Use of Fuzzy Neural Network in Industrial Sorting of Apples

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Abstract: In this paper, an automated system and methodology for nondestructive sorting of apples are presented. Different from the traditional manual grading method, the automated, nondestructive sorting equipment can improve the production efficiency and the grading speed and accuracy. Most popular apple quality detection and grading methods use two-dimensional (2D) machine vision detection based on a single charge-coupled device (CCD) camera detect the external quality. Our system integrates a 3D structured laser into an existing 2D sorting system, which provides the addition third dimension to detect the defects in apples by using the curvature of the structured light strips that are acquired from the optical system of the machine. The curvature of the structured light strip will show the defects in the apple surface. Other features such as color, texture, shape, size and 3D information all play key roles in determining the grade of an apple, which can be determined using a series of feature extraction methods. After feature extraction, a method based on principal component analysis (PCA) for data dimensionality reduction is applied to the system. Furthermore, a comprehensive classification method based on fuzzy neural network (FNN), which is a combination of knowledge-based and model-based method, is used in this paper as the classifier. Preliminary experiments are conducted to verity the feasibility and accuracy of the proposed sorting system.

Key words: Machine Vision, Laser, Sorting, Fuzzy Neural Network, Apples.

1 Introduction

The supply of good-quality agricultural products is a globally significant objective in the food sector. Apple is one of the most important agricultural products in the world. Sometimes, due to quality problems, the commercial value of apples will deteriorate, causing economic problems in a competitive market. Sorting is arguably the most complex yet important task that affects the quality of apples. The traditional method of fruit grading relies on human perception and hand-sorting, also called manual sorting. The shape, size, color, texture, and external damage of fruit can be judged by visual inspection and experience of the workers. The shortcomings of the detection and grading technologies will seriously affect the value of the product. It is believed that advanced technologies of sensing, signal processing, feature extraction, and decision making will lead to significant improvements in the speed, accuracy, repeatability of apple sorting. To achieve fully automated, online sorting and inspection, it is necessary to implement fast, accurate, and comprehensive non-destructive detection technologies into a sorting machine.

In developing non-destructive testing technologies, research and development have been carried out related to taste sensors, olfactory (smell) sensors, vision sensors, biosensor technology, laser, near-infrared spectroscopy, and ultrasonic technology. Van De Vooren used roundness, bending energy, sphericity and eccentricity to describe the shape characteristics of mushrooms [1]. Hao et al. [2] used machine vision technology to test the appearance quality of potatoes using three appearance indicators. In weight detection, the detection accuracy of different sizes of potatoes was achieved above 96%. Zhao et al. [3] used machine vision technology to extract the geometric parameters of watermelon and identify the defective fruits. The recognition accuracy of detecting the defective fruits reached 93.3%, and the non-destructive detection and classification of watermelon was realized. Chen from Nanjing Agricultural University studied the use of laser images to determine the quality of apples [4]. Erik et al. used a laser to sort different parts of squid, and the method exhibited good robustness [5]. Most of these methods use a single type of sensor to detect the quality of a product. However, that approaches lose some other important information, such as 3D information, of apples. Some workers have used advanced sensing methods like near infrared spectroscopy or ultrasonic sensor. However, the feasibility of their use in an automated system with moving food items with stringent hygienic standards, at high speed, and their economic viability, are debatable.

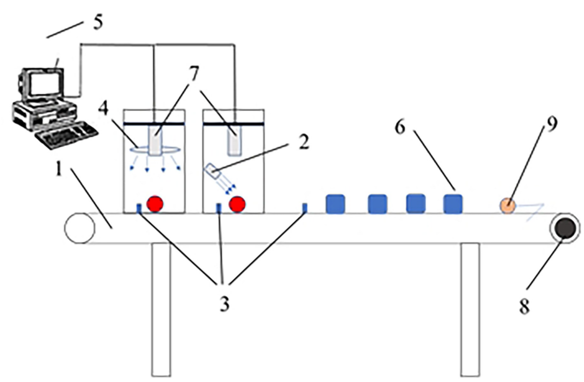
Classification is another critical issue in an automated apple grading system. Feng of Shenyang Agricultural University designed a classifier for apple quality classification using least squares support vector machine (LS-SVM) and a genetic algorithm combined with a back-propagation neural network (GA-BP) [6]. Ding used convolutional neural networks (CNN) and machine vision to detect and identify pepper, in which images were used as a direct input to the neural network without extracting the image features [7]. However, if more than one type of sensors are used, CNN may sacrifice its advantages. Fuzzy-logic theory and artificial neural network technology are two active fields of research and application. Actually, there is no clear line between the quality classes of apple, which means that the classification problem is somewhat qualitative, approximate, and somewhat vague. A fuzzy-logic system has the ability to utilize expert knowledge and experience to carry out reasoning and make decisions similar to how humans make decisions. The neural-network system obtained by properly integrating fuzzy logic and neural network will possess the advantages of both systems. Li uses fuzzy neural networks (FNNs) to learn an air quality assessment model and obtain an accuracy level of nearly 100%. Compared with BP neural network, it has obvious speed advantage and requires less memory [8].

The present paper is organized as follows. Section 2 introduces the prototype platform and the image preprocessing system. Section 3 presents the method of feature extraction using 2D and 3D information of apples. Then an FNN classifier, which integrates both fuzzy logic and neural networks, is introduced in section 4. The analysis and discussion of the experimental results are presented in section 5, while the work is concluded in section 6.

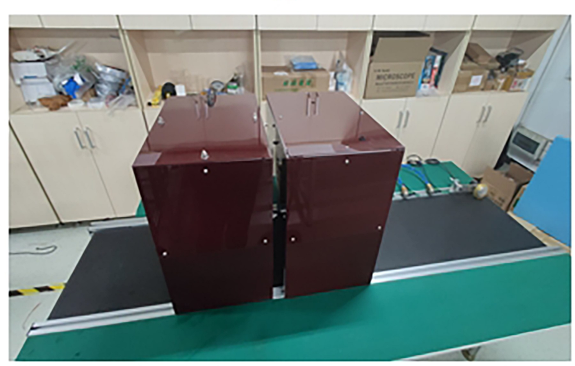
2 Prototype Platform and Image Preprocessing

2.1 Prototype platform

A prototype platform for automated sorting of apples has been developed to simulate the real grading progress in a factory, as shown in Figure 1. The belt conveyor is driven by an ordinary DC gear motor. An inverter is employed to regulate the speed of



(a)



(b)

Fig. 1 (a) Schematic diagram of the sorting system. 1-conveyor, 2-LED, 3- CCD cameras, 4- structured laser, 5-photoelectric switch, 6-high pressure jet system, 7-synchronous wheel encoder; (b) A view of the real system.

the motor. The conveyor belt is responsible for transporting the apples. A signal is sent to the control system when the photoelectric switch in the black box detects the apple, and the control system instructs the CCD camera to take an image. The cameras in the two black boxes capture color images and structured light laser image of each apple. These two images are collected by the image acquisition card into the computer. Then the apples are labelled on a predetermined babel automatically using the proposed neural network classifier. After the third photoelectric switch detects the apple, the computer sends the category signal to the control system, and the synchronous wheel encoder detects the current speed of the conveyor belt, from which the 'time' can be determined. This time is the distance from the third photoelectric switch to the corresponding actuator, divided by the speed of the conveyor. After this time is elapsed, the control system transmits a signal to the corresponding actuator, to eject the apple into the corresponding channel/bin, to achieve the purpose of sorting.

2.2 Image preprocessing

Image preprocessing is essential for the extraction of useful information [9]. In the present sorting system, image enhancement, graying and binarization, and image segmentation are used to process the images. Image enhancement, including image denoising, is used to remove any interference; image graying and binarization are used to accelerate the subsequent feature extraction process. Image segmentation is employed to separate the image background from the area of interest, thereby extracting the apple in an image. The image preprocessing steps are shown in Fig. 2, while the results of the preprocessing are illustrated in Fig.3. Among the sensors used in this system, the two cameras are of vital importance. They are CCD cameras (MER-504-10GM-P) with an imaging resolution of 2048x2448 pixels. They are suitable for capturing sharp images of objects moving at high speed. The power of the laser emitter is 100W, and it emits near-infrared light with a wavelength of 60 nm.

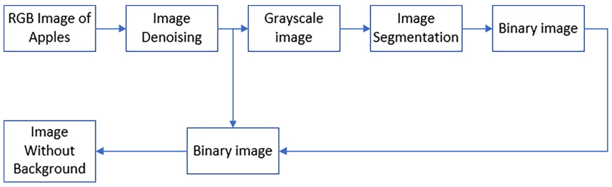
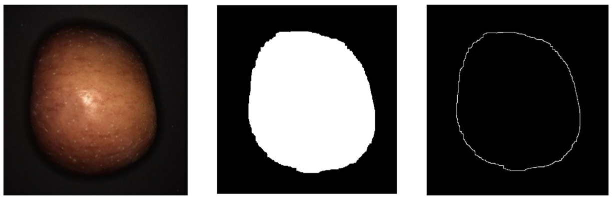


Fig. 2 Step of image preprocessing.



(a) (b) (c)

Fig. 3 (a) Original image; (b) Binary image; (c) Edge; (d) Image without background.

3 Feature Extraction and Data Reduction

Color, texture, 2D features including shape and size, and defects are the major features that indicate the quality of apples. This section introduces the extraction methods of these features, thereby determining the input of the classification system.

Color is a very useful feature in image processing and recognition, which is widely used for segmentation and extraction of different objects. Any color distribution in an image can be represented by its color moment [10]. The first moment μ_i of a picture is given by,

$$\mu_i = \frac{1}{N}\sum_{j=1}^{N} P_{ij} \tag{1}$$

where, P_{ij} represents the color component in the image, and N represents the number of pixels in the image.

Texture refers to the partial patterns that appear repeatedly in the image and their arrangement rules. Surface texture characteristics are critical indicators reflecting fruit maturity and internal quality. Wavelet transform and gray level co-occurrence matrix are the most widely used texture extraction schemes.

The multi-scale texture information of the image is extracted by wavelet transform. When an image has obvious texture at a certain frequency and direction, the output of the corresponding wavelet channel has a higher energy. The energy of low-frequency channel, high-frequency horizontal channel, high-frequency vertical channel, and high-frequency diagonal channel are extracted as feature values from the second-order wavelet decomposition subgraph.

The co-occurrence matrix is defined by the joint probability density of pixels at two positions. It not only reflects the distribution of the brightness, but also reflects the position distribution between pixels with the same brightness. Once a co-occurrence matrix is obtained, its correlation and entropy can be calculated to present the texture features.

Correlation is used to describe the similarity of elements in the row or column direction in a gray level co-occurrence matrix. When the matrix elements are evenly equal, the correlation is large, and vice versa.

$$COR = \sum_{i,j} (i - \mu_x)(j - \mu_y) P(i,j \mid d,\theta) / \sigma_x \sigma_y \tag{2}$$

where, d=1; theta=0,45,90.

Entropy is used to measure the randomness of the gray level distribution of an image, indicating the degree of non-uniformity of the texture in the image. A large entropy value indicates that the randomness is strong, and vice versa. The entropy value ENT of a co-occurrence matrix is given by,

$$ENT = -\sum_{ij} P(i,j \mid d,\theta) \lg P(i,j \mid d,\theta) \tag{3}$$

Shape and size are important parameters in human visual perception, recognition and understanding. The shape and size of apples have an important impact on the marketability of apples. They are categorized as two-dimensional (2D) features because they are obtained from 2D camera data. Shape are represented by the perimeter and the projected area of an apple, whereas the size is indicated by the roundness and equivalent radius of an apple.

The perimeter of an apple can be represented by the number of pixels in the edge, and the area of an apple in the image can be represented by the number of pixels inside the border. in the connected area of the same mark.

Roundness is used as the expression of shape because human vision system is sensitive to the roundness of an apple. The roundness of an apple, denoted by e, is given by:

$$e = R_s / R_l \tag{4}$$

where, R_s and R_l are the radii calculated from the area and the perimeter, respectively, that is,

$$R_s = \sqrt{S/\pi} \tag{5}$$

$$R_l = L/2\pi \tag{6}$$

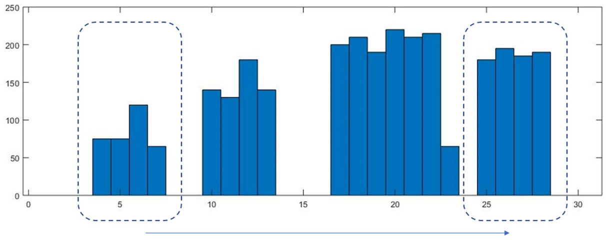


Fig. 4 Distance peak searching technique.

The structural light laser emitter and a CCD camera are used to extract the defect information of apples, for the robustness of the sensor system. This section proposes a novel method for defect detection using the structural light image acquisition system [11].

First, the laser image is processed with a threshold, which removes most of the noise points and excessive areas between the stripes. Then, a window of a certain width is used to find the gray level peak on the image. This method is called the distance peak searching technique, as shown in Figure 4.

The next step is to code the segments. The present paper uses a searching window with the size of 9 * 1 pixels. As in Figure 5, point (2,1) is the starting point. Then the center of the searching window moves to the point next to this point, (2,2). In this new searching window, we will find another new point (3,2). Then the point next to (2,2) will be next center. Finally, if there is no point in the window, the stripe examination comes to end.

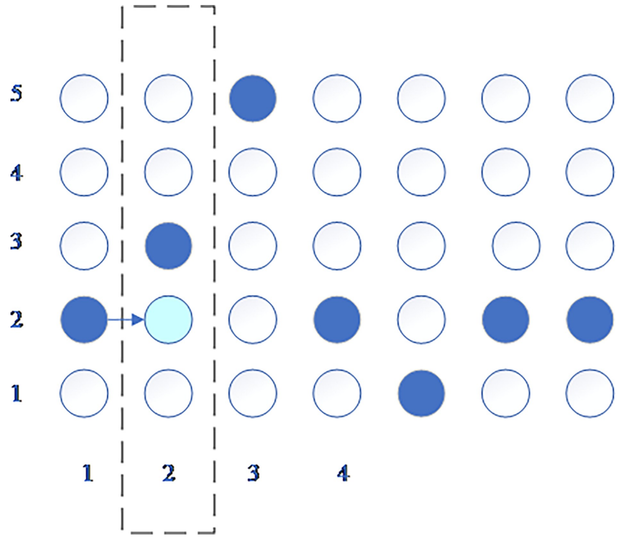
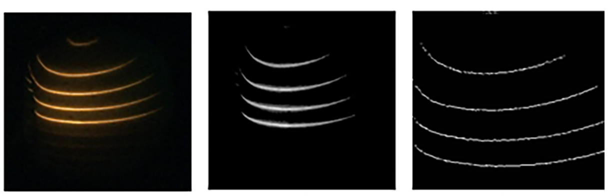


Fig. 5 Stripe extraction and coding.



(a) (b) (c)

Fig. 6 Stripe extraction results of an apple.
(a) Original image;
(b) Image after threshold segmentation;
(c) Extracted stipe.

The change of the line curvature can reflect the smoothness of the apple surface [11]. Once the laser lines on the surface of the apple are extracted, they are analyzed to extract the 3D shape information of the apple. The change of the line curvature can reflect the smoothness of the apple surface. For each extracted curve, the point C_i is the center point of the three points within the distance of δ (=20 in this paper). The center point $C_i(x,y)$ can be obtained using equation (1-1). So, for N points, we can get the number of center points as: $(N-1)/\delta$.

$$\begin{cases} (x_{1+(i-1)\times\delta} - x_{C_i})^2 + (y_{1+(i-1)\times\delta} - y_{C_i}) = r_i^2 \\ (x_{1+i\times\delta} - x_{C_i})^2 + (y_{1+i\times\delta} - y_{C_i}) = r_i^2 \\ (x_{1+(i+1)\times\delta} - x_{C_i})^2 + (y_{1+(i+1)\times\delta} - y_{C_i}) = r_i^2 \end{cases} \quad (7)$$

where, $i \in [1, N-1]$

Using these points, the direction vector can be obtained from the origin to the location of the center point of 3 points:

$$\vec{k_i} = \vec{x}\,Ci - \vec{x}\,(1+i)\times\delta \quad (8)$$

If the sign of vector $\vec{k_i}$ changes along the curve, the defect can be detected. On the other hand, the surface is smooth if each $\vec{k_i}$ is positive or negative, as shown in Figure 7.

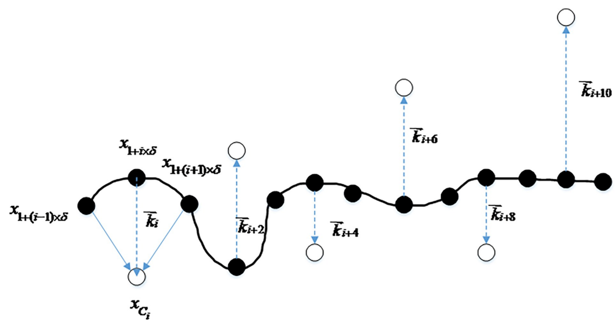


Fig. 7 Change of curvature.

If the original data is not processed by dimensionality reduction, it may cause data complexity. This will affect the learning efficiency of the classifier, and consume much memory. Therefore, we use principal component analysis (PCA) to perform data dimensionality reduction. PCA is a way to determine the most expressive data in the data space. It can reduce the feature data from high dimensionality to low dimensionality while retaining the main information of the data [12].

The vector $x_i (i=1,2,\cdots,N)$ is used to represent the D-dimensional features of the ith apple sample, and x_i is first normalized.

The sample mean is:

$$\bar{x} = \sum_{i=1}^{N} \frac{x_i}{N} \quad (9)$$

The covariance of the sample is:

$$C = \frac{1}{N} XX^T \quad (10)$$

where, $X = (\frac{x_1 - \bar{x}}{\sigma_1}, \frac{x_2 - \bar{x}}{\sigma_2}, \cdots, \frac{x_N - \bar{x}}{\sigma_N})$

X is the normalized form of x_i, and σ_i is the standard deviation of x_i.

Then we calculate the eigenvalues of the covariance matrix and the corresponding eigenvectors. $T=\{T_1, T_2, \cdots, T_d\}$ is a matrix composed of eigenvectors corresponding to the first d largest eigenvalues.

$$Y_k = XT_k \tag{11}$$

The feature matrix after dimension reduction is,

$$Z=[Y_1, Y_2, \cdots, Y_k] \tag{12}$$

Finally, we normalize the data and compress the element values of the feature matrix to [0,1] according to,

$$y_{ik}' = \frac{y_{ik} - y_{k\,\min}}{y_{k\,\max} - y_{k\,\min}} \tag{13}$$

4 Fuzzy Neural Network

Fuzzy neural network (FNN) is an effective method that combines fuzzy-logic theory with neural networks. It has significant capabilities of reasoning, learning, association, and information processing. The fundamental idea of combining neural networks with fuzzy logic is to adapt to the ubiquitous qualitative (including approximation, vagueness and uncertainty to some extent) in the real world while maintain the capability of learning as done by a human, to some extent. FNN makes it possible to process fuzzy information with a neural network [13]. In the present paper, the Takagi-Sugeno (T-S) model is used to form a fuzzy neural network for its ease of mathematical analysis, optimization, and decision making.

According to the T-S model [14], the designed fuzzy neural network has two parts: the antecedent network and the consequent network. The structure of this fuzzy neural network is shown in Figure 8, in which the antecedent network has 4 layers. The input layer transfers the input value to the next layer. There are 4 nodes in this layer, representing the four feature values after sensor fusion.

The second layer is called the membership function layer. Each node in this layer represents a linguistic variable value, such as 'large' or 'small'. This layer is used to calculate the membership function value of each input corresponding to each linguistic variable value, which belongs to a specific fuzzy set, thereby realizing the fuzzification process of the "crisp" input variable.

Each node in the fuzzy reasoning layer represents a fuzzy reasoning rule, which is used to match the antecedent of each fuzzy reasoning rule to context data and calculate the fitness α_j for that rule:

$$\alpha_j = \min\{\mu_1^{i_1}, \mu_2^{i_2}, \cdots, \mu_n^{i_n}\} \tag{14}$$

where $i_1 \in \{1,2,\cdots,m_1\}$, $i_2 \in \{1,2,\cdots,m_2\}$, $\cdots i_n \in \{1,2,\cdots,m_n\}$.

The last layer, the normalization layer, is used to normalize the output of the third layer, thereby converting the fitness of each fuzzy reasoning rule output to the weight in the consequent network.

$$\overline{\alpha_j} = \alpha_j / \sum_{i=1}^{m} \alpha_i \tag{15}$$

The consequent network consists of r parallel subnetworks of the same structure, each of which producing an output independently.

The first layer of each subnetwork is the input layer. The input of the 0th node of the input layer is set to 1, providing a bias term in the fuzzy reasoning rule. The second layer has $2\times2\times3\times2=24$ nodes, each of which representing a reasoning rule, and its output y_{ij} is given by,

$$y_{ij} = p_{j0}^i + p_{j1}^i x_1 + \cdots + p_{jn}^i x_n = \sum_{l=0}^{n} p_{jl}^i x_l \quad j=1,2,\cdots,m; i=1,2,\cdots,r \tag{16}$$

where, m = 24 is the number of nodes in this layer, and r=4 is the number of subnetworks in the consequent network.

The third layer is used to calculate the output of the FNN system. It integrates the training results of the antecedent and consequent network by means of weighted summation,

$$y_i = \sum_{j=1}^{m} \overline{\alpha_j} y_{ij} \quad i=1,2,\cdots,r \tag{17}$$

The first phase of building this fuzzy neural network is to determine the fuzzy segmentation number of the input component according to expert knowledge. In this task, the linguistic variables of the input color features are "red" and "yellow", the input texture features are described by "clear" and "even", the input 2D features are described by "big" "medium" and "small", while the defect feature is divided into "yes" and "no". That is, the fuzzy segmentation number of color, texture, 2D and defect feature is 2, 2, 3and 2, respectively.

The fuzzy neural network parameters obtained by the learning algorithm include the connection weight in the consequent network and the membership function in the second-layer of the antecedent network. In the present paper, Gaussian membership function is used, as,

$$\mu_i^j = \exp(-(x_i - c_{ij})^2/\sigma_{ij}^2) \tag{18}$$

where, c_{ij} and σ_{ij} represent the center and the width, respectively, of the membership function. These two parameters are determined by the learning algorithm. The loss function of the supervised training is:

$$E = \frac{1}{2}\sum_{i=1}^{r}(y_{di} - y_i)^2 \tag{19}$$

where, y_{di} and y_d represent the expected output and the actual output, respectively. The parameters p_{ji}^l are updated according to:

$$p_{ji}^l(k+1) = p_{ji}^l(k) - \beta\frac{\partial E}{\partial p_{ji}^l} \tag{20}$$

with β denoting the learning rate. Similarity, c_{ij} and σ_{ij} are updated according to,

$$c_{ij}(k+1) = c_{ij}(k+) - \beta\frac{\partial E}{\partial c_{ij}} \tag{21}$$

$$\sigma_{ij}(k+1) = \sigma_{ij}(k+) - \beta\frac{\partial E}{\partial \sigma_{ij}} \tag{22}$$

5 Experiments and Discussion

To evaluate the grading method proposed in this paper, we collected 1600 images of five kinds of apples using the image acquisition system. The four different classes of apples are mainly, (a) apples are large in size, red in color and even in texture; (b) apples are medium in size, the color is red, the texture is less and uniform (point texture); (c) the size is medium, the color is yellow, the texture is more and clear (bar texture); (d) the size is smaller, the color is red, and the texture is uniform.

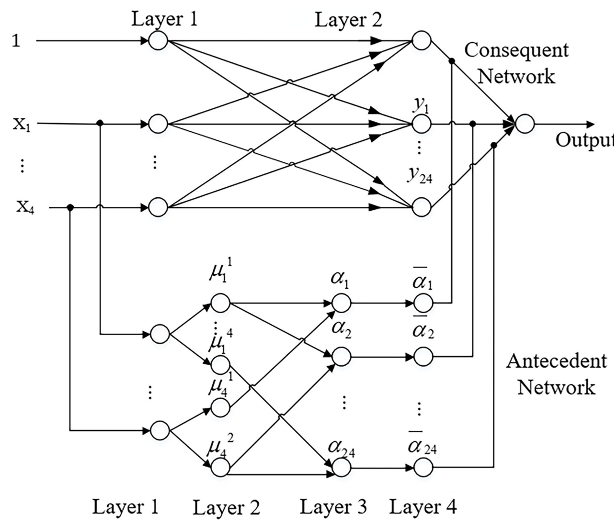


Fig. 8 Structure of FNN.

All products with obvious surface defects will be classified as Category 5, and damaged apples will be classified as Category 5. The basic progress of the classification method is shown in Figure 9. If the the apple is detected as defective, then the apple will be in the 5th grade. For the other 4 grades, we classify using FNN. Adaptive network-based fuzzy inference system (ANFIS) is an implementation of FNN based on Takagi-Sugeno model. It realizes the three basic processes of fuzzification, fuzzy reasoning and de-fuzzification by using neural networks. The learning mechanism of neural network is used to automatically extract rules from input and output data, to form an adaptive neuro-fuzzy system. This is realized by an algorithm that uses off-line training and online learning [15]. Using the ANFIS tool box of MATLAB, we establish an FNN with a consequent subnetwork for classification.

Feature extraction is conducted according to the method presented in Sections 3 and 4. Table 1 shows some of the data, where A to O represent mean of R, mean of G, mean of B, mean of H, second moment of H, third moment of H, correlation of gray level co-occurrence matrix, entropy of gray level co-occurrence matrix, low frequency component of wavelet transform, high frequency component of wavelet transform (mean), area, perimeter, roundness, equivalent radius, and proportion of R, with a total of 15 features.

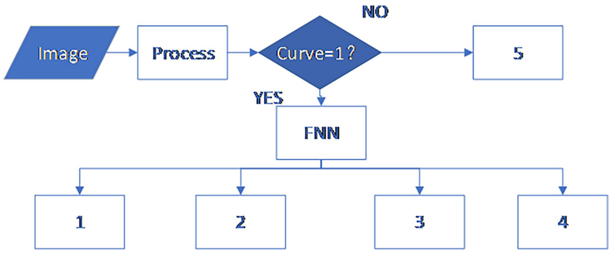


Fig. 9 The structure of the method.

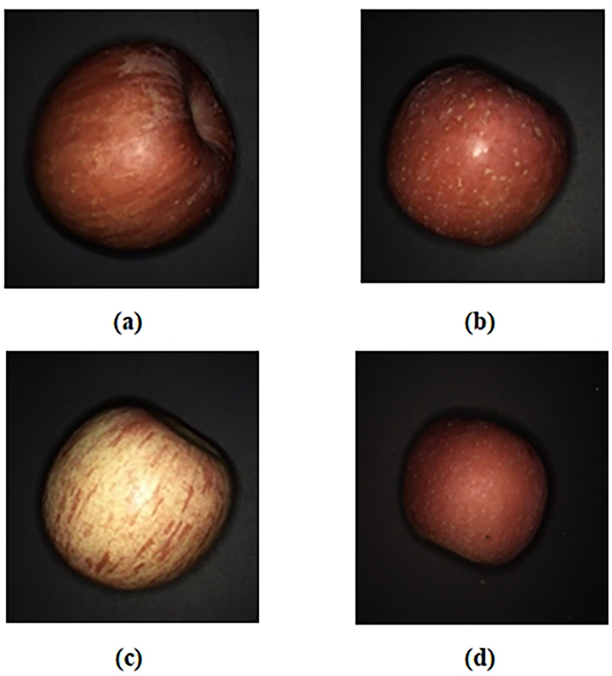


Fig. 10 Samples of apples.

Table 1 Original data.

A	B	C	D	E
0.1296	0.0493	0.0732	0.0117	0.0212
0.0792	0.0277	0.0380	0.0059	0.0175
0.1208	0.0540	0.0791	0.0147	0.0472
0.0653	0.0226	0.0292	0.0056	0.0357
F	G	H	I	J
0.02580	0.1529	1.2219	0.3439	0.0071
0.0510	0.3110	0.91060	0.1934	0.0055
0.1125	0.1255	1.1681	0.3493	0.0075
0.1014	0.2875	0.8407	0.1546	0.0053
K	L	L	M	O
246938	2083	0.8457	280.3619	0.5141
180377	1731	0.8698	239.6159	0.5284
206079	1941	0.8291	256.1191	0.4758
166178	1521	0.9501	229.9915	0.5576

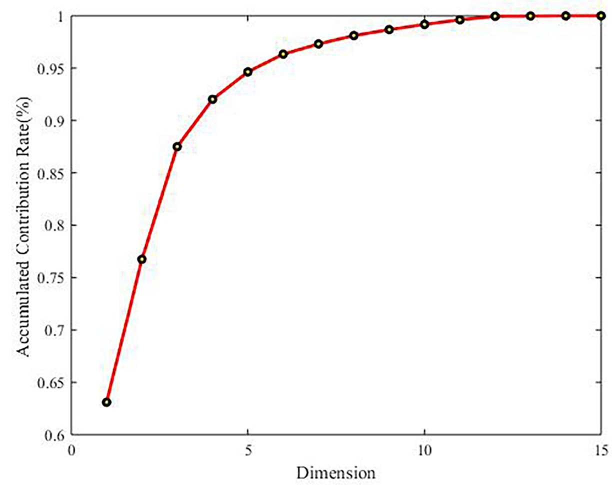


Fig. 11 Contribution rate of PCA.

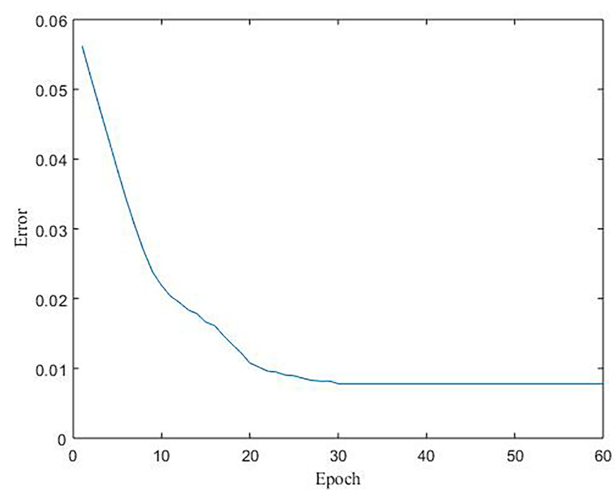
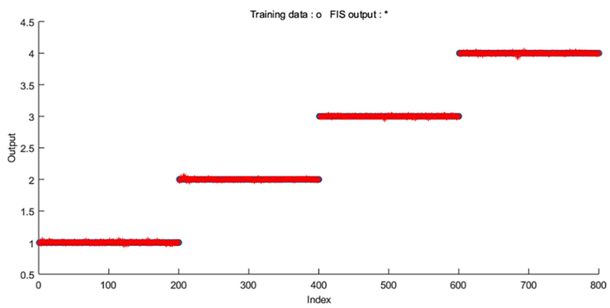
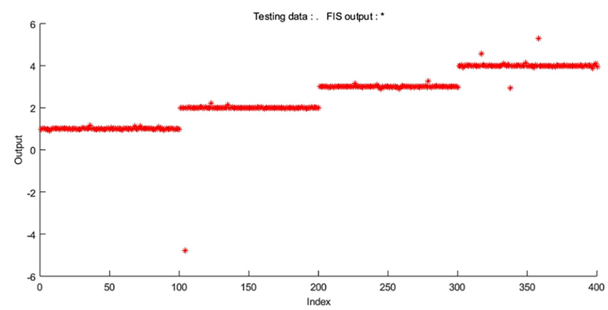


Fig. 12 Error of FNN.

Figure 11 shows the contribution rate of PCA. It is seen that the rate is over 92% after 4 feathers. So finally, we use the first four feathers for the input of FNN. Using the ANFIS tool box of MATLAB, we establish an FNN for classification. The Number of language variables for the inputs is 4. The membership function is a Gaussian function. After about 6 minutes, we get the result (800 training data, 400 testing data). The error becomes 0.078 after 60 epochs. The accuracy of the training data and testing data is shown in Figure 13. It is seen that the accuracy of training data is 100%, and the accuracy of testing data is 99% (four wrong points in 400).



(a)



(b)

Fig. 13 (a) Training result; (b) Testing result.

6 Conclusions

In this paper, the design and simulation of a system for non-destructive and automated sorting of apples were presented. The original data of apples were collected by the experimental platform. Color, texture, shape and size features of apples were extracted from the color image using color moment, wavelet transform, gray level co-occurrence matrix and pixel-level calculation methods. Moreover, the defect of apples could be represented by the curvature of the structured light strip, where the change in the curvature of the laser line reflected the state of the apple surface. Preliminary experiments indicated that the proposed FNN system performed well in the task of apple classification.

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