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Determining the ripeness of fruit juices based on image processing technology and neural network classification

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Abstract

In this paper, the ripeness of tomato is divided into three levels as reached, ripe and overripe by image processing and neural network classification. The physical properties including color and size of tomato and some of its chemical properties to develop a rating system were used as auto reviews. The automatic, three-stage maturity stage of the proceedings, the proceedings were also considered to handle. Finally, with the help of neural networks designed and trained, the classification was done for the fruits, chemical, mechanical and physical methods were checked and the most effective features for classification fruit were selected. The results showed that the neural network classification methods when used and trained, can be successful in 92%. The best structure of the neural network has been found by the search algorithm PSO.

Keywords: Tomato fruit, Image processing, Neural network, PSO alghorithm

Introduction

The computer vision algorithms have many applications in agriculture and other sciences and to improve their performance, many studies have been done in industrial systems. Tomato is a commercial product in Asian countries(FAOSTAT, 2012). Tomato delicate nature, context-sensitive, poor maintenance applications and shortage of storage facilities has caused that transport and control techniques to be very important for the rapid development of new and legacy systems(Garrido-Novell et al., 2012; Leemans et al., 2002, 1999). Today, the different grading system of agricultural products, machine vision has become a real alternative to visual inspection, compatible, rapid and is affordable(Helrich, 1990). Features color, a feature for assessing the quality of agricultural products, more than any other factor and color can be measured using visual and machine vision(Hosseinpour et al., 2012; Kang et al., 2008). Products such as apples and tomatoes, are often color changes significantly during the ripening stage. The most important strength plays a role in the tomato harvest, color parameter is usually used as an indicator of non-destructive harvesting(Lana et al., 2006a). In a computer-based machine vision to detect and remove unwanted material and pomegranate sort by different colors(Leemans et al., 1999). The automated system, grading strawberries based on image processing technique is designed to be functional system, grading strawberries into three characteristic is the shape and color and size. An image processing system is designed to detect the green fruit unripe citrus trees, the system is designed in such a way that the fruit unripe (green) in the early stages detects and corrects products. A method based on artificial neural network to accelerate and automate and predict the index to achieve the objective of producing more olives provided.

In this paper, based on the principles of machine vision has been developed, the physical properties including color and size of tomato and some of its chemical properties to develop a rating system and used auto reviews. The automatic, three-stage maturity stage of the proceedings, the proceedings are considered too handle. Finally, with the help of neural networks designed and trained, the classification is done fruits. The structure of the neural networks to help search algorithm PSO has been found.

Tomato fruit Stock appropriate features for classification

Physical Features

In Table 1. The mean values of physical and mechanical characteristics at different levels of ripeness tomato are displayed:

Table 1: The mean values of physical characteristics measured in the laboratory

Characteristic	Maturity stage		
	Unripe	Ripe	Overripe
Length (mm)	60.65	60.53	60.31
Width (mm)	64.62	64.01	52.76
Thickness (mm)	40.47	39.73	40.36
Geometric mean diameter (mm)	53.73	53.22	51.88
Equivalent diameter (mm)	46.3	45.78	44.5
Arithmetic diameter (mm)	46.58	46.09	44.81
Sphericity (%)	76.22	75.55	75.12
Surface area (mm2)	8776.49	8588.28	8132.83
Aspect ratio	0.95	0.958	0.96
Volume (cm3)	102.42	102.04	95.94

These features offered in the relations and equations (Li et al, 2011) and based on real examples and calculations are provided in the lab. These results indicate that no significant correlation between fruit ripening and aspect ratio and also there during the tomatoes. In addition, some minor differences for features width , thickness and reached the level of being there. In addition to geometric, equivalent, arithmetic diameters and thus the area and volume of overripe fruit, less than the other two. In general, according to Table 1 and physical specifications provided, tomatoes physical characteristics cannot be reached for classification as useful parameters being considered.

Chemical and mechanical properties

The mechanical properties of stiffness and elasticity of fruit juices and chemical properties include total soluble solids (TSS), acidity (TA) and the PH of the fruit. The properties of the samples were collected from each group were measured by the average values of the features and indicators to help measure the appropriate measurement tools in the laboratory and in Table 2.

Table 2: The mean values of physical characteristics measured in the laboratory

Characteristic	Maturity stage		
	Unripe	Ripe	Overripe
E modulus (GPs)	0.044	0.032	0.019
Firmness (N)	0.857	0.877	0.851
pH	5.21	5.16	5.31
Total soluble solid (TSS, ◦Brix)	15.21	17.54	19.42
Titratable acidity (%)	11.80	13.20	13.60
TSS/TA ratio	1.49	1.50	1.60

As can be seen in Table 2, whatever the ripening of fruit to rise, now elasticity and firmness in the tomato fruit is significantly reduced. Here were no significant differences in terms of PH at different levels of ripeness of the tomato fruit is found. The amount TSS also during fruit development, minor increase. So it can be concluded that during fruit growth, marked changes in the stiffness and elasticity of fruit, there will be little change when the chemical properties.

Color features

Table 3 provides information on the characteristics of the fruit color changes proposed. These values are based on the equations and formulas in (Lana et al., 2006a) and based on real examples calculated and presented in the laboratory.

Table 3: The mean values of physical characteristics measured in the laboratory

Characteristic	Maturity stage		
	Unripe	Ripe	Overripe
R	0.692	0.661	0.633
G	0.328	0.304	0.288
G. scale	0.22	0.198	0.181
L*	-52.25	-54.63	-71.86
a*	23.93	25.45	26.29
b*	61.41	55.65	50.29
Nr	0.0020	0.0020	0.0022
Ng	0.0008	0.00078	0.00079
Nb	0.0002	0.00026	0.00029
S	0.766	0.746	0.722

As can be seen in Table 3, between the three levels of ripeness of the fruit, there are major differences between G,R,S, gray scale, b * amounts. It should be noted that the difference in values between the ripe fruit and unripe fruit is almost equal to the difference in the process of being overripe. In fact, this type of dispute, and promising conditions for the classification of fruit provides a high level of success.

The proposed image processing operations

All processing is done in MATLAB software operation. The imaging chamber, four LED and two fluorescent lamps mounted. The bulbs are located in the upper part of the chamber. In addition, this system is a camera that will be connected to a computer via USB interface and image into the MATLAB software will be available. A special program that has been edited using MATLAB software, image sampling, pre-processing and image quality improvement functions such as apply filters and adjust the brightness will be performed on it. After the image was diagnosed fruit color features, these features with the characteristics of elasticity and firmness, the classification algorithm will be designed and reached a level that it will be detected.

Classification process

Here for the fruit of the class, the network was nervous. For the structure for optimum neural network and the number of layers and number of neurons in each layer of the optimized search algorithm PSO is used. Based on random particles in the search space with a neural network layer Tadad and certain neurons are formed and then the samples tomatoes images and error taught training and test errors are calculated and added together. Where the initial values for each training your network, each network is dependent on the random weight ten times ten times and been taught the value of error can be calculated for listed and, ultimately, the best training with the lowest error will be considered. The rest are made by the same 200 network as well as through training and the best mode for each. At each step of the algorithm PSO is the best network of selected network between the 200 and for comparison with the results of 50 repetitions is stored somewhere else.

Finally, after repeated 50 times the network obtained the best algorithm in this search process that consists of a total network of 10000 is reviewed, and considered for classification operations. It should be noted that all of this process of searching through the software MATLAB.

Results

Flowchart for simulation optimization algorithms PSO based on neural network, the number of particles in the search space 200, the number of repeat algorithm 50 and algorithm parameters PSO is equal to wmax=0.9, wmin=0.4, c1=c2=2 is intended. Review of operations performance optimization functions in the nervous system, internal layers tansig and the external layer purelin is intended. For each network, a maximum of 5 and a maximum of 50 hidden layer neurons in each layer optimization algorithm as specified limits. According to the characteristics selected for the classification in total 7 features(5 color features include S, gray scale, b * , G, R , two characteristics of elasticity and firmness) included, each network has 7 inputs and one output. The output value of the neural network for fruit not equal to 1, 2 and ripe fruit of overripe fruit is equal to 3 is considered. Finally, after the implementation of the optimization algorithm, the optimum network found in Figure 2 is obtained.

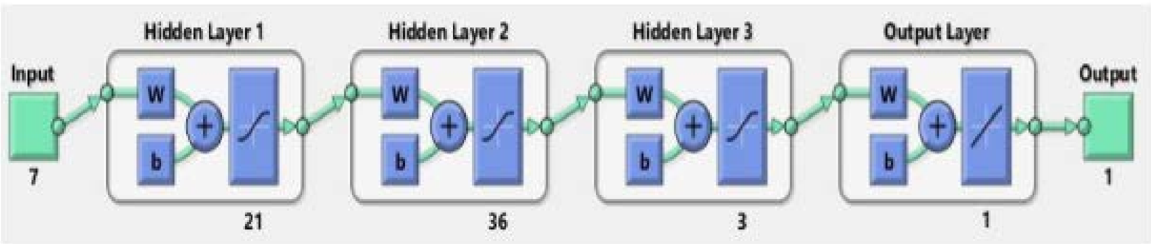

Figure 1: Neural network was optimized for the classification

Discussion and conclusion

In this paper, natural fruit juices to classify all the features of ripeness stages, including physical characteristics, mechanical, chemical and paint it on the basis of the calculation and measurement techniques presented in various references, was considered. The study of these properties, they selected the most effective and the operations classification neural network has been designed. The problem of finding the best structure for the neural network algorithm PSO to help optimize finder was resolved and the network classification is designed to test more than 90% of the class is successfully placed. The methods and algorithms presented in this paper is to explore a variety of other fruits or other developmental stages of tomato fruit cultivation, including the detection of pests and diseases be used.

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