Application of Genetic Algorithm（GA）Trained Artificial Neural Network to Identify Tomatoes with Physiological Diseases

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Abstract: We synthetically applied computer vision, genetic algorithm and artificial neural network technology to automatically identify the tomatoes that had physiological diseases. Firstly, the tomatoes' images were captured through a computer vision system. Then to identify cavernous tomatoes, we analyzed the roundness and detected deformed tomatoes by applying the variation of fruit's diameter. Secondly, we used a Genetic Algorithm (GA) trained artificial neural network. Experiments show that the above methods can accurately identify tomatoes' shapes and meet requests of classification; the accuracy rate for the identification for tomatoes with physiological diseases was up to 100%. [Nature and Science. 2005;3(2):52-58].

Key words: tomato with physiological disease; computer vision; artificial neural network; genetic algorithms

Introduction

In China, most traditional fruit quality tests still remain at the preliminary stage in which identification is determined by human sense organs. These subjective evaluations are affected by personal abilities, color resolution, emotions, fatigue and rays of light etc. Therefore these techniques are inefficient and inaccurate, and most of them are observational appreciations whose objectivity and accuracy are inadequate. The result is that China's export fruits are of inferior external appearances, and lack competitive power in international markets. Thus it is rather indispensable to improve the national test level of fruit quality[1]. Contrasted with other test technologies, the advantages of computer vision include high speed, multiple functions, capability to do assignments that man or mechanical grading machines are incompetent to do, and the ability to automatically achieve single time identifications of shape, size, degree of maturation, and surface flaws; all of which greatly help increase grading precision[2]. Early in 1985, Sarkar and Wolfe et al successfully developed a kind of quality grading equipment for fresh tomatoes, using computer vision with an applicable lighting fixture and direction finding mechanism. Its grading error is only 3.5%, far superior to the grading precision of manual tests, although still low speed.

1 Capture of the tomato's image

The tomato's image is captured by a computer vision system, which consists of computers, image acquisition cards, CCD (Charge Coupling Device) cameras, 20-watt annular incandescent lamps, etc. Because of the tomato's extremely-smooth surface, illumination results in serious specular reflection. It was found that if a soft-light sheet was added between a 20-watt annular incandescent lamp and the tomato, the tomato's image would no longer contain specular reflection[5]. Figure 1 shows the tomato's acquired image.

2 Network's establishment

2.1 Brief introduction to Genetic Algorithm

Genetic Algorithm (GA) is a kind of search and optimized algorithm that have been produced from simulating biologic heredities and long evolutionary processes of creatures. It stimulates the mechanism of "survival competitions; the superior survive while the inferior are eliminated, the fittest survive." The mechanism searches after the optimal subject by means of a successive iterative algorithm. Ever since the late 80s, GA, as a new cross discipline which has drawn

people's attention, has already shown its increasing vitality in many fields[6].

GA stimulates reproduction, mating, and dissociation in natural selection and natural heredity procedures. Each possible solution to problems is taken as an individual among population, and each individual is coded as character string; each individual is evaluated in response to predefined objective functions and a flexibility value given. Three of its elemental operators are selection, crossing, and mutagenesis[7].

Its main features are as follows:

(1) GA is to acquire the optimal solution or quasi-optimal ones through a generational search rather than a one-point search; (2) GA is capable of global optimum searching; (3) GA is a parallel process to population change, and provides intrinsic parallelism; (4) The processed object of GA is the individuals whose parameter set is coded rather than the parameters themselves, and this very feature enables GA to be used extensively[8].
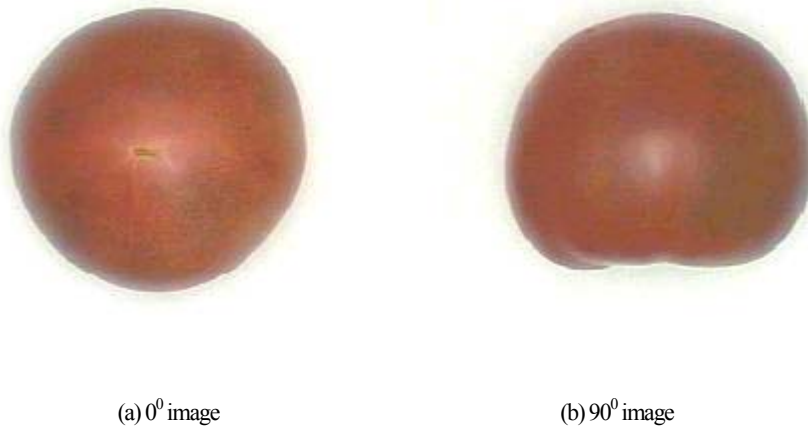

(a) 0^0 image   (b) 90^0 image

Fig.1 Tomato's image

2.2 Model establishment

1) Determination of the genetic encoding scheme

The first step, when GA is applied, is the determination of a genetic encoding scheme, namely to denote each possible point in the problem's search space

as a characteristic string of defined length. This is in order to be sure that GA will not only optimize network configuration but, in the meantime, genetic training will proceed on weight values. In this paper, weight values between each layer of the multi-layer feed-forward neural network are simultaneously coded as one chromosome.
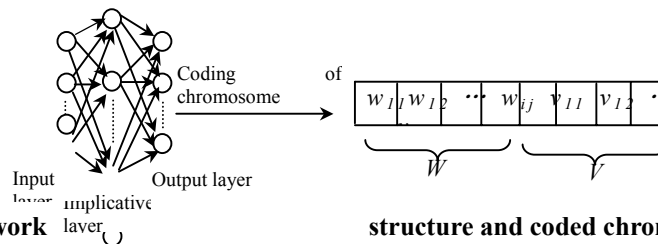

Figure 2. Neuron network structure and coded chromosome

Structure and weight value of the neuron network are mapped to this very chromosome, one of whose layers is the implicative layer whose nodes are

determined in accordance with actual demands. Both W as the weight array from the input layer to the implicative layer and V as that from the implicative

layer to the output layer are still arranged in row-to-column sequence and binary-coded. Although such genetic coding helps increase the length of chromosome string, yet each gene value is strictly simplified to either "0" or "1", which remarkably improves the algorithm's global search ability.

2) Definition of flexibility function and its transformation of scale

The second key step, when GA is applied to generate a neural network, is the definition of the flexibility function to evaluate the problem-solving ability of the neural network, which is denoted by a certain specific chromosome string. In this paper, objective function is generated from the cost factor *mean-square error* (*MSE*) of the neural network output, and then converted into a function via reciprocal transformation. Its computational formula is as follows:

$$MSE = \frac{1}{mp}\sum_{P=1}^{p}\sum_{j=1}^{m}(d_{pj}-y_{pj})^2$$

where; m=sum of output nodes; p=sum of trained samples; d_{pj}=expected output of network; y_{pj}=actual output of network.

In GA's later search period, sufficient varieties will probably still exist among population, whereas population's average flexibility value may approximate the optimal variation. If such status isn't changed, then amongst subsequent generations, the individuals that have average value and those optimal ones will approach identical reproduction quantities, so actually here almost no competition exists, which consequently slows down the convergence rapidity.

To avoid the above situation, reproduction quantity in the neural network evolutional process will be adjusted to improve algorithmic performance. Reciprocal scale transformation to the objective function is done as:

$$f(MSE) = \frac{K}{MSE}$$

in which the selection of K is quite crucial, as it determines the coerciveness of the selection procedure.

K is determined from experiments.

3) Three of GA's elemental operators

(1) Selection. In the paper, the disk gambling method is adopted, and calculated as

$$P_i = \frac{f_i}{\sum\limits_{i=1}^{N} f_i} = \frac{f_i}{f_{sum}}$$

in which; f_i=flexibility value of individual i; f_{sum}=total flexibility value of population; P_i=selective probability of individual.

It's obvious that individuals with high flexibility values are more likely to be reproduced[9].

(2) Crossing. In the paper, one-point crossing is adopted. The specific operation is to randomly set one crossing point among individual strings. When crossing is executed, partial configurations of the very point's anterior and posterior individuals are exchanged, and give birth to two new individuals.

(3) Mutagenesis. As for two-value code strings, mutagenic operation is to reverse the gene values on the gene bed, namely covert 1 to 0 or 0 to 1.

4) **Genetic control parameters**

Genetic control parameters in the paper are chosen as follows: N as population scale is 50, P_c as crossing probability is 0.4, P_m as mutagenic probability is 0.003, and network's terminative condition is $MSE \leq 0.05$.

3 Extraction of characters

Deformed fruits and cavernous ones result from two major physiological diseases. Cavernous fruit refers to ones with corner angles on their surfaces, and its tangential faces are mostly triangle in shape (Figure 3a). The chief characteristic of deformed fruits is its irregular shapes, such as abnormal, fingerlike projections or papillary (Figure 3b) fruitages, etc. Furthermore, the cavernous fruit can be identified through roundness value of 0° image, and the deformed one identified through variations of the fruit's diameter of 90º image.
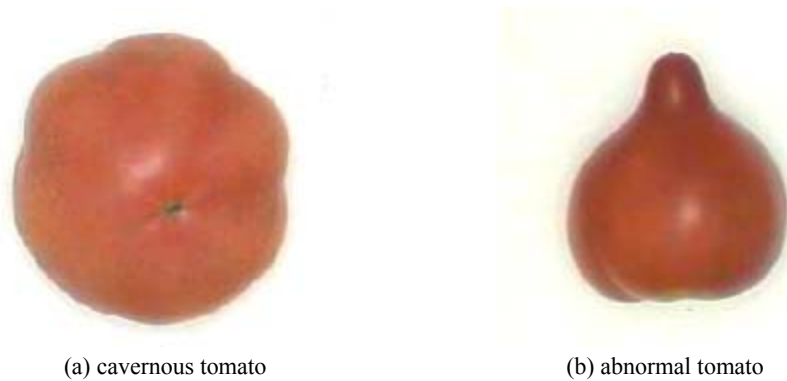
(a) cavernous tomato   (b) abnormal tomato
Figure 3. Tomatoes with physiological diseases

3.1 Roundness character

Roundness, which is derived from the area and the perimeter, measures the shape complexity. Its formula is[10]

$$e = \frac{4\pi A}{p^2}$$

in which *A*—the area; *P*—the perimeter.

It can be seen that, e=1 if round in shape. Since tangential faces of the cavernous fruit are triangular, its roundness is less than 1.
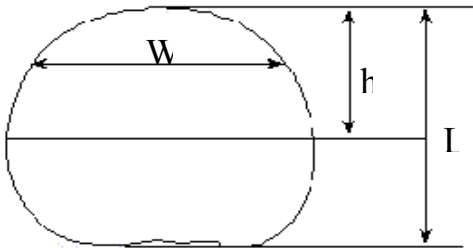
3.2 Variations of fruit's diameter

Figure 4. Characteristic parameters of tomato's shape

Variations of the fruit's diameter refers to the variations of diameter from tomato's top to its bottom [11] (Figure 4), which can be defined as the distance W_i between the two intersections derived from a line perpendicular to fruit's axis and tomato's edge. In this way, the tomato is divided perpendicular to fruit's axis into twelve equal parts, then W_1--W_{12} are extracted as characteristic parameters of variations of the fruit's diameter. Due to the unsmooth variations of its diameter, deformed fruits are detected by this means.

4 To identify tomatoes with physiological diseases

4.1 To identify cavernous tomatoes

Roundness is calculated via the perimeter *P* and the area. *P* is measured in millimeters, and *A* is measured in square millimeters, while both the length and the area in the plane coordinate system of image are measured in pixels. The quantitative relationship obtained from experiments of the tomato's perimeter in pixels at maximum transverse diameter is shown in Table 1, and the quantitative relationship of the tomato's area at maximum transverse diameter is shown in Table 2.

According to Table 1, the linear regression equation of the tomato's measured perimeter in pixels at maximum transverse diameter on the edge of 0° image is defined as

$$P = 0.2492\,n + 8.4294$$

in which *P*=tomato's estimated perimeter at maximum transverse diameter; *n*=pixels on the edge of 0′ image; and their correlation coefficient *R*=0.9990. The relationship obtained from experiments of the tomato's actual perimeter to estimated perimeter at maximum transverse diameter is shown in Table 3.

Table 1. Quantitative relationship between measured perimeter at maximal diameter and pixel in plane coordinate system of image

Sample	1	2	3	4	5	6	7
Pixels	928	787	667	861	806	937	767
Actual perimeter (mm)	240.19	203.59	175.90	223.10	210.41	241.51	200.23

Table 2. Quantitative relationship of tomato's area at maximum transverse diameter to pixels in plane coordinate system of image

Sample	1	2	3	4	5	6	7
Pixel	61918	44543	32127	53121	46822	62584	42579
Actual area (mm^2)	4590.94	3298.43	2462.13	3960.87	3523.02	4641.52	3190.41

Table 3. Relationship of tomato's actual perimeter to that of evaluated perimeter at maximum transverse diameter

Sample	Actual perimeter(mm)	Estimated perimeter(mm)	Absolute error(mm)	Relative error (%)
	197.31	199.57	2.26	1.15
2	217.43	217.26	0.17	0.08
3	173.13	173.65	0.52	0.30
4	221.59	220.25	1.34	0.60
5	237.08	234.95	2.13	0.90
6	218.95	217.26	1.69	0.77
7	245.32	244.92	0.40	0.16
8	247.74	244.67	3.07	1.24
9	194.17	193.09	1.08	0.56

Table 4. Relationship of actual area to evaluated area at maximum transverse diameter

Sample	Actual area (mm^2)	Estimated area (mm^2)	Absolute error (mm^2)	Relative error (%)
1	3098.03	3142.41	44.38	1.43
2	3762.08	3764.49	2.41	0.06
3	2385.34	2365.10	20.24	0.85
4	3907.50	3881.47	26.03	0.67
5	4472.82	4335.38	137.44	3.07
6	3814.99	3751.77	63.22	1.66
7	4789.09	4732.63	56.46	1.18
8	4884.31	4775.91	108.40	2.22
9	3000.11	2961.22	38.89	1.30

Seen from Table 3, the maximal error of the test perimeter exists within 3.07 mm, and the estimated perimeter at maximum transverse diameter gained by this means is of higher precision, which meets the

demand for identifying tomatoes.

According to Table 2, the linear regression equation of the tomato's estimated area in pixels at maximum transverse diameter inside the edge of 0° image is defined as

$$A = 0.0719n + 130.09$$

in which *A*=estimated area at maximum transverse diameter; *n*=pixels inside the edge of 0° image; and their correlation coefficient *R*=0.9995. The relationship obtained from experiments of the tomato's actual area to estimated area at maximum transverse diameter is shown in Table 4.

Seen from Table 3, the maximal error of the test area exists within 137.44 mm^2, and the estimated area at the maximum transverse diameter gained by this means is of higher precision, meeting the demand for identifying tomatoes.

4.2   To identify deformed tomatoes

Characteristic parameters of variations of fruit's diameter W_1—W_{12}, after being pretreated, are taken as inputs of the characteristic identification network.   The network outputs are divided into three states: normal,

passable and abnormal, which, if the *thermometer* method is adopted, can be respectively denoted as: (0, 0, 1), (0, 1, 1), (1, 1, 1).

The selection of GA's control parameters are as follows: population scale *N* is 50, crossing probability P_c is 0.4, mutagenic probability P_m is 0.001, and network's terminative condition is *MSE*≤0.05.

Through repeated selection, crossing, and mutagenesis, the sum of nodes that was ultimately obtained, in the optimal implicative layer of the characteristic network, was 8. Thus the valid network configuration was 12-8-3, and related connective weight values were stored in weight files. Twenty tomatoes were chosen as trained samples among which both normal fruits and deformed ones each composed half. Another twenty tomatoes were chosen as test samples. Experimental results are shown in Table 5.

Table 5. Identification results of deformed tomatoes

Identification results \ Variations of fruit's diameter	Normal	Deformed
Normal fruits	10	0
Deformed fruits	0	10

The experimental results shown above indicate that identification rate of deformed tomatoes derived from GA trained neural network reaches 100%.   It's necessary to emphasize that deformed fruits that are collectively selected for training must be sufficiently representative and comprehensive.

5   Conclusion

In the paper, roundness character is extracted from the tomato's image to identify cavernous fruit; and the character of fruit shape variations is used to identify deformed fruit. The character of fruit shape variations is analyzed by artificial neural network trained by GA.

Research results indicate that through analyses of tomatoes' shapes, fruits with physiological diseases can be absolutely identified.

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