USING ARTIFICIAL NEURAL NETWORKS TO VEGETABLES SORTING

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Abstract: *A study on applicability of color classification using an artificial neural network in the vegetables-sorting field is presented. Using the well-known network generalization property we investigate the applicability of this approach to the segmentation of colored images represented by the RGB color system. Jointly with color analysis, we also use some shape analysis to generate a robust and real time system that was tested for tomatoes classification.*

INTRODUCTION

One of the areas where Romania – in the perspective of its integration into the European Union – can have important commercial contributions in the export of agricultural products such as vegetables, fruits etc.

In the context of a large number of exporting countries spread on extensive geographical areas, classifying vegetables and fruits is a must. This requires taking into account their maturing state, the transport distance and conditions.

Manual sorting becomes a time and money-consuming problem particularly for large companies on the agricultural product market. Under these circumstances, it is compulsory to implement process control. The device –in-question should be able to recognize the shape and the maturing state of the product. Thus, one can efficiently use the artificial neural networks which are an effective tool in system designing and exploitation.

This work refers to recognizing and sorting of the tomatoes using artificial neural networks.

Tomatoes are an important and widely used product and have a few suitable characteristics to develop such a program: a quasiregular shape and a maturing state denoted by their color which varies from green to red.

Using the well-known network generalization property we investigate the applicability of this approach to the segmentation of colored images represented by the RGB color system.

Tomatoes can be selected to be delivered according to their color variation from green to dark red as a function of the system common tint.

FUNDAMENTALS

Color can be defined as an "attribute of visual perception that can be described by color names such as white, gray, black, yellow, orange, brown, red, green, blue, purple, etc., or by combinations of such names" [4]. The color of a material is determined by the spectral makeup of light reflected from its surface. Color measurement standards have been set by an international entity called the

Commission Internationale del'Eclairge (CIE). The CIE selected three primary monochromatic (single-frequency) red, green, and blue to create a color coordinate system or "color space". The CIE color measurement method is based upon the idea that it is possible to match any arbitrary color by superimposing appropriate amounts of three primary colors. This idea is known as the trichromatic theory and is represented in equation 1:

$$(C) = A1(P1) + A2(P2) + A3(P3) \qquad (1)$$

where (C) is an arbitrary color, the values *A1*, *A2*, and *A*3 give the relative proportions of the primary colors (*P1*), (*P2*), and (*P3*).

Tristimulus values are defined as the number of each primary source value that can be combined to create an unknown color [5]. They can be obtained from the spectral curve of a color. Tristimulus values of color stimulus are represented by *X*, *Y*, *Z*, and represent the relative amounts of x, y, z curves needed to match arbitrary colors. Tristimulus values can be expressed as dimensionless ratios called chromaticity coordinates. Chromaticity is the evaluation of color quality, and is defined by its chromaticity coordinates or by its dominant wavelength and purity. Chromaticity coordinates *x*, *y*, *z* are derived from the Tristimulus values *X*, *Y*, *Z* using the following equation:

$$x = \frac{X}{(X + Y + Z)}$$
$$y = \frac{Y}{(X + Y + Z)} \qquad (2)$$
$$z = \frac{Z}{(X + Y + Z)}$$

Because the relationship $x + y + z = 1$, only two of the chromaticity coordinates are needed for a chromaticity specification. Chromaticity can be graphically represented by plotting the trichromatic coefficients, *x* and *y*. These two methods are dominant wavelength and purity. Purity is defined as "a measure of the proportions of the amounts of a spectral stimulus and a specified neutral stimulus that, when addatively mixed, provides a color match to a given stimulus in question" [4].

Luminance is used to indicate the intensity of reflected light and is synonymous with brightness. It is measured quantitatively in lumens per square foot. Luminance, dominant wavelength, and purity can be used to create color solid or color space.

Due to the limited understanding of the human visual system, many methods of describing or modeling of color exist. The graphical representation of the modeling approach is considered a color space. One such model is the RGB color model as seen in Figure 1.

This model uses three primary colors (red, green, and blue) to describe a color within a color range and is considered the simplest color model [6]. The

RGB model describes a color image as a set of three independent grayscale images having 256 gray levels.

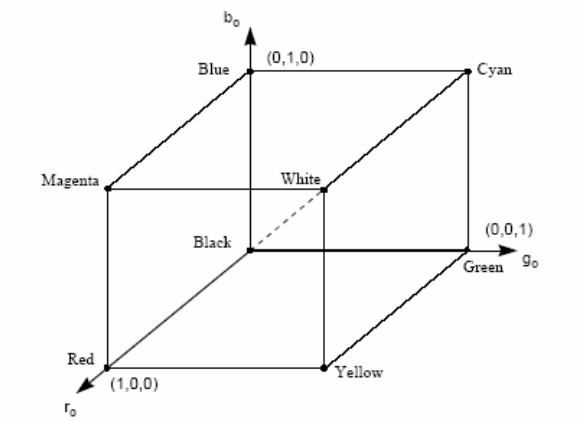

Fig. 1. - Graphical representation of the RGB colorspace [3].

TOMATOES SORTING AND CLASSIFICATION

Let us consider Figure 2. In this picture we can find tomatoes of three different classes sampled by a digital camera over a white background. In Figure 2a and 2b we can see a C3-class and a C1-class tomatoes, respectively, and in Figure 2c we can observe a typical rejected tomate. Transformed to the RGB color space, in these figures the spatial location of the pixels in the original images is unknown and each point is pictured using its own color, that is, the coordinates of pixels are also its colors.

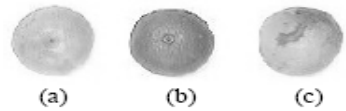

Fig. 2. Tomatoes images captured with camera: a) C3 class; b) C1 class; c) rejected.

Under a range of proper illumination conditions, the groups of colors (orange, green, brown, etc.) can be easily separated by edges. The problem of color classification can thus be seen as a problem of determination of optimum edges capable of a suitable partition of an RGB color space. These edges – capable of processing this separation – have some special characteristics: The edges are not necessarily regular; The edges of each class are not necessarily of same size; The edges must have some generalization level in such a way that pixels with small variations in color illuminations and saturation are evolved by the same edge.

In order to fulfill these requirements, we use an artificial neural network multilayer perceptrons, trained using the back-propagation algorithm [1]. The adopted network used is shown in Figure 3. In this network model, there are 3 input neurons (that receive the triple of color representation of each pixel in a

frame), one hidden layer with 10 neurons, and 7 output classes, corresponding to dark green, light green, yellow, light orange, dark red, blemished and white as a background class.

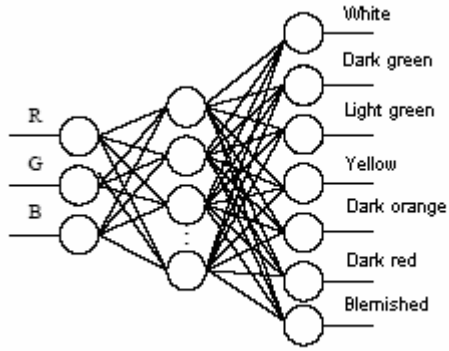

Fig. 3. - The artificial neural network trained for color recognition [6].

To train the network we extracted some pixel examples of the typical colors (dark green, light green, yellow, light orange, dark red and white) using some frames with a graphical interface. A frame corresponds to a digital image of tomatoes in white background. Once trained, the totality of pixels in a frame was presented to the network (pixel by pixel). The network returned all image pixels classifieds as one of the system typical colors. The network classification was stored (pixel by pixel) and we got an output image from the initial frame. Simple examples of the colors without brightness or saturation examples are enough to obtaining a satisfactory classification performance (about 97% with low illumination and color saturation variations) with low computational cost.

A few characteristics should be taken into account when sorting tomatoes, such as: size, color, and blemishes. Five different tomatoes classes are defined: a) C1, corresponding to dark green; b) C2 to light green; c) C3 to yellow; d) C4 to dark orange; e) C5 to dark red. These tomatoes classes are shown in Figure 4. Besides that, it is necessary to identify if the presence or absence of blemishes which is a reason for classifying as a rejected vegetable. Two accepted tomatoes of different classes and a rejected one (i.e., a blemished tomate) are shown in Figure 2.

(a) (b) (c) (d) (e)

Fig. 4. Tomatoes class patterns: a) C1; b) C2; c) C3; d) C4; e) C5.

In order to adequately model orange classes, some typical tomatoes (classified by humans) of each class were presented to the network (pixel by pixel). Observing its classified images we obtained the percentage of each system color present in each tomatoes class. Typical color vectors for all 5 classes (C1 to C5) are shown in table 1. So, the process of tomatoes classification can be seen as a problem of vector approximation. The exception to this rule is the rejected tomate: a tomate that presents a minimum level of blemished pixels was considered a rejected tomate.

Table 1.

Color	C1(%)	C2(%)	C3(%)	C4(%)	C5(%)
Dark green	80.6	43.6	0.4	0.1	3.1
Light green	13.2	9.8	0	0	0
Yellow	5.2	13.1	61	44.7	0
Dark orange	0	32.2	37.5	54.6	39.7
Dark red	0	0	0.2	0.4	54.3

RESULTS AND DISCUSSIONS

We developed a graphical interface in Matlab 7.0 for on-line viewing the images captured from a camera. Then, we developed a multilayer perceptrons class. For each new frame, the system looks for a colored region (vegetable) using the well-known region-growing algorithm [2]. Once located the vegetable, the system is able to classify the pixels of the region and to analyze its color composition. The colors vectors found were compared with the five previously stored patterns and the tomatoes was classified as belonging to the class that minimizes the distance from its color vector. After classification process, a visual indicator of the tomatoes class is added to the vegetables pixels in the graphical interface as shown in Figure 5. The rectangle color represents the chosen tomatoes class.

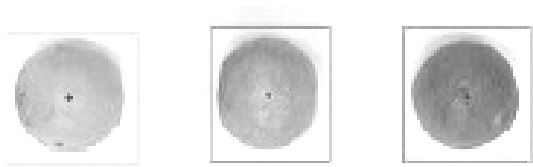

Fig. 5. A tipical screen with classified tomatoes.

Testing the robustness of this approach, 10 tomatoes of each class classified by a human were presented to the system. The classification errors for each tomatoes class are <20%. The average percentage of correct classification is under 94%.

CONCLUSIONS

In this study an approach for vegetable sorting and her implementation are presented. The percentage of color classes depicted in tomatoes images was using an artificial neural network multilayer perceptrons with the error backpropagation algorithm. The obtained vector of colors exhibited in a frame was compared to typical color vectors (defined by humans) of each tomatoes class.

A robust classification even under tomate color saturation variations, brightness, and non-homogeneous ambient illumination conditions is provided by use of an artificial neural network as a color classificator. The approach has proved to be robust with respect to color variations and consequently highly applicable to the proposed field. It also can easily be applied to sorting systems of other vegetables or fruits. However, the computational cost is high.

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