Journal of Food Engineering 104 (2011) 663–667

Contents lists available at ScienceDirect

Journal of Food Engineering

journal homepage: www.elsevier.com/locate/jfoodeng

Research Note

An adaptive neural-fuzzy inference system (ANFIS) for detection of bruises on Chinese bayberry (*Myrica rubra*) based on fractal dimension and RGB intensity color

Hong Zheng [a], Bo Jiang [b], Hongfei Lu [a,*]

[a] College of Chemistry and Life Science, Zhejiang Normal University, Jinhua 321004, China
[b] Department of Biological and Food Engineering, Changshu Institute of Technology, Changshu 215500, China

ARTICLE INFO

Article history:
Received 24 November 2010
Received in revised form 30 December 2010
Accepted 29 January 2011
Available online 4 February 2011

Keywords:
ANFIS
Bruise detection
Chinese bayberries
Fractal dimension
Myrica rubra
RGB

ABSTRACT

This paper introduces an adaptive neural-fuzzy inference system (ANFIS) model to detect bruises on Chinese bayberries as a function of fractal dimension (FD) and RGB intensity values. The ANFIS with different types of input membership functions (MFs) was developed. Our results showed that 'gauss2mf' MF performs much better than other mentioned MFs for defect inspection. The classification accuracy of the ANFIS with 'gauss2mf' MF was 100% and 78.57% for healthy and bruised fruits, respectively, and the total correct classification rate was 90.00%. Therefore, this study indicated the possibility of developing a potentially useful classification tool using the ANFIS technique based on FD and RGB values for detecting bruises of not only Chinese bayberries, but also of other fruits during processing, storage and distribution.

1. Introduction

Bruising is one of the major defects occurring on the fruit surface during harvest, transport and handling. The bruise affects not only the extrinsic quality of fruit, but also accelerates fruit spoilage. Thus, removing bruised fruit is essential to fruit commercialization. Baritelle and Hyde (2001) reported that an annual payback to reduce bruising in fruit and vegetable industries can be in billions of dollars worldwide. The automatic inspection of quality in the agro-industry, therefore, is becoming of great importance in order to decrease production costs and increase product quality (Brosnan and Sun, 2002). The Chinese bayberry (*Myrica rubra* Sieb. & Zucc.) is a highly perishable fruit due to its soft texture, no epicarp protection and the hot and rainy ripening season, so its bruise detection has become an increasingly important problem. Bruised areas are usually discoloration and surface structure destruction. Therefore, fractal dimension and RGB values of the fruit surface will be used as indicators for bruise detection in this paper.

In recent years, learning techniques have been widely applied to develop unsupervised systems for food quality evaluation (Du and Sun, 2006). The adaptive neural-fuzzy inference system (ANFIS) is a multilayer feedforward network, which uses neural network learning algorithms and fuzzy inference systems to model the input–output relationships (Jang and Sun, 1995). In comparison with other learning techniques, ANFIS has a higher speed of training, the most effective learning algorithm and simplicity of the software (Jang and Sun, 1995). Moreover, Altug et al. (1999) reported that ANFIS is faster in convergence and provides better results when applied without any pre-training. Therefore, interest in using ANFIS as a modeling tool in agriculture and food technology is increasing (Riverol et al., 2004; Ghoush et al., 2008; Madadlou et al., 2010). However, by taking account of these recent works, there is no published data in the literature on defects detection on red bayberries using ANFIS based on fractal dimension and RGB intensity values.

The aims of this research are (1) to evaluate the effectiveness of bruise detection on bayberries by fractal analysis and RGB values, (2) to develop ANFIS classification models for detecting bruises and (3) to compare the accuracy of classification models with different membership functions.

Abbreviations: ANFIS, adaptive neural-fuzzy inference system; FD, fractal dimension; MFs, membership functions; RGB, red, green and blue.

* Corresponding author. Tel.: +86 0579 8228 2284.
E-mail address: luhongfei63@yahoo.com.cn (H. Lu).

0260-8774/$ - see front matter
doi:10.1016/j.jfoodeng.2011.01.031

2. Materials and methods

2.1. Fruit materials and image acquisition

The choice of fruits, the dropping test and image acquisition are described in detail in our earlier paper (Lu et al., 2011).

2.2. Fractal dimension (FD) and RGB intensity values

The basic procedures for the calculation of FD are shown in Fig. 1: (i) the surface topology of fruits was studied with ImageJ plug-in Interactive 3D Surface Plot v2.32 (Barthel, 2008); (ii) the 3D surface image was converted to the binary image; (iii) the FD value was then determined by the box counting method of the ImageJ software. In addition, average RGB intensity values from fruit images were obtained using the color histogram tool of ImageJ.

2.3. ANFIS modeling

The ANFIS architecture of the first-order Takagi–Sugeno inference system is shown in Fig. 2(a), where, the ANFIS structure consists of five layers, namely, the fuzzification layer (I), the rule layer (II), the normalization layer (III), the defuzzification layer (IV), and the output layer (V).

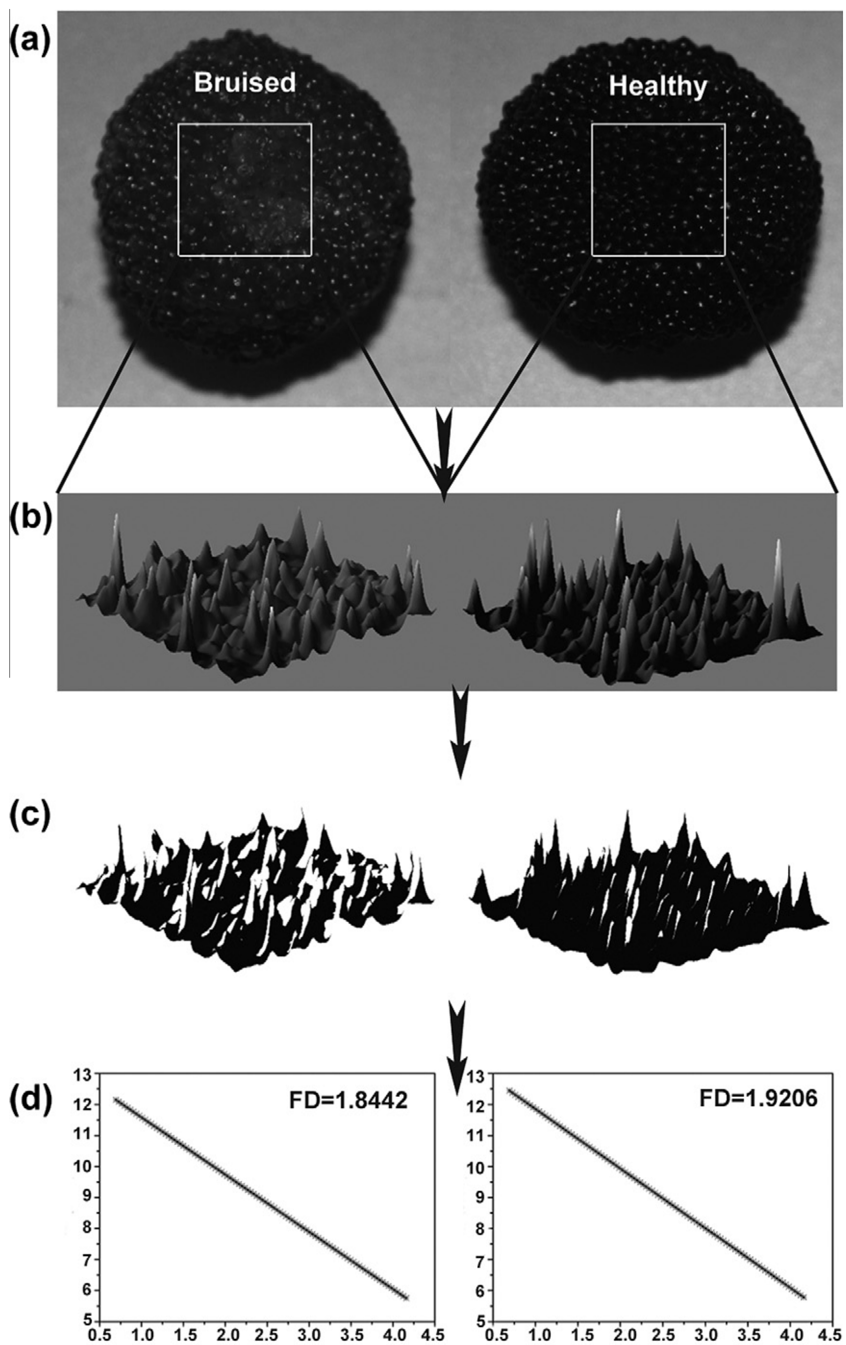

Fig. 1. Graphical representation of the fractal dimension (FD) calculated from the 3D surface plot of red bayberry surface. (a) Healthy and bruised fruits; (b) 3D surface plot of the fruit surface; (c) binary image; (d) the determination of FD by the box counting method.

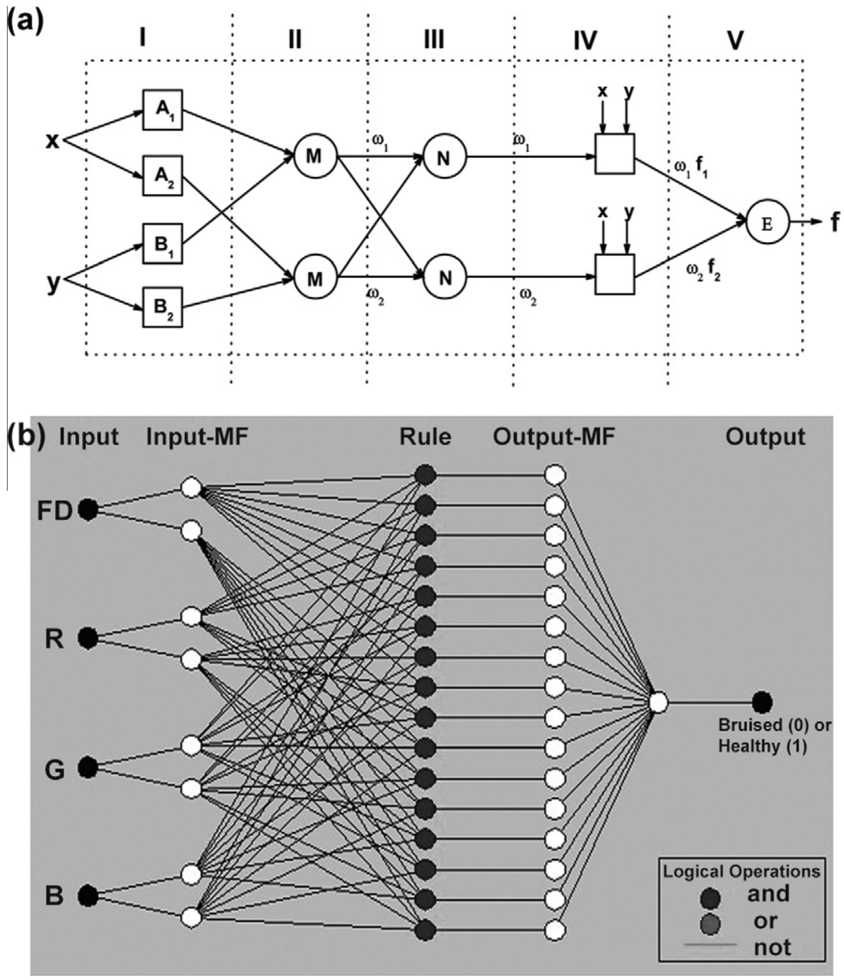

Fig. 2. ANFIS architectures: (a) the first-order Takagi–Sugeno inference system and (b) multiple input single output models consisting of four inputs (FD, R, G and B) and one output (healthy or bruised).

In this study, modeling was performed using ANFIS Toolbox in MATLAB (R2010a, the MathWorks Inc., USA) and Sugeno-type fuzzy inference systems were used in the modeling of detection of bruises on the Chinese bayberry. The grid partition method (Jang and Sun, 1995) is utilized to classify the input data and in making the rules. Fig. 2(b) shows the ANFIS structure of FD, R, G and B values as the four input parameters and two linguistic values (healthy or bruised) as the output parameters. We use eight different types of input MFs: 'trimf', 'trapmf', 'gbellmf', 'gaussmf', 'gauss2mf', 'psigmf', 'dsigmf', and 'pimf'. A linear function was used as output MFs. In addition, a hybrid learning algorithm that combines the least-squares estimator and the gradient descent method (Jang and Sun, 1995) is employed to determine the optimum values of the FIS parameters of the Sugeno-type.

3. Results and discussion

The FD and RGB values derived from healthy and bruised fruits were determined by using the ImageJ software, and shown in Fig. 3. One hundred and fifty data were used for the model. This data set was divided randomly into two subsets of 120 fruits for training and 30 fruits for testing purposes. The initial ANFIS model was generated using the grid partition, and the eight different types of MFs were used for the fuzzification of input data in the current study. Hybrid learning updates the parameters of adaptive neurons in each epoch to minimize the error (Jang and Sun, 1995). Fig. 4 demonstrates the MFs after developing the ANFIS model by grid partitioning.

After training the ANFIS model, prediction performance was tested. The performance of ANFIS with different types of MFs for detecting bruises on bayberries is reported in Fig. 5, and the classification accuracies are given in Table 1. According to Table 1, the best total classification accuracy of 90.00% was achieved by the ANFIS classifier with 'gauss2mf', followed by the classifiers with 'trimf' (86.67%), 'gaussmf', 'dsigmf' and 'psigmf' (83.33%), and 'trapmf' and 'gbellmf' (80.00%). Therefore, it can be concluded that the 'gauss2mf' MF results in the best correct classification rate. This MF is a combination of two gaussian membership functions determining the shape of the left and right curves. Vernieuwe et al. (2003) also reported that 'gauss2mf' MF performs much better than other mentioned MFs ('trimf', 'trapmf', 'gbellmf', and 'gaussmf') for the rainfall-discharge prediction.

Our previous study showed the classification accuracy of SVM based on RGB values was 89.47% for healthy fruits and 80.00% for bruised fruits, and the total accuracy rate was only 85.29% (Lu et al., 2011). In this study, however, the ANFIS classifier with 'gauss2mf' based on fractal parameters and RGB values achieved 100% and 78.57% accuracies for healthy and bruised fruits, respectively, and the total classification accuracy can reach up to 90.00%.

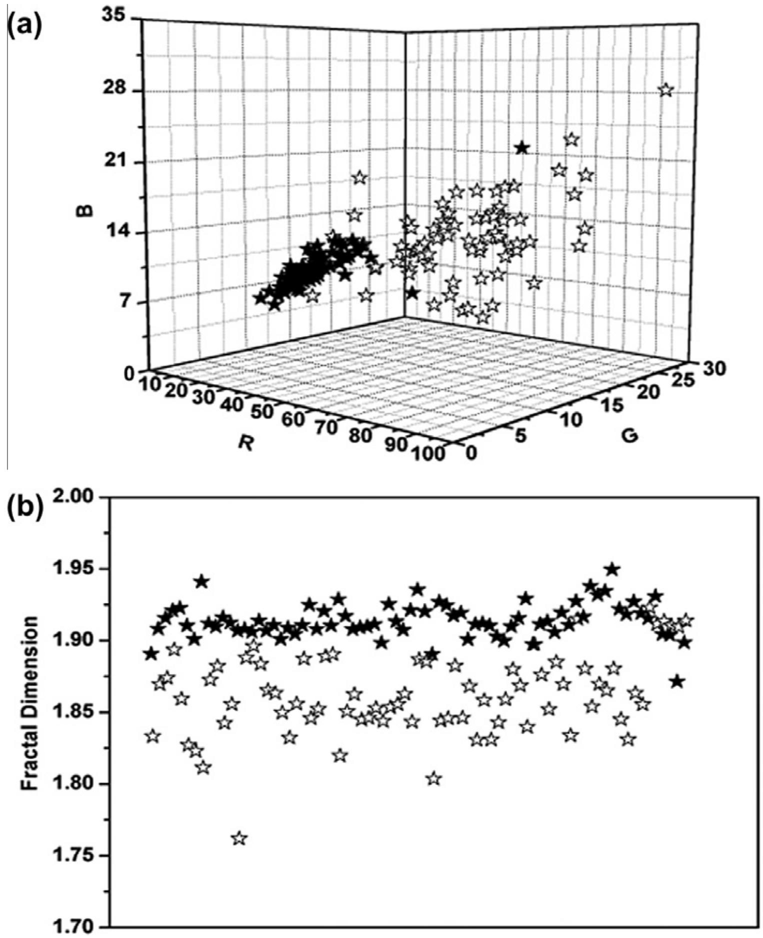

Fig. 3. The RGB values (a) and fractal dimension (b) derived from healthy (★) and bruised (☆) fruit surfaces.

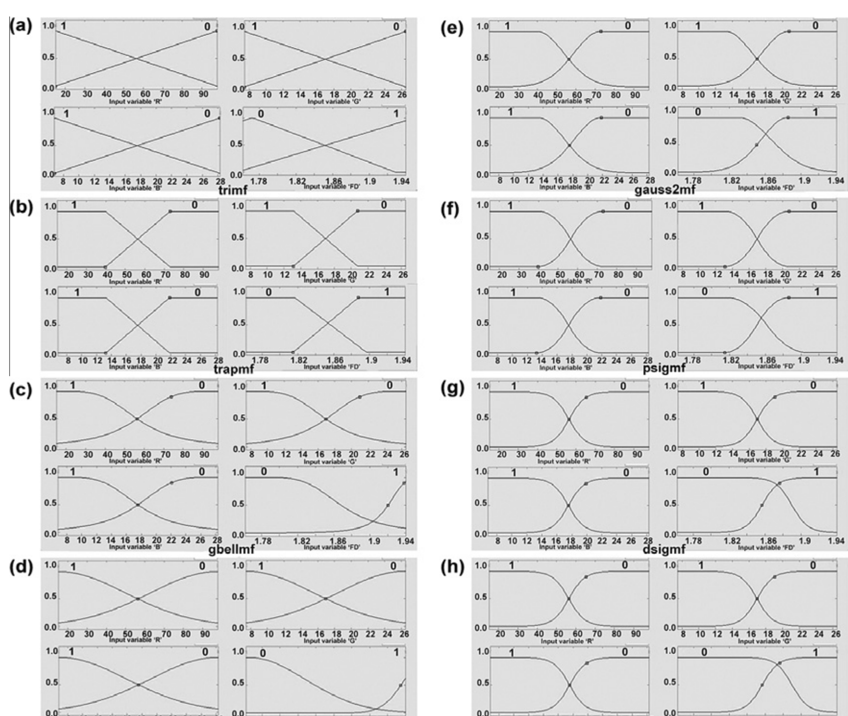

Fig. 4. The membership functions (MFs, eight different types) after developing the ANFIS by grid partitioning used in this study: (a) 'trimf', (b) 'trapmf', (c) 'gbellmf', (d) 'gaussmf', (e) 'gauss2mf', (f) 'psigmf', (g) 'dsigmf', and (h) 'pimf'. The output result of ANFIS is healthy (1) or bruised (0) fruits.

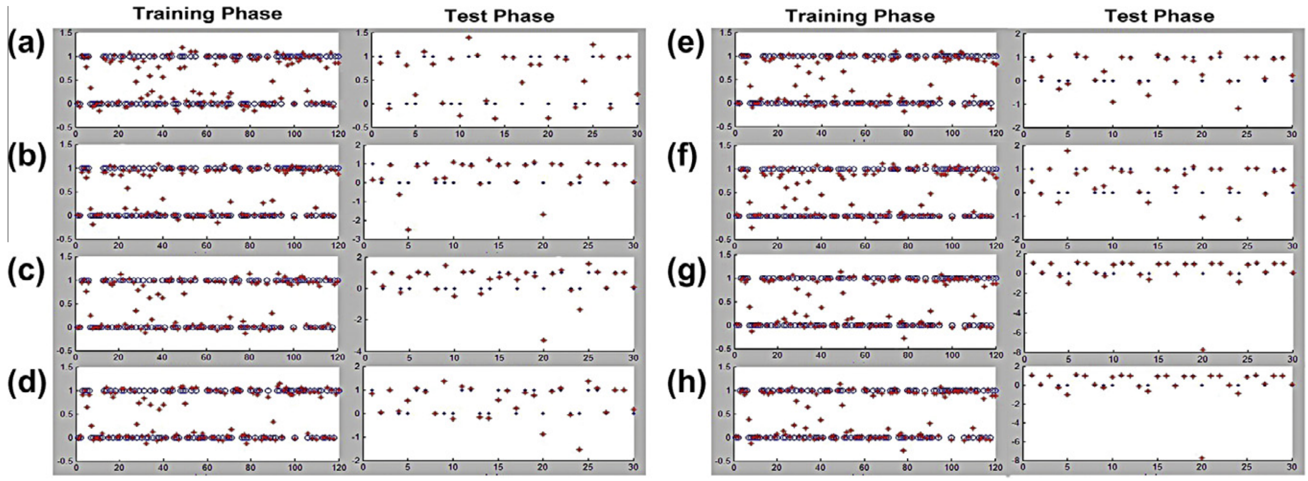

Fig. 5. The classification performance of ANFIS with different types of membership functions (MFs) for determining which red bayberries were bruised (0) or healthy (1) in training and test phases: (a) 'trimf', (b) 'trapmf', (c) 'gbellmf', (d) 'gaussmf', (e) 'gauss2mf', (f) 'psigmf', (g) 'dsigmf', and (h) 'pimf'; actual degree (○/●) and predicted degree (∗).

Table 1
The success rate for bruise detection based on ANFIS model with different types of input membership functions.

Membership functions	Healthy		Bruised		Total success rate
	True	False	True	False	
trimf	16/16 (100%)	0/16 (0.00%)	10/14 (71.43%)	4/14 (28.57%)	26/30 (86.67%)
trapmf	15/16 (93.75%)	1/16 (6.25%)	9/14 (64.29%)	5/14 (35.71%)	24/30 (80.00%)
gbellmf	16/16 (100%)	0/16 (0.00%)	8/14 (57.14%)	6/14 (42.86%)	24/30 (80.00%)
gaussmf	15/16 (93.75%)	1/16 (6.25%)	10/14 (71.43%)	4/14 (28.57%)	25/30 (83.33%)
gasuss2mf	16/16 (100%)	0/16 (0.00%)	11/14 (78.57%)	3/14 (21.43%)	27/30 (90.00%)
pimf	15/16 (93.75%)	1/16 (6.25%)	8/14 (57.14%)	6/14 (42.86%)	23/30 (76.67%)
dsigmf	16/16 (100%)	0/16 (0.00%)	9/14 (64.29%)	5/14 (35.71%)	25/30 (83.33%)
psigmf	16/16 (100%)	0/16 (0.00%)	9/14 (64.29%)	5/14 (35.71%)	25/30 (83.33%)

4. Conclusion

In this study, ANFIS models based on fractal analysis and RGB intensity values were developed to sort the Chinese bayberries based on the presence of bruises. Results show that the best total classification accuracy of 90.00% could be achieved from the ANFIS model with 'gauss2mf'. In addition, the total correct classification rates of the ANFIS classifiers were 86.67% with 'trimf', 83.33% with 'gaussmf', 'dsigmf' and 'psigmf' and 80.00% with 'trapmf' and 'gbellmf'. Therefore, these results reveal that a new approach studied here can be adequate for the task of bruise detection on the Chinese bayberry.

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