and 2.74 GB RAM, running under Windows XP.
Figure 9 shows the output image after the analysis. The image is converted to grayscale, remaining in color only the segments corresponding to the olives. The remaining gray olives do not meet the parameters of the neural network; in addition, the perimeter of the olives is shown with a red graph is plotted in which the super ellipses and finally yellow numbers represent the unique code from the image and the output.

Figure 10 shows a summary in Excel format of the processed pictures. One file tab for each image analyzed, including estimates of equatorial and polar diameters, eccentricity, volume, weight and average color properties. Finally adds a tab summarizing data from all tabs according to their central tendencies.

![Fig.11 Example of processed files](image1.png)

Figure 11 shows the image to analyze (a and c) and the analyzed image (b and d). Figures (a) and (b) show 20 olives with 11 occluded, the software only takes the top 7 that meet the specifications of the neural network. Figures (c) and (d) show that software analyzes only 3 of the 6 olives readable it is not classified as olive. One can clearly see the color difference between the figures (a) to (d), since the background color is constant. The color depends on the time of image capture or lighting conditions.

Figure 12 illustrates two cases where the software includes most of the olives in the analysis because it meets the morphological and colorimetric requirements. Cases of over and under estimation of the size of the olive of an image, to become irrelevant, because after analyzing is only taken central tendencies around the 50th percentile, which are immune to extreme data. In neural networks, different data are used: one for learning phase and other for test stage, a completely separate data set. The performance achieved by the first neural network, with output correction, is good, surpassing the 97% correct classification, and for the second case reaches 88.8%. Paradoxically, the classification error of the first network itself is good, discarding olives that do not meet the standards of their training (false-positive), suggesting that the final results would only be affected mainly by overlapping copies. In the morphological analysis for analyzing olive overlapping division and discarded copies exists the possibility of including copies mutilated may incur estimation errors of equatorial and polar diameters. The model used tends to underestimate the weight of the olives. With the data analyzed, is possible to determine the key variable the equatorial diameter, for calculating the olives weight that is robust for a population of olives and it is not affected when the specimens are transverse to the image. It is found that the cumulative absolute error was always low. The underestimation for the season analyzed, the maximum absolute error in the estimated cumulative weight was less than 3 grams for total data analyzed. Thus, the model is a good tool to be able to estimate the crop yield well in advance and improves the selling prices of the products.

![Fig. 12 Examples of processed files](image2.png)
6. Conclusions

A new method for olive fruits recognition was presented. The information regarding size and weight of olive fruits is used for estimating the best harvesting moment of the olive trees. The recognition is performed by analyzing the RGB images obtained from olive tree pictures. The decision includes two stages, the first focused on discerning whether or not the candidate corresponds to olive and the second one oriented to olives overlap. To meet these requirements neural networks are used. The proposed model allows not only to identify correctly the olives but also to measure millimeter caliber of each specimen.

The decision includes two stages, the first focused on discerning whether or not the candidate corresponds to olive and the second one oriented to olives overlap. Feedforward neural networks are used with backpropagation learning algorithm. The second stage, a network has fewer layers, with a greater number of neurons. A different data are used: one for learning phase and other for test stage.

The performance achieved by the first network is good with 97% correct classification. The second network reaches a performance of 88.8%. With a morphological analysis for analyzing overlapping division, it is concluded that the shape of the projected area of the olives has a super elliptical form.

The model used tends to underestimate the weight of the olives. A key variable for calculating the weight of the olives is the equatorial diameter and it is not severely affected when the olives are transversal to the image. The lowest estimate is less than 3 grams for total data analyzed. This mean the results of this paper are very helpful to provide information to estimate harvest in advance.

References