Iran Agricultural Research, Vol. 32, No. 2, 2013
Printed in the Islamic Republic of Iran
Shiraz University

Design, Development and Evaluation of an Orange Sorter Based on Machine Vision and Artificial Neural Network Techniques

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Received 19 October 2013, Accepted 4 May 2013, Available Online 1 June 2014

ABSTRACT- The high production of orange fruit in Iran calls for quality sorting of this product as a requirement for entering global markets. This study was devoted to the development of an automatic fruit sorter based on size. The hardware consisted of two units. An image acquisition apparatus equipped with a camera, a robotic arm and controller circuits. The second unit consisted of a robotic actuator with required electronic circuits. For sorting purposes, an appropriate image processing technique was applied and two models of size thresholds were developed and incorporated in a number of image processing algorithms, which were, in turn, combined with Artificial Neural Network (ANN) techniques for classifying purposes. Multi Layer Perceptron models with various training functions and diverse numbers of neurons were also applied. Each algorithm was used to sort oranges into desired size groups (Small, Medium and Large). The sorter test rig was able to classify the product into three categories with considerably low errors. Although all twelve algorithms had acceptable results, those based on Red and Green segmentation were more satisfactory. For real time evaluation purposes, four algorithms, segmenting based on R color band, and two size threshold models were combined to form 8 comprehensive algorithms, which were used along with the ANN model at the evaluation stage. Results showed that algorithms based on Area, Perimeter and the ANN model, exhibited lower errors. Sorting records of each algorithm were compared to the relevant sorting data brought about by experts. Results show that sorting error can be as low as 1.1%. Although the average capacity of the single sorter was limited to 1 $t.h^{-1}$, the capacity can be markedly increased by adapting a bank of sorters in parallel mode. The study revealed that orange fruits can be sorted using the introduced techniques at high speed, high accuracy and low costs.

Keywords: Artificial Neural Network, Citrus sorter, Orange Size

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INTRODUCTION

Orange (*Citrus sinensis*) is one of the major fruit products in Iran. According to the FAO, Iran was among the top 10 orange-producing countries in 2007 (FAO, 2007). High production of orange fruit calls for quality sorting of this product for both domestic and global markets.

The use of intelligent machines in agriculture to raise the quality of the produce, to lower production costs and to reduce the manual labor is promising. Adoption of robotic technology is inevitable in modern agricultural systems and can increase the efficiency of post-harvest tasks such as sizing and sorting fruits.

Quality sorting of fruits requires visual inspection. Machine vision can perform this task automatically with lower production costs. Numerous investigations have been carried out in this field. Brosnan and Sun (5) used different computer vision systems for blemish and disease detection of horticultural products. Garcia-Ramos et al. (7) reviewed non-destructive sensors used for fruit firmness determination. Butz et al. (6) compared different technologies for internal qualification of fruits and vegetables.

In recent years, the use of Artificial Neural Networks (ANN) has been increased. The ANN models can be constructed by interconnecting several nonlinear computational elements, known as neurons or nodes, operating parallel to each other, and arranging in patterns similar to biological networks (18). Thai and Shewfelt (20), Bardot et al. (3), Wilkinson and Yuksel (22) used ANN for prediction. Lippmann (11) revealed that ANNs are suitable for modeling complex unstructured human judgment (2). Miller (13) employed Neural network and Bayesian models to grade citrus fruits according to their external quality. Leemans et al. (8) used a new method to grade the blobs by using the image segmentation.

Among the external quality of fruits, size is one of the most important parameters identified by consumers. Furthermore, size information is vital in packing houses. Size can be estimated by image processing techniques (4, 15, 19, 21) or neural network techniques.

New innovations tend to decrease processing times and costs of the task as well as increase its accuracy. For real time sorting, there are several methods of estimating the size of fruits using real-time machine vision technology (18). In common systems, fruits are placed on a cup conveyor belt while two cameras monitor the trajectories (1, 9, and 12). Aleixos et al. (1) state that using cup belts can bring about some errors which occasionally occur in three situations: (a) when a large fruit is in contact with a neighboring fruit, (b) when a fruit travels between two fruits that are correctly positioned on their cups, or (c) when two or more small fruits travel in the same cup. In all these cases, calculation of size from the apparent boundaries leads to an over-estimation of the fruit size (1). Moreover, because all the fruits are carried by cup belt in these sorters, information about the position of each fruit at a given time should be defined for the controller unit which actuates the sorter ejector accordingly. These sorters will therefore need accurate instruments such as non-friction encoders to determine the exact speed of the cup belt and a control computer to actuate the ejectors in a specific time as well as a vision computer to estimate the size of the fruits. Eventually, common sorters will have to include complicated arrangements for fruit guidance which can result in high costs and a number of errors. Furthermore, the efficiency of sorting by cup belt is severely affected by its shape and size as well as those of the fruits, which can lead to the misclassification of the fruits.

Considering the existing problems which increase fruit classification errors and also high initial costs of belt conveyors and expensive control systems, this paper describes the development and evaluation of a machine vision system which consists of new control and actuator electronic circuits. The new system is expected to sort the fruits without using complicated and costly equipment. The target system should be able to quantify size and to sort the fruits into size groups in a real-time mode. This study concentrates on the development of appropriate algorithms together with information on their application accuracies. The rig components including the robot elements along with other necessary hardware and software are also described.

MATERIALS AND METHODS

The designed and developed prototype fruit sorter consisted of an image acquisition and processing unit and a sorting unit (Fig. 1). The image acquisition and processing unit included an image acquisition platform with a black background; a webcam (Creative) installed on the top of the platform to acquire the desired image (600×800 pixel, RGB), connected to a computer (Pentium 4, Dual CPU, E 2160 at 1.80 GHz). The illumination system inside the platform consisted of six white LEDs* located on the top inner side of the platform. The LEDs were used to avoid flicker effects. To prevent shadows and to strengthen the light, the inner walls of the platform were painted white. Inside the platform, a robotic arm was accommodated to stop incoming fruits while the acquisition system captured images (Fig. 2). This arm is controlled by a step motor connected to a microcontroller (AVR, ATmega16) and finally to the serial port of the computer. Fig. 3 shows the main parts of the step motor running circuit; transformers, diode bridges and a transistor IC (ULN2803). An interface device (MAX232 IC) was also incorporated in the circuit to enable the connection between the microcontroller and computer through a serial port.

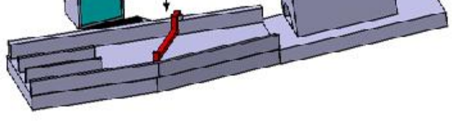

Fig. 1. Schematic view of the sorting test rig

* . Light Emitting Diode

Considering the importance of constant light intensity within the image acquisition platform, a light intensity controller circuit was designed and incorporated in the platform. This circuit included a photo-transistor, a V-F convertor (AD654 IC) and a microcontroller (Fig. 3). As the phototransistor senses the light, it emits voltage which is converted to frequency by a v-f circuit. The microcontroller counts the output frequency periodically. If the frequency is lower than a specific level (in this study 30000 Hz), an alarm LED will switch on as a sign for an immediate remedy.

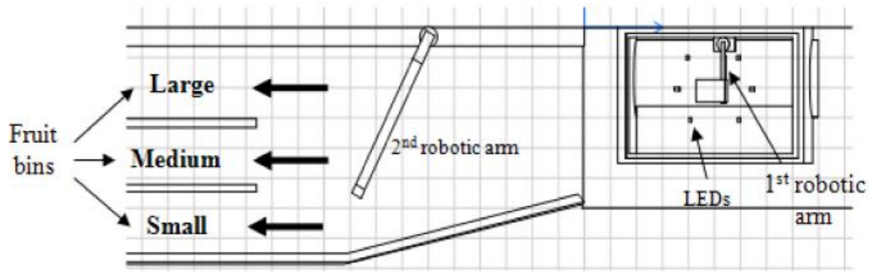

Fig. 2. Top view of the sorting rig

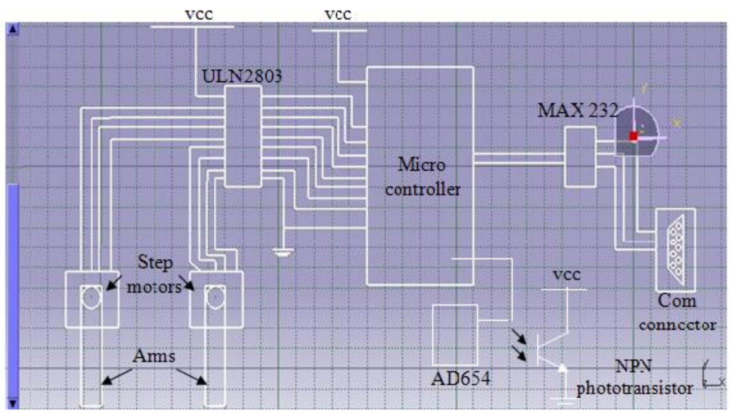

Fig. 3. Layout of the control circuit

The sorting hardware consists of another robotic arm and step motor connected to the microcontroller introduced earlier (Fig. 1).

A gentle but adjustable slope was considered to promote fruit removal from the sorting table to the fruit bins (Fig. 1).

A number of programs were developed in MATLAB7 for image processing purposes. These programs measured the pixel values of each incoming fruit picture. In addition, a number of artificial neural networks were developed and combined with the image processing algorithms for sorting purposes. A comprehensive program was developed for programming the microcontroller to control the robot arms using CodeVision AVR software of the "C" programming language.

Performance Tests

Evaluation tests were carried out in three subsequent stages as follows:
Preliminary stage

In this stage, a batch of orange fruits *(Novel variety)* was selected. For each fruit, three perpendicular axial dimensions were measured. The following equation was used to calculate the geometric mean diameter (GMD) of each fruit as a criterion of its actual size.(14).

$$GMD = \sqrt[3]{abc} \tag{1}$$

where a is the longest intercept, b is the longest intercept normal to a and c is the longest intercept normal to a and b (14). The color of the sample orange fruits ranged from green to orange.

The fruits were divided into two groups labeled as "off line" (80 fruits), and "evaluation" (45 fruits) groups.

Development of Image Processing Algorithms and Primary Evaluation

A number of image processing algorithms were developed to identify pixel values of each fruit and to determine its size. Four fruit parameters (Area, Perimeter, Max-diameter and Min-diameter) based on three color intensity bands (Red, Green and Blue) were considered as criterions for sorting. Each algorithm determined one parameter based on one color intensity band. Hence, a total of 12 algorithms were developed (for instance, algorithm #1 determined the area of the fruit based on the Red color intensity band and algorithm #2 determined the perimeter of the fruit based on the Red color band and so on). To evaluate each algorithm, the pixel information of each fruit given by the particular algorithm was compared to the relevant size information measured manually to test the strength of their relationships. Therefore, each fruit was placed into the image acquisition platform and the webcam was triggered to capture an image and send it to each of the 12 processing algorithms developed earlier in the MATLAB software. Each algorithm would then segment the object and calculate pixel values relevant to one of the mentioned parameters. Segmentation was used to transform RGB images to binary ones. Segmentation determined which regions of an image corresponded to the background and which represented the object itself. Fig. 4 illustrates the histogram of the Red color band of an orange randomly selected from the sample fruits. The left side of the Fig. represents the pixel values of the background and the right side shows the pixel values for the object itself. For the same fruit, histograms based on Green and Blue color bands were also prepared and threshold values for segmentation were concluded.

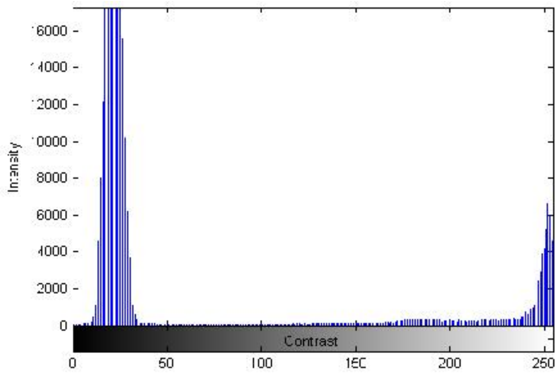

Fig. 4. Typical Histogram of red intensity color of an orange fruit

Once the RGB image was changed into a binary image, the mentioned parameters were calculated as follows:

Area:

After making the binary image, the number of "on" pixels represented the area of the fruit in pixels.

Perimeter:

The perimeter of the fruit is represented by the number of pixels on the border of the fruit picture in the binary image.

- Max diameter and Min diameter:

To determine max and min diameters, the coordinates of each pixel of the binary image are first calculated and considered as a data point. Then, a matrix of the two variables of each pixel (x, y) is formed where x is the length and y is the width of each pixel coordinate. Assuming N as the length of vector of each pixel, the following equations are employed to calculate the max diameter and min diameter values:

$$u_{xx} = \frac{\sum x^2}{N} + \frac{1}{12} \tag{2}$$

$$u_{yy} = \frac{\sum y^2}{N} + \frac{1}{12} \tag{3}$$

$$u_{xy} = \frac{\sum xy}{N} \tag{4}$$

$$\text{common} = \sqrt{(u_{xx} - u_{yy})^2 + 4u_{xy}} \tag{5}$$

$$MaxDiameter = 2\sqrt{2}\sqrt{u_{xx} + u_{yy} + common} \tag{6}$$

$$MinDiameter = 2\sqrt{2}\sqrt{u_{xx} + u_{yy} - common} \tag{7}$$

Furthermore, correlations between pixel values, as identified by each program with the corresponding actual size of the fruit (GMD), were established. Each test was carried out in five replications.

To allocate a single fruit into one of the three size groups; Small, Medium and Large; two thresholds ((TH1&TH2) or (TH3&TH4)) had to be identified and expressed in terms of pixels. To identify threshold values, a subroutine program was developed. Although the two thresholds were defined based on Iranian consumer standards as default thresholds, the new program was flexible. In other words, size thresholds are modifiable according to the users' desires. The subroutine program was able to calculate hreshold values for each algorithm based on the following. The models were arbitrarily defined and found to give rational threshold values:

$$TH1 = \frac{MaxS + MinM}{2} \qquad TH2 = \frac{MaxM + MinL}{2} \tag{8}$$

$$TH3 = \frac{MeanS + MeanM}{2} \qquad TH4 = \frac{MeanM + MeanL}{2} \tag{9}$$

where MaxS, MaxM and MaxL are Maximum pixel values of the Small, Medium and Large groups, respectively,

MinS, MinM and MinL are Minimum pixel values of the Small, Medium and Large groups, respectively, and

MeanS, MeanM and MeanL are Mean pixel values of the Small, Medium and Large groups, respectively.

The above equations can be used to calculate threshold values based on either Area, Perimeter, Max diameter or Min diameter.

The 4 selected algorithms from the off-line stage, that is, the four algorithms segmenting one of four parameters (Area, Perimeter, Max diameter or Min diameter) based on Red color band, were combined with the two relevant thresholds models to form 8 comprehensive algorithms to be used in real time tests.

Therefore, as the subroutine program calculates the relevant threshold values, the values are exported to each of the 8 comprehensive algorithms. These algorithms are capable of measuring fruit parameter and comparing it with the threshold values to conclude fruit size group. For instance, if the algorithm measures Area, the following subroutine can conclude the sorting decision for that particular fruit:

If (Area $\leq$TH1) $\Rightarrow$ Group= Small

If (TH1< Area$\leq$ TH2) $\Rightarrow$ Group = Medium

If (Area > TH2) $\Rightarrow$ Group= Large

Artificial Neural Networks

In this study, a number of Artificial Neural Network (ANN) algorithms, which were combinations of image processing and Artificial Neural Network (ANN) techniques, were developed and used for classification. The Multilayer Feed-forward Neural Network (MFNN) was used for orange classification. The MFNN model can be constructed with more than 1 layer and is able to learn nonlinear and complex relationships by using a training algorithm with a set of input-output pairs (10). For orange fruit classification, a back propagation network model with various training functions including variable learning rate back propagation MLP-GDM, Resilient back Propagation (MLP-RP) and Scaled Conjugate Gradient (MLP-SCG) were used for ANN modeling. A logarithmic sigmoid transfer function (logsig) was applied in the first layer of the network, and a linear transfer function (Purelin) was used in the final layer. For ANN modeling, several hidden layers and nodes can be employed; but generally, one hidden layer has been found to be adequate, and only in some cases, a slight advantage may be gained by using two hidden layers. In order to sort oranges into three size groups, one hidden layer was employed for modeling; however, the number of neurons in the hidden layer differed from 1 to 6.

For training the ANN, the fruit batch of the off-line stage, pre-classified based on the GMD, was used. The batch, consisting of 80 orange fruits, was fed into the sorter unit. Then, the algorithm started to capture images, segment the object and calculate pixel values for the four mentioned parameters (Area, Perimeter, Max diameter and Min diameter) based on the Red color band for each orange through image processing techniques. The data for image processing was then regarded as input information for the series of ANN classifiers. Since the input information had various values, the inputs and outputs were normalized, gaining a value between [0,1] before being fed into the network. Finally, the ANNs were trained based on the pre-classified batch and the training ANNs were qualified to be employed for classifying the oranges in real time conditions.

Real-time Evaluation of Image processing Algorithms and ANNs

Since no singulation unit was incorporated prior to the sorting rig, the fruit was fed manually in a single array. Oranges were put one by one on the inclined plane, in front of the gate of the image acquisition platform. As a single orange arrived into the case, it would collide with the first robot arm and come to a stop. Pictures were continuously captured by the camera and simultaneously exported to one of the comprehensive algorithms introduced earlier. As soon as the decision on fruit size was made by the program, a signal was transmitted to the sorting hardware. This signal was received by the microcontroller via a serial port of the PC. The microcontroller actuated the second arm which guided the fruit into the appropriate bin accommodated at the bottom end of the rig. The microcontroller turned on a LED installed at the gate of image acquisition platform simultaneously, to signal the termination of the sorting process and the admission of the next fruit. Fig. 5 illustrates the comprehensive algorithm developed for sorting based on Area and Fig. 6 shows the microcontroller algorithm controlling the two arms.

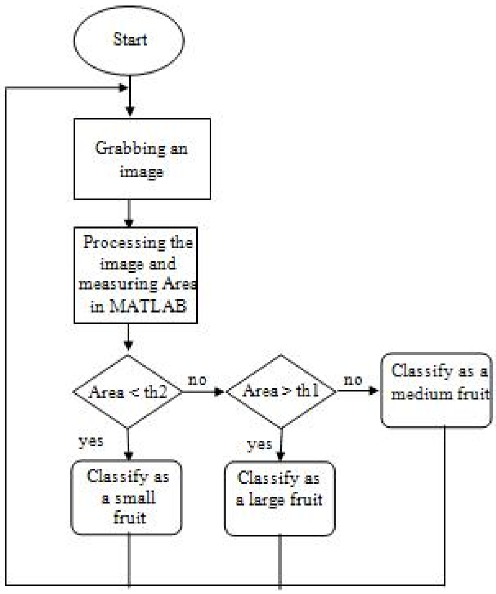

Fig. 5. Comprehensive sorting algorithm based on area

Considering the continuous images captured by the webcam, only pictures containing orange images were imported to the comprehensive algorithms. Two methods were tried to implement this decision.

In the first method, a laser transmitter and receiver was accommodated to sense the presence of the orange fruit. However, preliminary evaluation indicated that this system was inherently associated with long delays and was therefore not chosen for the task.

In the second method, pixel information from the background picture was correlated to pixel information of the complete subsequent picture. If correlations less than 50% are established, the system acknowledges the fruits' presence and further processing starts, otherwise picture capturing continues until the condition is met. Fig. 7 shows the algorithm specifically developed for this purpose.

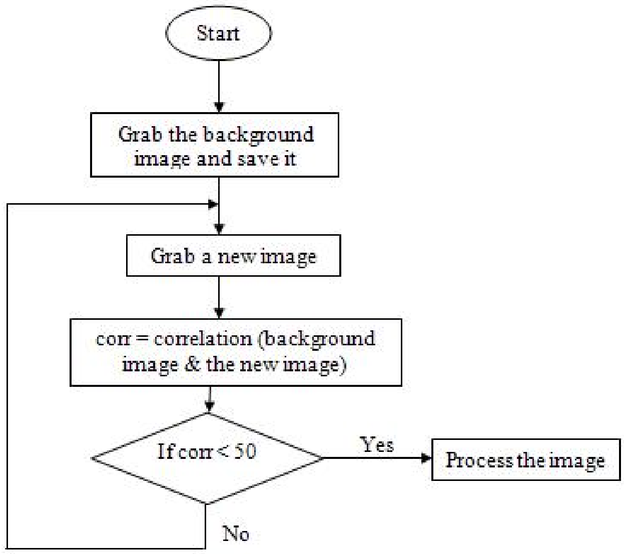

Fig. 6. Comprehensive microcontroller algorithm for controlling the arms

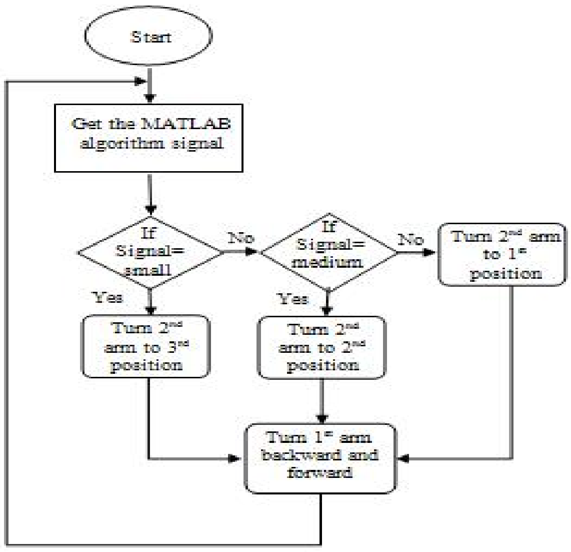

Fig. 7. Algorithm developed for efficient real time image grabbing

To evaluate the ANN algorithms and to find the most accurate neural network model with optimum layers and epochs to classify the fruits, the evaluating batch of the fruits was used in real time mode. To achieve this, similar to the previous stage, the fruits of the batch were fed to the image acquisition platform indiscriminately and the trained ANN algorithms, which were the combinations of image processing and neural network techniques, were employed to classify the fruits of the evaluation batch into three size groups. For each algorithm and neural network pattern, various layers of perceptron were applied. Finally, sorting records for each neural network algorithm were compared with the relevant sorting data based on GMD and the most accurate algorithm with the optimum layers was found.

Sorting Elapsed Time

To measure the duration of operation, a stopwatch program was developed, based on the CPU frequency of the computer, and could provide information regarding elapsed time when a particular algorithm is processed. This program was also capable of measuring the duration of the arms' movements (first/ second). The collected data were used to calculate the throughput rate of the test rig.

RESULTS AND DISCUSSION

Three subsequent stages of evaluation tests were carried out to find the sorting accuracy and time required to sort a single fruit as well as the throughput capacity of the sorting unit.

Preliminary Test Results

To evaluate the developed algorithms, equal batches of small, medium and large oranges were chosen from the fruit market based on local consumer preferences expressed in terms of GMD. Table 1 shows information on the orange sizes measured/calculated for each batch.

Table 1. GMD of fruit batch used in preliminary evaluation

Type	Average GMD(cm)	Max GMD(cm)	Min GMD(cm)
Small	6.16	6.42	5 .72
Medium	7.19	7.41	6.92
Large	7.65	7.87	7.59
Overall	7.00	7.87	5.72

Off-line Tests Results

Aat this stage, fruits were fed into the unit in a single array indiscriminately. The correlation coefficients between pixel values identified by each of the above 12 algorithms with the corresponding actual size of the fruit (GMD) were computed in 5 replications (Table 2). The table reveals that segmentations based on Red and Green color bands were more satisfactory as compared to the Blue color band as far as high correlation coefficients were concerned. This indicates larger differences between contrasts of an orange fruit and its background image in R and G color bands. For the real time evaluation, considering equal correlation values between algorithms based on

R and G color bands (Table 2), only the four algorithms based on the R color band were employed and evaluated in the real time stage.

Table 2. Correlation coefficients between machine vision size measurements vs. GMD

Segmentation methods	parameters	Rep1	Rep2	Rep3	Rep4	Rep5	Average	overall
Based on Red	Area	0.98	0.97	0.98	0.97	0.98	0.98	
	Perimeter	0.98	0.97	0.97	0.97	0.97	0.97	
	Max Diameter	0.97	0.95	0.97	0.96	0.95	0.96	0.97
	Min Diameter	0.98	0.97	0.97	0.97	0.98	0.97	
Based on Red	Area	0.98	0.97	0.98	0.97	0.97	0.98	
	Perimeter	0.98	0.97	0.98	0.98	0.98	0.98	0.97
	Max Diameter	0.97	0.95	0.97	0.95	0.95	0.96	
	Min Diameter	0.98	0.97	0.97	0.98	0.98	0.98	
Based on Red	Area	0.96	0.95	0.95	0.96	0.96	0.96	
	Perimeter	0.96	0.95	0.96	0.96	0.96	0.96	0.82
	Max Diameter	0.97	0.96	0.66	0.85	0.84	0.86	
	Min Diameter	0.96	0.91	0.92	0.94	0.94	0.93	

Real-Time Tests Results

As mentioned, real-time evaluation was conducted in which the complete test rig (image acquisition and sorting units) was used.

In this stage, the two models of size thresholds introduced earlier were incorporated in the four image processing algorithms selected for the real time study, therefore, a total of 8 comprehensive algorithms were developed and evaluated. To investigate which combinations of algorithms and thresholds provided a more accurate performance, the outputs of the system's classifications were compared to the classification data based on GMD and the errors were calculated in 4 replications.

The same evaluating process was then carried out for ANNs and the errors of each Neural Network classifier were computed.

Table 3 demonstrates that the Multi-Layer Perceptron with RP and SCG transferring functions had least errors (1.1%). Since increasing the number of neurons in each layer increases processing time, the number of neurons has to be optimized. The optimum neuron number for MLP-SCG is 4 for the input layer, 3 for the hidden layer and 3 neurons for the output layer. Similarly, the optimum number of neurons for MLP-RP is 4 neurons for the input layer, 3 for the hidden and 3 for the output.

Table 3. Percentage of errors associated with neural network classification as compared to classification based on GMD

	Percentage of errors (%)					
Type of training function	Neural Network Structure					
MLP-GDM	4-1-3	4-2-3	4-3-3	4-4-3	4-5-3	4-6-3
MLP-SCG	43.33	41.11	37.22			
MLP-RP	27.22	7.78	1.1*	1.1*	1.1*	1.1*
MLP-RP	28.33	7.78	1.1*	5.55	1.1*	1.1*

Classification errors of eight image processing algorithms as well as errors for the most accurate ANN model (MLP-SCG or MLP-RP with 3 neurons in the hidden layer) are shown in Table 4. This table reveals that algorithms #5 (based on Area & TH3, 4), algorithm #6 (based on Perimeter & TH3, 4) and ANN have the least errors (1.1%) and algorithm #3 (based on Max diameter & TH1, 2) has the maximum error rate (7.78%) when sorting the fruits.

Table 4. Percentage of errors associated with classification based on the machine vision and ANN as compared to the classification based on GMD

Sorting based on	% error				
	Rep1	Rep2	Rep3	Rep4	Average
Area&TH1,2	4.44	0.0	0.00	2.2	1.66
perimeter& TH1,2	0.00	2.2	0.00	4.44	1.66
Max diameter & TH1,2	8.89	8.89	6.67	6.67	7.78
Min diameter&TH1,2	4.44	0.00	2.2	6.67	3.33
Area&TH3,4	2.2	2.2	0.0	0.00	1.1
perimeter& TH3,4	2.2	2.2	0.0	0.00	1.1
Max diameter & TH3,4	8.89	6.67	2.2	4.44	5.55
Min diameter&TH3,4	6.67	4.44	11.11	2.2	6.11
ANN	0.00	2.2	2.2	0.0	1.1

To show the validity of adapting the analysis of variance to error results, Fig. 8 and table 5 are presented, which reveal the presence of a normal distribution within the error output (Table 4).

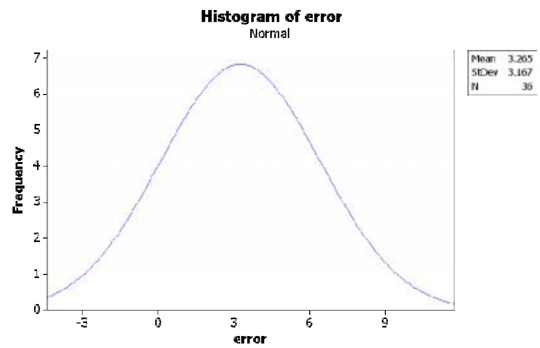

Fig. 8. Sorting error histogram for normality test

Table 5. Tests of normality for sorting errors

	Kolmogorov-Smirnov[9]			Shapiro - wilk		
error	statistic	df	Sig.	statistic	df	sig
	243	36	000.	.367	36	.000

Statistical analysis (Table 6) revealed that there were significant differences among algorithms. However, there were no significant differences among replications which mean that different rest positions did not have significant effects on the sorter's performance.

Table 6. Results of the real-time tests' statistical analysis

Source	DF	SS	MS	F	P
Replication	3	13.579	4.5264	0.86^{ns}	0.474
Algorithms	8	211.559	26.4448	5.04**	0.001
Error	24	125.940	5.2475		
Total	35	351.078			

^{ns} Not significant

**** Highly significant differences (p<0.01)**

Comparing the sorting mean errors by LSD† (Table 7) indicates that although algorithms #5 (based on Area & TH3, 4), #6 (based on Perimeter & TH3, 4) and ANN exhibit lower errors (1.1%), there are no significant differences between algorithms #1 (based on Area & TH1, 2 - with 1.66% error), #2 (based on Perimeter & TH1, 2 - with 1.66% error) and #4 (based on Min diameter & TH1, 2 – with 3.33% error). As a result, adoption of each of the above 6 algorithms does not make a difference.

Algorithms #5 and #6 (1.1%) have highly significant differences (0.01p) with algorithms #3 (7.78%) and #8 (6.11%) and have significant difference (0.05p) with algorithm #7 (5.55%). Therefore, algorithms #3 (based on Max diameter & TH1, 2), #7 (based on Max diameter & TH3, 4), and #8 (based on Min diameter & TH3, 4), are not recommended for sorting as compared to algorithms #5 and #6.

To summarize, both threshold models were reliable for sorting and adopting algorithms #1, #2, #4, #5 and #6. In addition, ANN is recommended for sorting purposes because it shows the least possible sorting error.

Throughput Rate

The total time required for real time sorting, including time required for software and hardware operations, was measured during evaluation. The first position of the second arm was considered as the initial point for measuring operation times. Table 8 shows that when image processing algorithms were used, the test rig sorted oranges into three size groups (Large, Medium and Small), in periods of 530, 755 and 935 ms/fruit, respectively. However, when image processing algorithms and ANN were used, sorting speeds were 569, 794 and 974 ms/fruit, for Large, Medium and Small fruits, respectively. The degrees of the second arm's movement are the main cause of time differences.

Minimum and maximum speeds were about 1fruits/s and 2fruits/s, depending on the uniformity of the fruits. Measuring the throughput rate of the single sorter revealed that it could sort 1t of orange fruits into three size groups in 1 hour, the average speed for sorting the fruits being found to be 1.87 fruits/second. Although the average throughput rate for the single sorter was limited to $1t.h^{-1}$, it could easily be increased to

† . Least significant difference test

the desired capacity by accommodating a number of sorters in a parallel bank arrangement.

Table 7. Mean error comparisons for various sorting algorithms based on individual errors

type	1# Area&TH1,2	2# perimeter &TH1,2	3# Max diameter & TH1,2	4# Min diameter& TH1,2	5# Area&TH3,4	6# perimeter&TH3,4	7# Max diameter & TH1,2	8# Min diameter &TH3,4
2# perimeter & TH1,2	1.000							
3# Max diameter & TH1,2	.001**	.001**						
4# Min diameter &TH1, 2	.309	.309	.010*					
5# Area&TH3,4	.730	.730	000**	.177				
6# perimeter& TH3,4	.730	.730	000**	.177	1.000			
7# Max diameter & TH1,2	.023*	.023*	.177	.178	.010*	.010*		
8# Min diameter&TH 3,4	.010*	.010*	.307	.095	.004**	.004**	.733	
ANN	.730	.730	0.000**	0.177	1.000	1.000	0.010*	0.004**

Significant differences according to LSD test ($p < 0.05$)
Highly significant differences according to LSD test ($p < 0.01$)

Table 8. Details of time requirements for sorting a single fruit

Task	Large-orange Sorting time (ms)	Medium-Orange sorting time (ms)	Small-Orange sorting time (ms)
Image processing	309	30	30
ANN	69	69	69
Arms movement	500	725	905
Total time for image processing algorithm	530	755	935
Total time for ANN	569	794	974

CONCLUSIONS

The sorter test rig was able to classify the fruits into three categories with considerably low errors. Although all twelve algorithms had acceptable results, those based on Red and Green segmentations were more satisfactory. For real time evaluation purposes, four algorithms that segment according to the R color band, and two size threshold models were combined to form 8 comprehensive algorithms. These comprehensive algorithms along with the ANN model were used at evaluation stages. Results showed that although algorithm #5 (based on Area & TH3, 4) and algorithm #6 (based on Perimeter & TH3, 4) and the ANN model exhibit smaller errors, there are not significantly different from algorithms #1 (based on Area & TH1, 2), #2 (based on Perimeter & TH1, 2) and #4 (based on Min diameter & TH1, 2). The real time performance revealed that a single test rig unit could sort fruits at minimum and maximum rates of about 1fruit/s and 2 fruits, respectively.

The overall results revealed that image processing and neural network techniques used in the present test rig along with state of the art electrical circuit were capable of sorting orange fruits at high speed, high accuracy and low costs as compared to common sorters which use cup belt technology.

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طراحی، ساخت و ارزیابی یک سورتر پرتقال بر اساس ماشین بینایی و فناوری شبکه عصبی مصنوعی

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چکیده- تولید انبوه مرکبات در ایران لزوم درجه بندی کیفی این محصولات را برای ورود به بازار های جهانی ایجاب می کند. تحقیق حاضر به منظور طراحی و ساخت یک دستگاه سورتز میوه بر اساس اندازه انجام گرفت. سخت افزار متشکل از دو بخش بود. بخش اول واحد جمع آوری تصویر شامل یک دوربین، یک بازوی روبات و مدارهای کنترل بود. واحد دوم یک عملکرد روبات و مارهای مربوطه را شامل بود. به منظور انجام عمل سورتینگ ابتدا تصاویر اخذ گردید هر دو مدل برای تعیین آستانه اندازه انتخاب گردیدند. از سوی دیگر الگوریتم دو مدل یاد شده با شبکه عصبی مصنوعی (ANN) ادغام گردید. سپس مدل پرسیپترون ضد لایه با مقدار متنوعی تابع آموزشی و مقداری نوسان تشکیل گردید. از هر کدام از الگوریتم های یاد شده برای تقسیم پرتقال به سه گروه اندازه های کوچک- متوسط و بزرگ استفاده گردید. نتایج سوتینگ انجام شده با اندازه واقعی میوه ها که توسط فرد متخصصی تعیین شده بود مقایسه شد. نتایج به دست آمده حاکی از آن است که حداکثر خطا در تقسیم میوه ها محدود به ۱/۱ درصد می باشد. اندازه ظرفیت متوسط دستگاه برابر با یک تن بر ساعت است که با به کار گیری واحد های موازی تا ۱۰ تن بر ساعت قابل افزایش است. نتایج کلی حاکی از آن است که میوه هایی نظیر پرتقال می تواند با فناوری معرفی شده با هزینه کم و دقت بالا تفکیک گردد.

واژه های کلیدی: اندازه پرتقال، سورتر مرکبات و شبکه عصبی مصنوعی

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