SORTING TOMATOES FOR INDUSTRIAL PROCESSING THROUGH OF COMPUTER VISION SYSTEM BASED ON NEURAL NETWORKS

Claudio Denis, cddenis@uol.com.br
Wânderson de Oliveira Assis, wanderson.assis@maua.br
Alessandra Dutra Coelho, alessandra.coelho@maua.br
IMT – Instituto Mauá de Tecnologia, Praça Mauá, 1 - 09580-900 - São Caetano do Sul - SP - Brasil

Abstract. *This paper presents a method of sorting tomatoes based on image processing. The approach uses a webcam camera for simultaneously classify the tomatoes based on shape and color. At shape classification, the approach uses an algorithm of image processing developed in object oriented language and based on Sobel's filter. At color classification, the approach applies a methodology of color treatment using a multilayer perceptron neural network software. The approach looks for a robust classification with respect to the variation of illumination and color brightness and tolerant to errors in the sampling process. The application is intended to automation of tomatoes where these fruits are used at production of sauce in industrial systems.*

Keywords*: image processing, neural networks, computational vision, Sobel's filter*

1. INTRODUCTION

Even after automation of many industrial processes, the inspection of tomatoes is still performed by humans with better quality than by artificial means. Most of the automatic approaches to this task are concentrated on the analysis of any type of digital image of the spectrum visible or not visible, such as X-rays, to assess such fruits. The selection of tomatoes is usually performed by humans taking as basis standardizations carried out by specialized institutions. The United States agriculture department presented the Standard for Tomatoes intended to industrial processing: the General Standard 51.3310 (Anon, 1993). In the specific case of tomatoes in Brazil, one of the few references is the Center for Quality in Horticulture (CEAGESP, 2006), which became standard Brazilian and proposes the classification of tomatoes based on patterns of color and quality.

Some studies have been proposed using techniques for processing digital images for analysis of the shape and size of fruit and for the detection of defects (Desmukh, 2005) (Usó *et al.*, 2006). In recognition of pattern of colors, in the field of agriculture, some approaches use statistical methods, artificial neural networks (Louro, 2006) (Simões and Costa, 2003) and analysis of characteristics (Kondo *et al.*, 2000). Although many studies have been proposed in this direction, particularly the classification of fruit based on color parameter still remains as an open problem.

This paper proposes a methodology for classification of tomatoes for industrial processing based on visual information, with emphasis on the treatment of the pattern of color using neural networks, and size and format selection using algorithm of image processing based on Sobel's filter (Denis, C, 2009).

2. TOMATOES' SELECTION

Sort means separating the product by variety, size, color and quality so that the set of fruit resulting presents uniformity. The tomato is categorized by groups and classes. The classification by group is used to characterize the groups of cultivars I, II, III, IV and V as Fig. 1. The classification by classes is defined by the equatorial diameter of the fruit (CEAGESP, 2006). Thus, it is classified into eight categories: 0 (less than 40mm diameter), 40 (diameter greater than or equal to 40 to 50mm); 50 (diameter greater than or equal to 50 to 60mm), 60 (diameter greater than or equal to 60 to 70mm); 70 (diameter greater than or equal to 70 to 80mm), 90 (diameter greater than or equal to 90 to 100mm), 100 (diameter greater than 100mm).

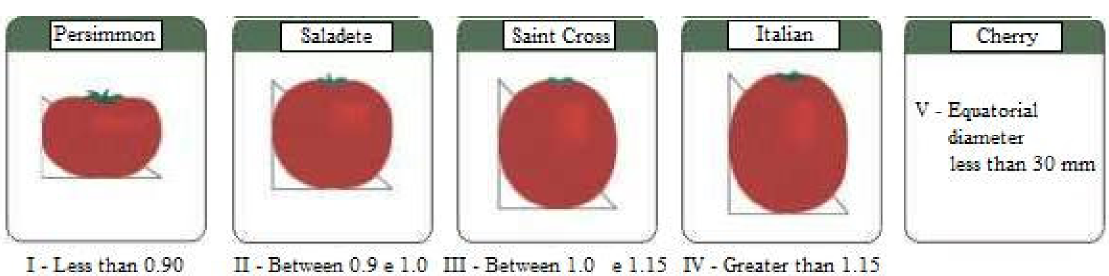

Figure 1. Classification of tomatoes by group – format of fruit is defined by length divided by the equatorial diameter, except for cherry tomatoes

Regarding the classification of the parameter fruit color, the pattern of Brazilian according to the classification of tomatoes (CEAGESP, 2006), proposes the following categories of colors: Red, Pink Color, Orange and Yellow, as illustrated in Fig. 2. There are two types of red tomatoes being the first one used for salads and cooking and another for industrial processing to obtain products such as sauces, tomato pulp, ketchup, etc. The ripening of tomatoes determines the change of color of their skin and features three subgroups: I - Painted; II - Colorful; III - Ripe, as illustrated in Fig. 3. This classification is typically used for classification of tomatoes for industrial processing.

Within this context, this work presents a methodology for classification of tomatoes for industrial processing based on visual information, with emphasis on the treatment of the pattern of color and format (Fig. 1).

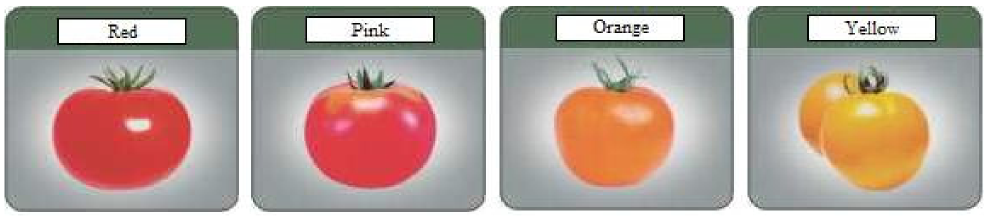

Figure 2. Classification of tomatoes by color

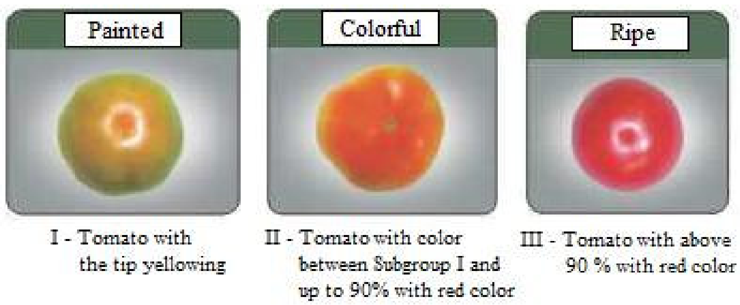

Figure 3. Classification of industrial processing tomatoes

3. SELECTION OF COLORS AND FILTERING

The international standard in the field of colorimetry is the ICE - International Commission on Illumination (Commission Internationale de l'Eclairage). Most of their standardizations were established in the decade of 30 and remain until today, such as RGB and XYZ. However, some other standards were established worldwide for working with color, even without the standardizations of CIE, even adopting other forms of representation non-trichromatic.

Since the human visual system has cells capable of detecting a wavelength of three different sizes: red, green and blue, the bands high, medium and low end of spectrum, respectively, are the immediate use of a wavelength on tracks similar to the composition of triple representation. Often, the difficulty to specify or select elements by color using RGB standard is the variation of measured parameters when occurs variation on tone of color or luminance.

3.1. Selection of colors

The idea of selection of colors comes from human visual system that consists to grouping of elements based on visual characteristics such as proximity, similarity and continuity. In computational vision systems this process is called images separation of segments, that which means the extraction of colors or characteristics of segments on images allow associates them with elements in the scene. In that sense, we try to divide the digital image into separated regions, in order that each pixel can only belongs to one of the regions. One of the algorithms used at this process is the growth of regions by analyzing the vicinity. It is a process by which pixels with similar characteristics are aggregated into larger regions (Gonzales and Woods, 2002). It is proposed that if every pixel near to the region presents a difference less than a limit then it will be aggregated to this region. Algorithms based on discontinuities analysis and grouping regions generally use comparison of levels of luminous intensity of the pixels of image imposing thresholds. The method of imposing thresholds can be considered a method of classification, since sub-divide the space of entry into discrete regions that can be interpreted as classes. In order to get better ratings, more elaborate tools can be used, as for example artificial intelligence tools and concepts as image filtering. A natural approach and with great ability to generalization is that of artificial neural networks (ANNs). Another important concept related to image processing, that can be used in order to define the classification based on size of elements is the Sobel's filter.

3.2. Sobel's Filter

The Sobel's filter is an operation used in image processing, especially in applied algorithms to detect contours (Kimmel *et al.*, 2005). In technical terms, the filter is an operator that calculates finite differences, giving an approximation of the gradient of color intensity on the pixels from image. The Sobel's filter calculates the gradient of color intensity of image at each point, giving the direction of changing, clear-dark, and the amount of variation in that direction. So, get itself a sense of how the brightness varies in each section, more smooth or abrupt. With this is possible to estimate the presence of a clear-dark transition and its direction. The intense variations on clear-dark transitions correspond to well-defined on borders between objects that can be used to detect contours.

4. ARTIFICIAL NEURAL NETWORKS

The neuron can be understood as a device that has many inputs and only one output. In that sense, Rummelhart *et al.* (1986) proposed a nonlinear model for biological neuron, illustrated at Fig. 4, which is widely accepted by the scientific community.

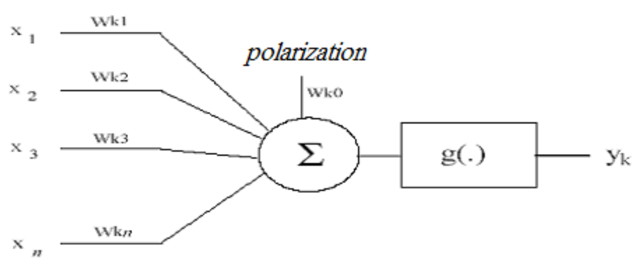

Figure 4. Non-linear model of a neuron

Where: X is the input vector of neuron k; x_i is the input into the synapse i; Y_k is the answer (or output) of neuron k; w_{ki} is the synaptic weight of input from neuron k; w_{k0} is the synaptic weight of input polarization from neuron k; $g\ (.)$ is the function of the neuron activation. This consists basically a function of perceptron with semilinear activation (Haykin, 1998). The perceptron models a neuron, processing a weighted sum of their inputs and uses the results at a layer of processing thresholds (g (.)) (Fig.4). In the case of perceptrons, this layer consists of a step function, mapping the exits at binary 0 or 1, naturally a highly non-linear function. The perceptron was developed by Rosenblatt in 1962 as explained in (Haykin, 1998). Years later were developed a principle of learning for networks with semi-linear function of activation which was called backpropagation error neural network which provided the architecture and training of Multilayer perceptron (MLP) (Rummelhart *et al.*, 1986). The MLP can be understood as a collection of neurons k arranged in layers, usually with an input layer, the last output layer and others hidden layers.

5. TOMATOES CLASSIFICATION SYSTEM

The system of selection of tomatoes for industrial processing consists of a camera-type web-cam which is responsible for capturing the image and transmits the scanned image to the computer. A program was developed in object oriented language specifically to capture this image and create an interface for the user as illustrated in Fig. 5. When clicking a button, the program analyzes the captured image and performs the filtering using Sobel's filter. At the image filtered an algorithm performs the contour detection and counts the number of pixels on horizontal and vertical lines, respectively length and equatorial diameter. Using these values the computer defines the classification of tomatoes by format as illustrated at Fig. 1.

Figure 6 shows an image of tomato after and before the filtering. At the example the algorithm obtains length of approximately 5.3 cm (200 pixels) and equatorial diameter of approximately 5.8 cm (222 pixels). The group of tomato is defined by length divided by the equatorial diameter resulting in 0.91: Saladete tomato. Using the values obtained after filtering is possible to reduce the image. In the next step, at the image cropped, the average values R, G and B were obtained and sent to a classifier formed by one artificial neural network. The neural network used (Fig. 7) is the MLP-Multilayer Perceptron developed in Visual Basic, but trained in MATLAB® software that has three entries (R, G and B), a hidden layer with 10 neurons and three outputs (Pt (Painted), Cl (Colorful), Rp (Ripe)) showing the classification of tomatoes as illustrated at Fig. 3.

At the Fig. 7, *nj (i)* indicates the output of neuron *(i)* of layer *(j)* respectively for the four neurons of hidden layer *(j=1, i = 1, 2, 3, 4)* and *nk (i)* indicates the output of neuron *(k)* of layer *(j)* respectively for the three output neurons *(j=2, k = 1, 2, 3)* before the activation function. The variables *nbj (i)* and *nbj (k)* are the outputs of these neurons (*i* and *k*) in layers *(j)* after the sigmoidal activation function; *E(m)* are the inputs of the network *(m = 1 , 2, 3)*; *S(k)* are the outputs of the network *(k = 1 , 2, 3)*; the terms *b1 (i)* and *b2 (k)* indicates the bias of neurons and the parameters *IW1(i,m)* and *IW2 (k, i)* indicate the synaptic weights for the neurons *(i)* and *(k)* of layers *1* and *2* respectively.

Tests were performed using others different configurations and more neurons in hidden layer, presenting small changes in the results obtained.

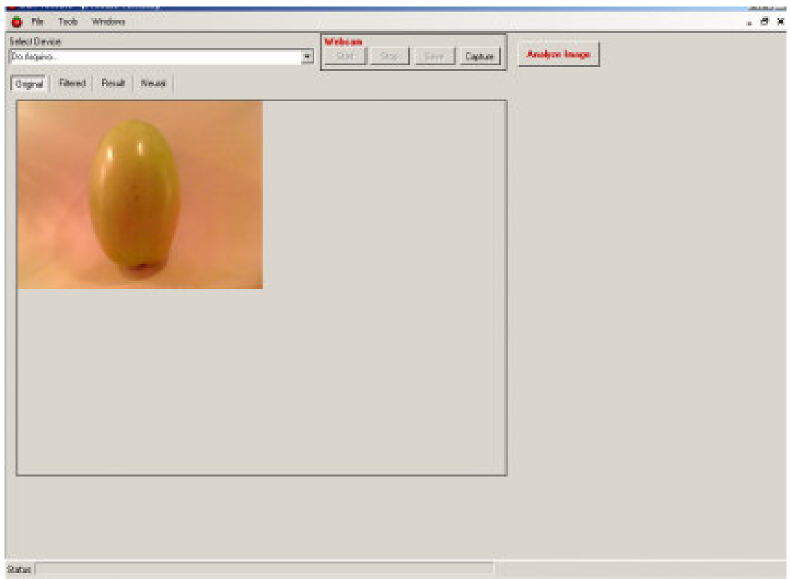

Figure 5. Programming interface developed in Visual Basic®

Figure 6. Image of tomato after and before the filtering

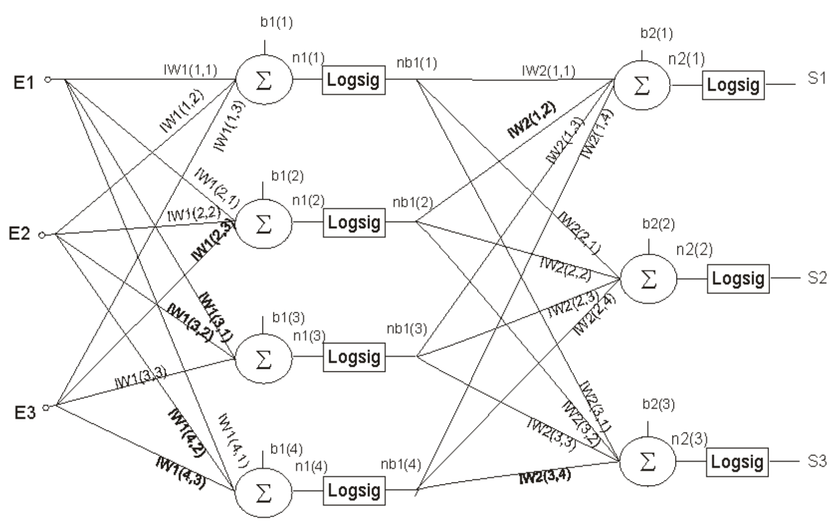

Figure 7. Image of tomato after and before the filtering

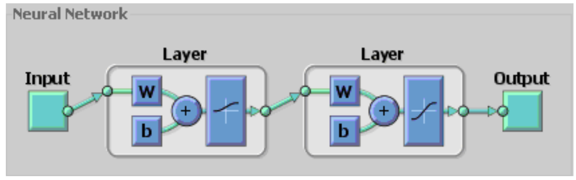

Figure 8. The neural network system for selecting tomatoes

After several tests with defined activation functions as for example hyperbolic, tangent and sigmoid, the sigmoid functions were chosen because presented better results.

The use of neural network is necessary because of the changes in brightness in the environment. The recognition of the tomato by the neural network is independent of the variation in brightness. In an industrial environment, the luminosity is typically between 500 to 1000lux, range used in this work.

The network was trained using the RGB data of 180 images of tomatoes, including 30 images of Painted tomatoes at 500 lux, 30 images of Painted tomatoes at 1000 lux, 30 images of Colorful tomatoes at 500 lux, 30 images of Colorful tomatoes at 1000 lux, 30 images of Ripe tomatoes at 500 lux and 30 images of Ripe tomatoes at 1000 lux. At training the network built in MATLAB® (Fig. 8) were used the following setup parameters: steps = 1000, mu = 0.001; mu-dec = 0.1, mu-inc = 10; mu-max = 1000000000; show = 25, time = infinity. In the training the network showed excellent convergence with quadratic error of 0.0622581 after 10,000 epochs, so with an error tending to zero. The training generated the graph illustrated at Figure 9 that shows the response of the network performance, where the error MSE (mean square error) decreases to about the 20th epoch when the training was stopped for having reached a stop early (early stopping) avoiding the over training.

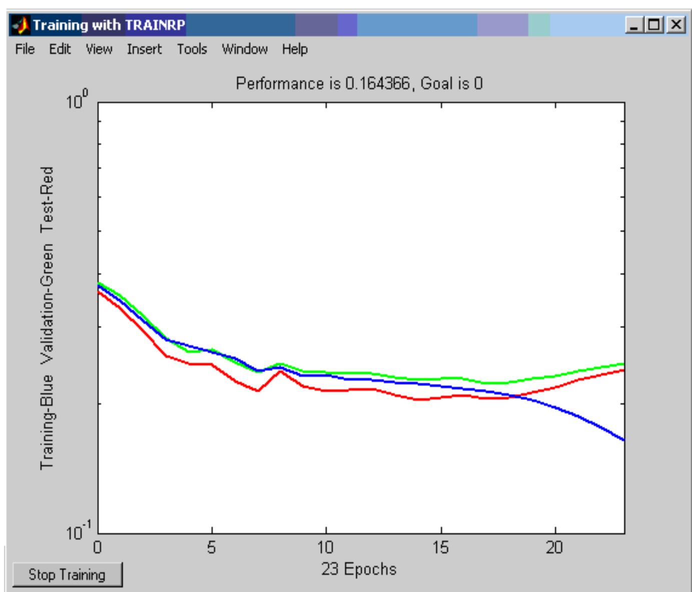

Figure 9. Performance of the network after training

The results after training with the network are obtained with the vector weights neural (synaptic weights) and bias as shown below, which were used in the program developed in Visual Basic® to classify tomatoes.

IW1(i,m)=[-96.6786 -121.8544 253.5232; 152.77 -639.1494 598.7545;-155.6476 -97.7333 193.0715; -67.0508 -131.0674 183.0207];

IW2(k,i)=[2353.4422 -224.842 158.9038 -2503.6931; -5.0008 178.673 339.0306 8.1298; -7212.3037 41.6834 -558.0864 7206.8051];

b1(i)=[61.8043;-1.9784;71.2827;50.5857]

b2(k)=[216.7093;-181.802;-35.706]

To evaluate the performance of the network after the training were used other 30 images of tomatoes captured at 1000 lux, with 10 images of each specimen. These images are different than those used in training of the network. The results are shown graphically in Fig. 10-12.

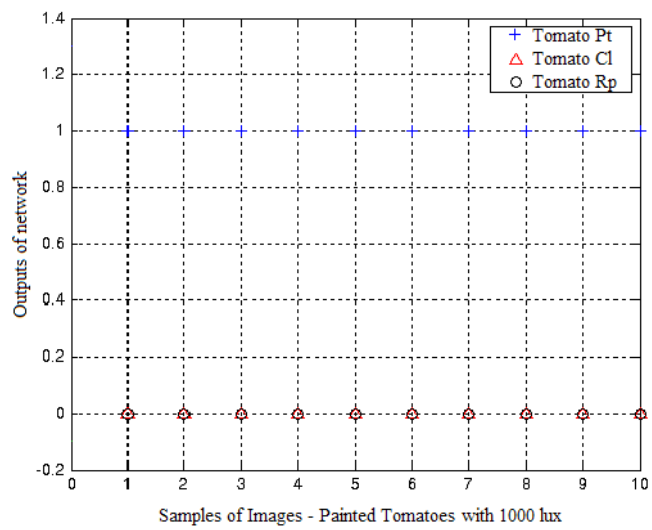

Figure 10. Results obtained by neural network for 10 images of Painted Tomatoes – 1000 lux

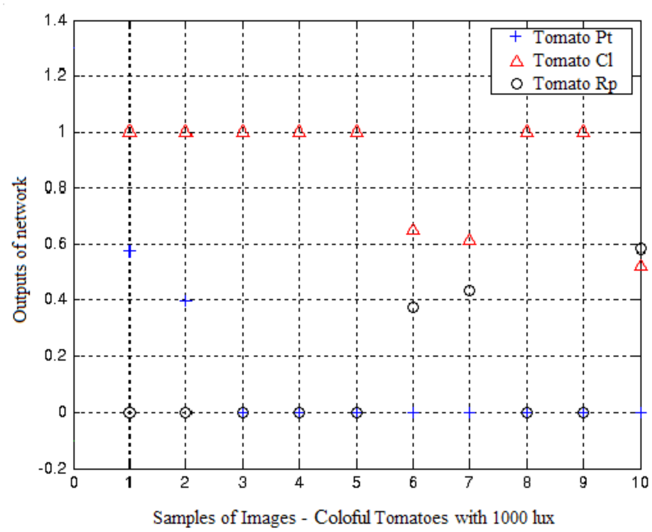

Figure 11. Results obtained by neural network for 10 images of Colorful Tomatoes – 1000 lux

The results show that the rate of correct responses was 100% for Painted tomatoes, 90% for Colorful tomatoes and only 60% for Ripe tomatoes. It was observed that the network has difficulty to identify the Ripes tomatoes especially when the color of the pixels of the tomato is close to 90% of the final color. At these cases, as shown at Figure 3, although the tomatoes classified with the group III (Ripe) it has a color very close to Group II (Colorful). Note that this difficulty of identifying the correct selection occurs even in the classification by humans, and therefore can be said that most errors made in the automatic classification may also occur if the classification was done manually.

For the image processing algorithm to determine the size of the tomatoes using Sobel's filter, the approach has good accuracy in the classification obtained with relative efficiency rating in the categories I (Persimmon Tomato), II (Saladete Tomato), III (Saint Cross Tomato), IV (Italian Tomato) and V (Cherry Tomato). Taking up two copies of each category, the index of success was 70%. The errors in the classification of tomatoes by size occurred mainly due to the presence of shadow in the image captured by the system. This can be seen, for example, at the results shown in Figure 13, which illustrates the images of a tomato Saint Cross. After the filtering the tomato was classified as Saladete due to incorrect measurement of the diameter Equatorial obtained from the shadow at the base of the tomato.

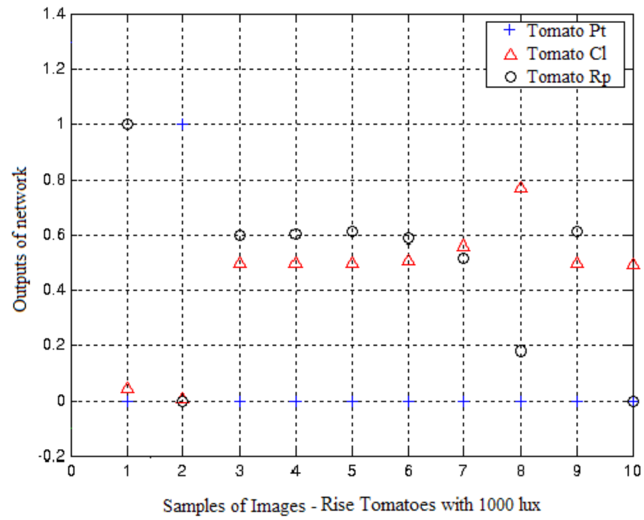

Figure 12. Results obtained by neural network for 10 images of Ripe Tomatoes – 1000 lux

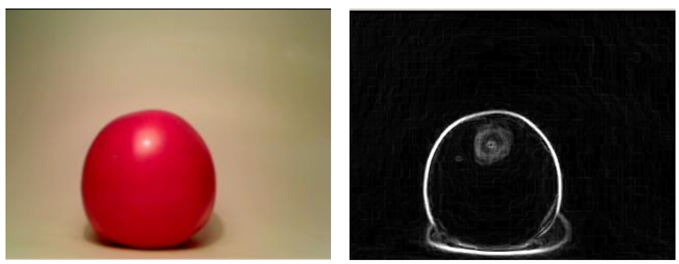

Figure 13. Example of images of Santa Cruz tomato before and after Sobel's filter

We conclude that in analyzing the results, the developed system provides an interesting solution for the automation of the tomatoes classification by color and format getting results with relative accuracy.

6. FINAL COMMENTS

An approach for tomatoes classification based on image processing and using techniques as Sobel's filter and artificial neural networks, was proposed in this paper. The solution concerns the obtaining of a classification by color and shape as close to human as possible. The solution uses a system formed by a webcam camera that transmits images to the computer and a program developed specifically to make the processing of the image.

The algorithm analyzes the captured image and performs the filtering using Sobel's filter. At the image filtered the program performs the detection of contour and counts the number of pixels on horizontal and vertical lines, respectively length and equatorial diameter. Using these values the computer can define the classification of tomatoes based on their format and obtain the groups of cultivars I (Persimmon Tomato), II (Saladete Tomato), III (Saint Cross Tomato), IV (Italian Tomato) and V (Cherry Tomato).

The neural network used is an MLP-Multilayer Perceptron which has three entries – R, G and B and three outputs: Pt (Painted), Cl (Colorful), Rp (Ripe) showing the selection of tomatoes for industrial processing based on their color. Applying this classification system in an environment with variations in brightness it can be observed that the neural network presents a good performance and excellent rate of convergence. The system takes less than 2s to perform the complete analysis of a tomato. Thinking an industrial application, the classification could be made with tomatoes queued through a wake. Thus the system could select around 30 tomatoes per minute. But, for this case, would be necessary to apply other techniques of analysis and segmentation of images that were not used in this system. The results of the tests indicated a good index of accuracy. In addition, the approach proposed uses low-cost components in the development of proposal. Improvements developed in the solution are very welcome may occur through other works of continuity, where the main aspects that may be assessed are: integration between software and hardware to enable the processes of image capture, classification of tomatoes and control of devices fully automated; improve the stability of the filter of images, to ensure better accuracy in the selection of tomatoes so, even when there is presence of shadows in the image; evaluate other types and configurations of networks to improve the efficiency of the system; improve the system for allows not only select the tomatoes by color and size, but also detect defects in the fruit and discard them automatically; evaluate the use of the methodology proposed in other applications where the concepts of image processing can be advantageous.

7. REFERENCES

Anon, 1993. “United States Standards for Grade Evaluation of Tomatoes for Processing” In Code of Federal Regulations, Title 7, Sections 51.3310-51.3327. The Office of the Federal Register, National Archives and Records, Washington, DC, USA.

CEAGESP – Center for Quality in Horticulture, 2006. “Classification of Tomato” ABH, São Paulo, SP, Brazil.

Denis, C., 2009, “Methodology for Selection of Tomatoes for Industrial Processing Through the Computer Vision and Neural Networks”, Master`s thesis, IMT – Instituto Mauá de Tecnologia, January.

Desmukh, K.S., Shindle, G.N., 2005, “An Adaptive Color Image Segmentation” ELCVIA – Electronic Letters on Computer Vision and Image Analysis, Computer Vision Center of Universidade Autonoma de Barcelona, Barcelona, Spain.

Gonzales, R.C., Woods, R.E., 2002, “Digital Image Processing”, 2nd ed., Prentice Hall, Upper Saddle River, NJ, USA.

Haykin, S., 1998, “Neural Networks: A Comprehensive Foundation”, 2nd edition, Prentice-Hall, 842 p.

Kimmel, R., Shaked, D., Elad, M., 2005, “Irwin Sobel: Space-dependent Color Gamut Mapping: A Variational Approach”, IEEE Transactions on Image Processing, Vol. 14(6), p. 796-803.

Kondo, N., Ahmad, U., Monta, M., Murase, H., 2000, “Machine Vision Based Quality Evaluation of Iokan Orange Fruit Using Neural Networks”, Elsevier – Computers and Electronics in Agriculture, Vol. 29.

Louro, A.H.F., Mendonça, M.M., Gonzaga, A., 2006,“Classification of Tomatoes Using Artificial Neural Networks”, Proceedings of WVC'2006 - II Workshop of Computational Vision, São Carlos, SP, Brazil, pp.239-244.

Rummelhart, D.E., Hinton, G.E., Williams, R.J., 1986, “Learning Internal Representations by Error Propagation. Parallel Distributed Processing”, MIT Press, Cambridge, MA.

Simões, A.S., Costa, A.H.R., 2003, “Classification of Oranges Based on the Visual Patterns”, Proceedings of the VI SBAI – Brazilian Symposium on Intelligent Automation, Bauru, SP - Brazil.

Usó, M.A., Pla, F., Sevilha, S.G., 2005, “Multispectral image segmentation by energy minimization for fruit quality estimation”, 30 Mar. 2009, <http://www.vision.uji.es>.

8. RESPONSIBILITY NOTICE

The authors are the only responsible for the printed material included in this paper.