Journal of Agricultural Technology 2013 Vol. 9(7):1703-1713
Available online http://www.ijat-aatsea.com
ISSN 1686-9141

Date fruits grading based on some physical properties

V. Nozari[1*] and M. Mazlomzadeh[2]

[1]Department of Mechanic, Islamic Azad University,Izeh Branch, Khoozestan, Iran, [2] Higher Educational complex of Saravan, Saravan, Iran

V. Nozari and S.M.Mazloumzadeh (2013) Date fruits grading based on some physical properties. Journal of Agricultural Technology 9(7):1703-1713.

Mozafati is the most valuable variety of the dates in Iran and contains 28 percent date production of this country and Iran is the second largest producer in the world. Date grading is an important process for producers and affects the fruit quality evaluation and export market. In this research Adaptive Network Fuzzy Inference System (ANFIS) was applied as a decision making technique to classify the Mozafati dates based on weight and some geometric parameters. Four date parameters including the weight, length, width and thickness were measured for 1000 date fruits. These dates were graded by both a human expert and ANFIS. Grading results obtained from fuzzy system showed 93.5% general conformity with the experimental results.

Key words: ANFIS, physical parameters, whight, date fruit.

Introduction

In recent years, efforts to develop automated fruit classification systems have been increasing. Date grading is an important process for producers and affects the fruit quality evaluation and export market. However, the high costs, low speed andvariation associated with manual sorting have been forcing the post harvest industry to apply mechanization and automation in sorting operations(Anon, 2010). Automatic segregation of various date fruits cultivars required a deep knowledge of each cultivar physical characteristics. The aim of grading is to produce packed fruit which is uniform in size, shape, color, texture and moisture. For each variety the standards are different. Client's requirements can also determine the criteria during grading. For example varieties with a certain texture can be mechanically sorted for size using sorting machines (Zaid, 2002). Relatively few papers on date quality evaluation have appeared in the literature. Based on the evaluation criteria, they can be categorized into: dryness (Wulfsohn *et al*. 1993), firmness (Schmilovitch *et al*. 1995), moisture

*Corresponding author: Nozari, V; e-mail: valinozari2000@gmail.com

(Dull *et al*. 1991; Schmilovitch *et al*. 2003, 2006), and automatic date grading (Lee *et al*. 2008).

AL-Janobi (1998) applied the line-scan based vision for inspecting fast moving on a grading conveyor belt date fruits, where it is capable of determining the color/quality of date fruits. AL-Janobi (2000) developed a color computer vision system consisting of a micro-computer with an image frame grabber and a charged-coupled device (CCD) color camera for sorting and grading Saudi dates based on color threshold technique. Many attempts have been made to make this process more efficient by automatic grading, but owing to the complexity of the processes and the difficulty of imitating human senses, especially that of vision, no perfect solution has yet been found for date grading without human hands.

Self-learning techniques such as neural networks and fuzzy logic (Zadeh, 1965) seem to represent a good approach. Adaptive Network-based Fuzzy Inference System (ANFIS) can be used. It provides a mathematical framework that can convert a complicated set of variables into an automatic evaluation strategy (Mazloumzadeh *et al*. 2008, 2009).

ANFIS is a fuzzy based system that uses Artificial Neural Networks (ANNs) theory in order to determine the properties (fuzzy membership functions and fuzzy rules) of data samples. ANFIS combines fuzzy logic and ANNs, by utilizing the mathematical properties of ANNs in tuning rule based Fuzzy Inference Systems (FIS) that approximates the way man processes information. ANFIS which is a specific approach in neuro-fuzzy developments has shown significant promise in modeling nonlinear functions. It learns features of the data set and adjusts the system characteristics according to a given error criterion. Fuzzy set theory has been applied to a wide range of problems in control, image processing, filter design, data clustering, pattern recognition, and event classification .

In recent years, more and more applications of fuzzy theory to agriculture have been reported: Chao *et al*. (1999) used a neuro-fuzzy based image classification system that utilizes color-imaging features of poultry viscera in the spectral and spatial domains was developed for this approach. Combining features of chicken liver and heart, a generalized neuro-fuzzy model was designed to classify poultry viscera into four classes. The classification accuracy was 86.3% for training and 82.5% for validation. Verma (1995) developed a fuzzy decision support system (DSS) to aid decisions related to quality sorting of tomatoes. Lameck *et al.*(2002) used application of fuzzy-neural network in classification of soils using ground penetrating radar imagery. Classifications of uniform plant, soil, and residue color images were conducted with fuzzy inference systems by Meyer (2004). Mazloumzadeh *et al*.

(2008) used the Mamdani fuzzy inference system (MFIS) to evaluate and classify alternative date harvesting machines in the Iranian date harvest industry. The results obtained with MFIS showed an 86% agreement with those obtained by an expert. Grading and classification using fuzzy logic is always successful and may be better than conventional approaches, as shown by Simonton (1993), Chen and Roger (1994), Mirabbasi *et al.* (2008), Mazloumzadeh *et al.* (2008, 2009), Alavi *et al.* (2010) and Alavi (2012).

The main purpose of this study was to introduce a method of date quality grading using fuzzy logic and to compare the accuracies of the predicted results with grades directly suggested by a human expert.

Materials and methods

Fuzzy inference system

Zadeh (1965) introduced the theory of fuzzy sets. This theory proposes making the membership function operations over the range of real numbers [0, 1]. New operations for the calculation of logic membership functions were proposed and showed to be a reasonable tool to generalize classic logic. The use of linguistic variables and mathematical relationships in this technique, gives the decision making process more adequacy. Fuzzy logic systems are particularly suited to model the relationship between variables in environments that are either ill-defined or very complex. Fuzzy systems provide the means of representing the expert knowledge of humans about the process in terms of fuzzy (IF–THEN) rules. A fuzzy rule is the basic unit for capturing knowledge in fuzzy systems. A fuzzy rule, like a conventional rule in artificial intelligence, has two components: an 'if' part and a 'then' part which are also referred to as antecedent and consequent, respectively.

Adaptive Network-based Fuzzy Inference System (ANFIS)

ANFIS is an adaptive-network-based fuzzy inference system. ANFIS was used for developing TSK type of FIS. It can be trained by a Back-Propagation (BP) algorithm to model some collection of input/output data for the prediction of output according to the input. Functionally, it is equivalent to the combination of neural network and FIS.

ANFIS was first introduced by Jang (1993) which is suitable for TSK type of FIS proposed by Takagi and Sugeno (1985) and Sugeno and Kang (1988). In this paper, to state the general framework of ANFIS a system containing two inputs x and y and one output f are considered.

As mentioned above, for better explaining of the model we suppose there are two input variables x and y. We assume that each input has two membership functions A_1 and A_2 and B_1 and B_2, respectively. Then, a first-order TSK type of fuzzy if-then rule could be set up as:

$$\begin{aligned}&\textit{Rule } i: \textit{IF } x \textit{ is } A_i \textit{ and } y \textit{ is } B_i\\&\textit{THEN } f_i = p_i x + q_i y + r_i \quad \mathrm{i} = 1,2,...,\mathrm{n}\end{aligned} \tag{1}$$

where f_i are the outputs within the fuzzy region specified by the fuzzy rule, n is the number of rules and p_i, q_i and r_i are the design parameters that are determined during the training process. The architecture of the ANFIS is shown in Fig. 1. The ANFIS consists of five layers including, the fuzzy layer, product layer, normalized layer, de-fuzzy layer and total output layer.

In the first layer (fuzzy layer), x and y are the inputs of adaptive nodes A_i and B_i, respectively. A_i and B_i are the linguistic labels used in the fuzzy theory for describing the membership functions. The outputs of layer 1 are the fuzzy membership degree of the inputs which can be expressed as below:

$$O_i^1 = \mu_{A_i}(x),\ i = 1,2,...,n \tag{2}$$

$$O_i^1 = \mu_{B_i}(y),\ i = 1,2,...,n \tag{3}$$

where $\mu_{A_i}(x)$ and $\mu_{B_i}(y)$ denote the membership functions degree.

Second layer is the product layer that consists of two fixed nodes labeled with Π. The output w_1 and w_2 are the weight functions of the next layer. The outputs of this layer can be represented as:

$$O_i^2 = w_i = \mu_{A_i}(x)\mu_{B_i}(y),\ i = 1,2,...,n \tag{4}$$

where O_i^2 is the output of layer 2.

The third layer is the normalized layer, whose nodes are also fixed and labeled with N. The outputs of this layer can be represented as:

$$O_i^3 = \overline{w}_i = w_i \Big/ \sum_{i=1}^{n} w_i,\ i = 1,2,...,n \tag{5}$$

where O_i^3 is the output of Layer 3.

The fourth layer is the defuzzification layer. In this layer, the nodes are adaptive nodes. The relationship between the inputs and output of this layer can be expressed as below:

$$O_i^4 = \overline{w}_i(p_i x + q_i y + r_i) \quad i = 1,2,...,n \tag{6}$$

where O_i^4 is the output of Layer 4 and p_i, q_i and r_i are the constant parameters of the node.

The fifth layer is the output layer, whose node is labeled with S. This node performs the summation of all incoming signals, which represents the results of cleaning rates. The overall output of the model is given by:

$$O_i^5 = \sum_{i=1}^{n} \overline{w}_i f_i \quad i = 1,2,...,n \tag{7}$$

where O_i^5 is the output of layer 5 and the output of the system.

The proposed evaluation system

In this study, we have four sets of input data: weight, length, width and thickness. To determine the ANFIS input/output data, approximately 1000 Mozafati dates were selected from different locations. A five terms rating system of Very good, Good, Medium, Bad and Very bad was established and applied to all 1000 dates. A numerical value was then assigned to each of the above mentioned terms: i.e. Very good=1, Good=2, Medium=3, bad=4 and Very bad=5.

TheANFIS model was implemented in Matlab software system. Matlab supports first-order ANFIS that has a single output and unitary weights for each rule (MathWorks, 2004).

In the ANFIS procedure, utilizing date grading a score between 1 and 5 to each date sample was assigned. The data set was divided into twosmaller sets namely: the training data set (700 samples) and the testing data set (300 samples). Purpose of the training process was tominimize the error between actual target and ANFIS output through training. This allowed ANFIS tolearn features from the training data that it observes, and implementthem in the system rules. In the performance phase,a new data set (test data) that is not present in the training set wasintroduced to the learned system for evaluation.

If the test error was adequatelysmall, it indicated that thesystem has a good generalized capability.

The training data set was used to train the ANFIS, whilethe testing data set was used to verify the accuracy and theeffectiveness of the trained ANFIS model for the computationof the date quality evaluation. Fuzzy system was implemented using the following FIS properties (Table 1):

Table 1. Specifications of the fuzzy inference system

Type	**Sugeno**
Decision method for fuzzy logic operators AND (intersection)	Product
Decision method for fuzzy logic operators OR (union)	Probabilistic or
Output combination method (Defuzzification)	Weighted average
Number of membership functions for input #1	11
Number of membership functions for input #2	11
Number of membership functions for input #3	11
Number of membership functions for input #4	11
Type of membership functions	Gaussian
Number of rules	11
Output function	Linear
Number of training epochs	250

The main structure of the proposed method is given by Fig. 1. Here, we used the inputs (correspond to x and y in the above section) and the output was considered to be the quality of date (correspond to f).

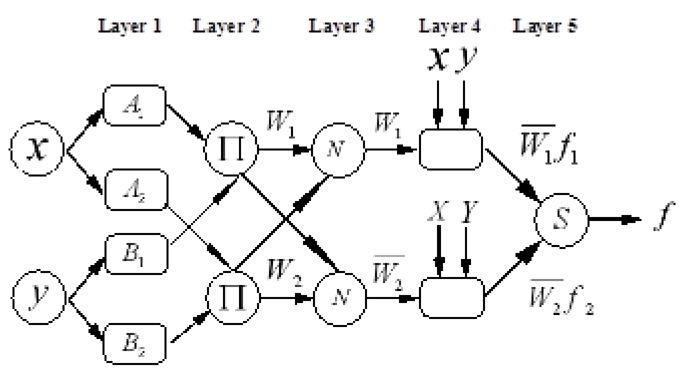

Fig. 1. ANFIS architecture.

The FIS parameters with minimum validation set error were selected as optimal. Using the training data set, Matlab simulator found the best performance by ANFIS in modeling the problem at hand with 11 fuzzy rules and 11 Gaussian membership functions for each input. Fig. 2 also shows the fuzzy rule architecture of the ANFIS model using Gaussian shaped membershipfunctions.

Results and discussions

In this study, the concentration Mozafati date values of length, width and thickness were combined together by an ANFIS model to generate a new evaluation system that can be applied to evaluate Mozafati dates. We used the proposed method to learn the input-output relation according to learning data set. The learning phase the ANFIS firstly made the suitable membership functions for each input. In the sequel, the membership functions were tuned according to error correction training method by using BP algorithm. Also, the constant parameter of the linear output functions were adapted during to learning phase based on LMS algorithm. ANFIS model utilizes 300training data over the 100training periods.

ANFIStest results (predicted data) were compared with results obtained from expert (measured data) in Fig. 2. Horizontal access shows 300 testing data (30% of 1000 data) and vertical access shows date quality classes from Very good to Very bad. From thisfigure, one can see that the results obtained by ANFIS are in good agreement (93.5%) with theresults of the expert.

In a previous study (Alavi, 2012), Mamdani Fuzzy inference systems (MFIS) was used to evaluate date quality and was found to have 91% accuracy. However, the ANFIS classifier presented in this study was found to be of higher accuracy than the MFIS model. In that system, in order to achieve the best results, optimal membership functions were selected through trial and error for that specific inputs; which was the main deficiency of that system. However, the proposed approach can be used in a general way for every data set.

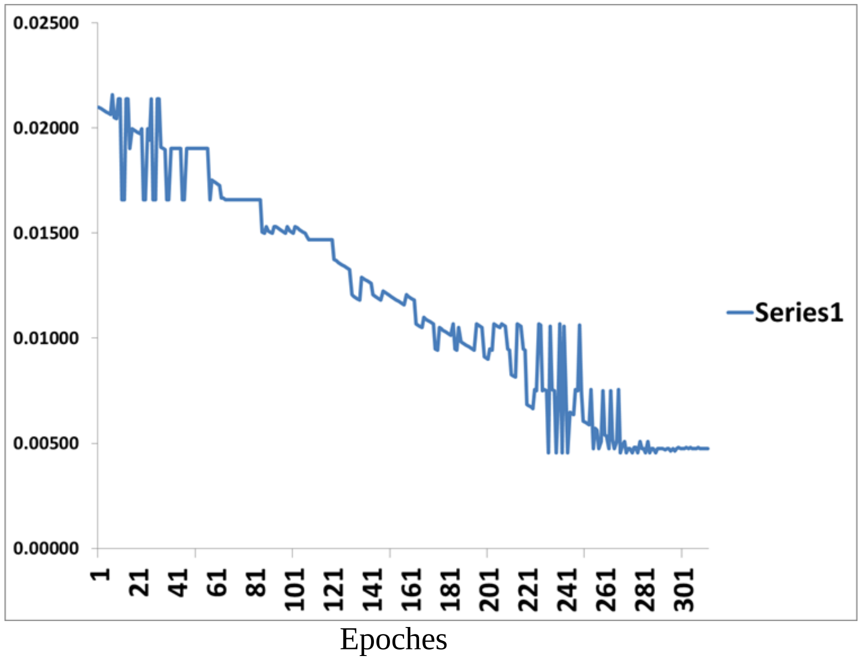

Fig. 2. The curve of network error convergence of ANFIS

In commonly used fuzzy inference systems, optimal membership functions were selected by trial and error. Furthermore, the rule structure was predetermined by an expert person for themodel. In practice, these models may not performsatisfactorily due to limited knowledge of the experts, and improper selection of membership parameters (Jang *et al*. 1997). In the proposed ANFIS based methodology, theparameters were tuned automatically during the learning stage, hencethe membership functions can properly represent the non-linear behavior of thesystem being studied with optimal performance.

In comparison with application of diagrams under the same conditions, the proposed methodology significantly decreases calculation time. For example, to evaluate 1000 date samples one can spend up to 2 hours, whereas, the proposed system decreases this time to only 2 minutes.

Membership functions to be used for agricultural applications should contain the non-linearity that exists between the input features and output categories. The nature of agricultural systems created the need for modeling systems that were robust, noise tolerant, adaptable for multiple uses, and were extensible.

Lee *et al.* (2008) developed a machine vision system for automatic date grading using digital reflective near-infrared imaging. They could grade date samples with accuracy of 87%. Fuzzy logic in date grading has not been used yet as a grading technique in date industry, but many studies show it was powerful technique for grading and classifying. For example,Shahin and Tollner (1997) obtained 72% classification accuracy in classifying apples according to their water core features using fuzzy logic.

Kavdir and Guyer (2003) used fuzzy technique for apple grading. Grading results obtained from their system showed 89% general agreement with the results from the human expert. They combine trapezoidal or triangular membership functions with an exponential function, as in their study, improved classification accuracy of the system. In this research ANFIS was successfully applied to serve as a decision making technique in grading dates.

The application of soft computing techniques such as fuzzy logic to fruit classification will enhance the automation in this sector. In future studies, the performance of classification based on fuzzy logic should be compared with other mechanical and automated sorting techniques in addition to manual sorting.

Conclusion

A new application of ANFIS to evaluate and classify date quality was presented. In this study, the concentration values of weight, length, width and thickness were combined together through an ANFIS model to generate a new method that can be used instead of the expert. ANFIS models were powerful tools for building complex nonlinear relationships between inputs and outputs by learning from a data set.

The comparison between results of ANFIS and expert showed that the overall classification accuracy of the ANFIS model was 93.5%. It showed that the ANFIS model has much better predicting capability than the MamdaniFuzzy Inference System (MFIS) with only 91% accuracy, which was created by an expert. Results indicated that ANFIS modeling is a promising alternative to the traditional approach and it significantly decreases calculation time in determining date quality.

References

Alavi, N. (2012). Using Mamdani fuzzy inference system for quality determination of Mozafati dates. Journal of the Saudi Society of Agricultural Sciences, http://dx.doi.org/10.1016/j.jssas.2012.10.001.

Alavi, N. Nozari, V. Mazloumzadeh, S.M., Nezamabadi-pour, H. (2010).Irrigation water quality evaluation using adaptive network-based fuzzy inference system.Paddy and Water Environment.DOI 10.1007/s10333-010-0206-6.

AL-Janobi, A.A. (1998). Colorline scan system for grading date fruits. ASAE Annual International Meeting, Orlando, Florida, USA, 12-16 July, ASAE Paper No. 983028 .

Al-Janobi, A.A. (2000). Date inspection by color machine vision. Journal of King Saud University, 12(1):69-79.

Anon. (2010). Iranian ministry of agricultural statistics. http://www.agri-jahad.ir.

Chao, K. Chen,Y. Early, R.H., Park, B. 1999.Color image classification systems for poultry viscera inspection. Applied Engineering in Agriculture. 15(4):363-369.

Chen, S., Roger, E.G. (1994). Evaluation of cabbage seedling quality by fuzzy logic. ASAE Paper No. 943028, St. Joseph, MI .

Dull, G.G. Leffler, R.G. Birth, G.S. Zaltzman, A., Schmilovitch, Z.E. (1991). The near infrared determination of moisture in whole dates.HortScience, 26 (10):1303–1305.

Jang JSR. (1993). ANFIS: adaptive-network-based fuzzy inference system. IEEE Trans on Sys, Man, and Cybern, 23(3):665–685.

Jang JSR, Sun C, Mizutani E. (1997). Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence. Prentice-Hall, NJ, America.

Kavdir, I., Guyer, D.E. (2003). Apple Grading Using Fuzzy Logic.Turkish Journal of Agriculture. 27:375-382.

Lameck, O. Odhiambo, Robert S. Freeland, Ronald E. Yoder., Wesley Hines, J. (2002). Application of fuzzy-neural network in classification of soils using ground-penetrating radar imagery. ASAE Paper No. 023097. St. Joseph, MI .

Lee, D-J *et al*. (2008). Development of a machine vision system for automatic date grading using digital reflective near-infrared imaging. Journal of Food Engineering, 86:388–398.

MathWorks.(2004). Fuzzy Logic Toolbox User's Guide, for the Use of Matlab.The Math Works Inc. http://www.mathworks.com./

Mazloumzadeh, S.M. Shamsi, M., Nezamabadi-pour, H. (2008). Evaluation of general-purpose lifters for the date harvest industry based on a fuzzy inference system. Computers and Electronics in Agriculture, 60, 60-66. doi:10.1016/j.compag.2007.06.005.

Mazloumzadeh, S.M. Shamsi, M., Nezamabadi-pour, H. (2009. Fuzzy logic to classify date palm trees based on some physical properties related to precision agriculture, precision Agriculture. doi:10.1007/s11119-009-9132-2.

Meyer, G.E. (2004). Digital camera operation and fuzzy logic classification of uniform plant, soil, and residue color images. Applied Engineering in Agriculture. 20(4):519-529 .

Mirabbasi, R. Mazloumzadeh, S.M., Rahnama, M.B. (2008). Evaluation of irrigation water quality using fuzzy logic. Res J Environ Sci 2: 340-352. doi: 10.3923/rjes.2008.340.352.

Schmilovitch, Z. Zaltzman, A. Hoffman, A., Edan, Y. (1995). Firmness sensor and system for date sorting. Applied Engineering in Agriculture. (4),554–560.

Schmilovitch, Z. Hoffman, A. Egozi, H. Grinshpun, J., Korotin, B. (2003). System determination of single date water content by novel RF device. In: Presentation at the 2003 ASAE Annual International Conference, Las Vegas, Nevada, USA 27–30 July 2003.

Schmilovitch, Z. Hoffman, A. Egozi, H., Grinshpun, J. (2006). Determination of single-date water content by a novel RF device. Applied Engineering in Agriculture, 22(3):401–405.

Shahin, M.A., Tollner, E.W. (1997). Detection of watercore in apples using X-ray linescans feature extraction and classification. In: Proceedings of the Sensors for Nondestructive Testing International Conference and Tour, pp. 389–400.

Simonton, W. (1993). Bayesian and fuzzy logic classification for plant structure analysis. ASAE Paper No. 933603, St. Joseph, MI .

Sugeno M, Kang GT .(1988). Structure identification of fuzzy models. Fuzzy Sets and Systems 28, 15.

Takagi T, Sugeno M .(1985). Fuzzy identification of systems and its applications to modeling and control. Trans on Sys, Man, and Cybern, 15(1):116-132.

Verma, B. (1995). Application of fuzzy logic in post harvest quality decisions. Proceedings of the National Seminar on Post harvest Technology of Fruits. Bangalore, India: University of Agricultural Sciences.

Wulfsohn, D. Sarig, Y., Algazi, R.V. (1993). Defect sorting of dry dates by image analysis. Canadian Agricultural Engineering. 35(2):133–139.

Zadeh, L.A. (1965). Fuzzy sets. Information and Control, 8:338-353.

Zaid, A. (2002). Date palm cultivation, FAO publication No. 156, Rome.

(Received 19 April 2013; accepted 22 December 2013)