Journal of Agricultural Technology 2012 Vol. 8(4): 1243-1254
Available online http://www.ijat-aatsea.com
ISSN 1686-9141

Date grading using rule-based fuzzy inference system

N. Alavi*[1]

[1]Department of Agricultural Machinery, Shahid Bahonar University of Kerman, kerman, Iran,

N. Alavi (2012) Date grading using rule-based fuzzy inference system. Journal of Agricultural Technology 8(4): 1243-1254.

Date grading is an important process for producers and affects the fruit quality evaluation and export market. However, the high costs, low speed and variation associated with manual sorting have been forcing the post harvest industry to apply mechanization and automation in sorting operations. As a step toward mechanized grading, in this research Mamdani fuzzy inference system was applied as a decision making technique to classify the Mozafati dates. Three date quality parameters including the quantity of juice, size and freshness were measured for 100 date fruits in one orchard. These dates were graded by both a human expert and a fuzzy inference system designed for this purpose. Grading results obtained from fuzzy system showed 86% general conformity with the results from the human expert.

Key words: Date grading, fuzzy logic, fuzzy inference system

Introduction

In recent years efforts to develop automated fruit classification systems have been increasing. 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: moisture (Dull *et al.*, 1991a; Schmilovitch *et al.*, 2003, 2006), water and soluble solids (Schmilovitch *et al.*, 1997, 1999, 2000), firmness (Schmilovitch *et al.*, 1995), dryness (Wulfsohn *et al.*, 1993) and automatic date grading (Lee *et al.*, 2008).

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)

* Corresponding author: Alavi, N.; e-mail: seyed.naser.alavi@gmail.com

seem to represent a good approach. Fuzzy logic is an extension of Boolean logic dealing with the concept of partial truth. Whereas classical logic holds that everything can be expressed in binary terms (0 or 1, black or white, yes or no), fuzzy logic replaces Boolean truth-values with degrees of them. Fuzzy logic permits the use of linguistic values of variables and imprecise relationships for modeling system behavior and it is a powerful concept for handling non-linear, time-varying and adaptive systems. 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. Simonton (1993) and Chen and Roger (1994) used FL in the classification of plant structures. They found good agreement between the results from fuzzy prediction and human experts. 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 *et al*. (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 85% agreement with those obtained by an expert. The main purpose of this study was to introduce a method of date grading using fuzzy logic and to compare the accuracies of the predicted results with grades directly suggested by a human expert.

Materials and methods

Components of fuzzy models

In classical models variables have real number values, the relationships are defined in terms of mathematical functions, and the outputs are numerical values "crisp". Models with fuzzy logic have variables which influence system behavior and relationships among the variables which describe the system. In fuzzy logic, the values of variables are expressed by linguistic terms such as "large, medium, and small", the relationships are defined in terms of if-then rules, and the outputs are fuzzy subsets which can be made "crisp" using defuzzification techniques. The crisp values of system variables are fuzzified to express them in linguistic terms.

Fuzzification is a method for determining the degree of membership that a value has to a particular fuzzy set. This is determined by evaluating the membership function of the fuzzy set for the value.

Fuzzy expert system

Human reasoning can handle uncertain and vague concepts in an appropriately manner, however, it cannot be expressed precisely. Fuzzy logic provides a methodology to model uncertainty and the human way of thinking, reasoning and perception (Abraham, 2005). In Boolean logic, we have only two concepts of 'True' and 'False', which are represented by 1 and 0, respectively. This means any proposition can be true or false. Fuzzy logic is an extension of Boolean logic that allows intermediate values between these two extremes. In this approach, the classical theory of binary membership in a set is extended to incorporate memberships between 0 and 1. This means each proposition can be true and false to a degree simultaneously. Let X be a space of objects and$x$ x be an element of X . A classical set $A, A \subseteq X,$ is defined as a collection of elements $x \in X,$ such that x can either belong or not belong to the set A. In other words, the set A is described by

$$A = \{x | x \in X\}, \tag{1}$$

whereas, a fuzzy set A in X is defined by

$$A = \{(x, \mu_A(x)) | x \in X\}, \tag{2}$$

where $\mu_A(x)$ is called the membership function for the fuzzy set A. Here, A is a linguistic term (label) that is determined by the fuzzy set. The membership function maps each element of X to a membership grade between zero and one $(\mu_A(x) \in [0,1])$. For example, this set can present X as 'Medium', which is a linguistic term that can be described by a fuzzy set with soft boundaries. Figure 1 shows two sets, one based on Boolean logic and the other on fuzzy logic.

Fuzzy inference system

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. Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. The goal is to obtain a conclusion consisting of one or more consequents from a premise consisting of one or more antecedents. The mapping then provides a basis from which decisions can be made, or patterns discerned. The process of fuzzy inference involves: membership functions, fuzzy logic operators, and if-then rules. There are two types of fuzzy inference systems that can be implemented in the Fuzzy Logic Toolbox: Mamdani-type and Sugeno-type. These two types of inference systems vary somewhat in the way outputs are determined. 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. The main structure of the fuzzy rule is given by Eq. 3.

$$IF \quad \text{<antecedent>} \quad THEN \quad \text{<consequent>} \tag{3}$$

The antecedent of a fuzzy rule has a condition that can be satisfied to a degree. Like conventional rules, the antecedent of a fuzzy rule may combine multiple simple conditions into a complex one using AND, OR and NOT logic operators. The consequent of a fuzzy rule can be classified into two main categories: Fuzzy consequent (Eq. 4, in which C is a fuzzy set), functional consequent (Eq. 5, in which p, q and r are constant).

Basically, fuzzy inference systems (FIS) incorporate an expert's experience into the system design and they are composed of 4 blocks (Fig. 2). A FIS comprises a fuzzifier that transforms the 'crisp' inputs into fuzzy inputs by membership functions that represent fuzzy sets of input vectors, a knowledge-base that includes the information given by the expert in the form of linguistic fuzzy rules, an inference-system (Engine) that uses them together with the knowledge-base for inference by a method of reasoning and a defuzzifier that transforms the fuzzy results of the inference into a crisp output using a defuzzification method (Herrera and Lozano, 2003).

The knowledge-base comprises two components: a data-base, which defines the membership functions of the fuzzy sets used in the fuzzy rules, and a rule-base comprising a collection of linguistic rules that are joined by a specific operator. The generic structure of a FIS is shown in Fig. 2. Based on the consequent type of fuzzy rules, there are two common types of FIS, which vary according to differences between the specifications of the consequent part (Eqs. 4 and 5). The first fuzzy system uses the inference method proposed by Mamdani in which the rule consequence is defined by fuzzy sets and has the following structure (Mamdani and Assilian 1975).

$$IF \quad x \text{ is } A \quad and \quad y \text{ is } B \quad THEN \quad f \text{ is } C. \tag{4}$$

The second fuzzy system proposed by Takagi, Sugeno and Kang (TSK) contains an inference engine in which the conclusion of a fuzzy rule comprises a weighted linear combination of the crisp inputs rather than a fuzzy set (Takagi and Sugeno, 1985). The TSK system has the following structure

$$IF \quad x \ is \ A \quad and \quad y \ is \ B \qquad THEN \qquad f = px + qy + r\,, \qquad (5)$$

where p, q and r are constant parameters. The TSK models are suitable for approximating a large class of non-linear systems.

The knowledge-base containing the database and rule-base of an FIS can be constructed from an expert's knowledge. For this, the expert selects the membership functions and rules. In this way, fuzzy models can help in extracting expert knowledge at an appropriate level.

Fuzzy systems can also be constructed from data, which alleviates the problem of knowledge acquisition. Various techniques have been used to analyze the data with the best possible accuracy. There are two common approaches for constructing a FIS based on available data. In the first, often the rules of the fuzzy system are designated *a priori* and the parameters of the membership functions are adapted during the learning process from input to output data using an evolutionary algorithm, such as a genetic algorithm. In the second approach, the fuzzy system can be generated from data by hybrid neural nets. The neural net defines the shape of the membership functions of the premises. This architecture and learning procedure is called an adaptive network-based fuzzy inference system (Jang *et al*., 1997).

The Sugeno and Mamdani types of fuzzy inference systems can be implemented in the fuzzy logic toolbox of MATLAB (Mathworks, 2004). When the output membership functions are fuzzy sets, The MFIS is the most commonly used fuzzy methodology (Mazloumzadeh *et al*., 2008). The MFIS in Matlab was selected to evaluate and classify the data on productive date trees to produce the TTQM. The main idea of the Mamdani method is to describe the process states by linguistic variables and to use these variables as inputs to control rules.

To apply the technique, a total of 100 Mozafati dates were selected. For each date, membership function of quality parameters such as the juice quantity, size and freshness were recorded in three quality features "Low, Mid, High" (Fig 2 through 4). For fruit size (length) membership functions (Fig. 2), the largest dimension of fruits were measured and recorded as the fruit length and three levels of (0-3), (2.5-3.5), (3-4) allocated to Low, Mid and High classes. For fruit juice membership functions (Fig. 3) and for fruit freshness membership functions (Fig. 4), three levels of (0-9), (5-15), (13-20) were allocated to "Low, Mid and High" classes. Table 1 shows the results of measurements. Based on expert date grower knowledge, figure 5 shows the output of fuzzy system in five quality features "Very poor, poor, Medium, Good, Excellent".

In this research, a four input, one output Mamdani fuzzy rule-based system in fuzzy toolbox of Matlab software was used for date grading. Based on considered membership functions for inputs the Mamdani fuzzy rule based system has 3×3×3=27 rules.

The fuzzy system is implemented using the following FIS properties:
Type: ‘Mamdani’
Decision method for fuzzy logic operators AND (intersection): ‘MIN’
Decision method for fuzzy logic operators OR (union): ‘MAX’
Implication method: ‘MIN’
Aggregation method: ‘MAX’
Defuzzification: ‘CENTROID’ (center of gravity)

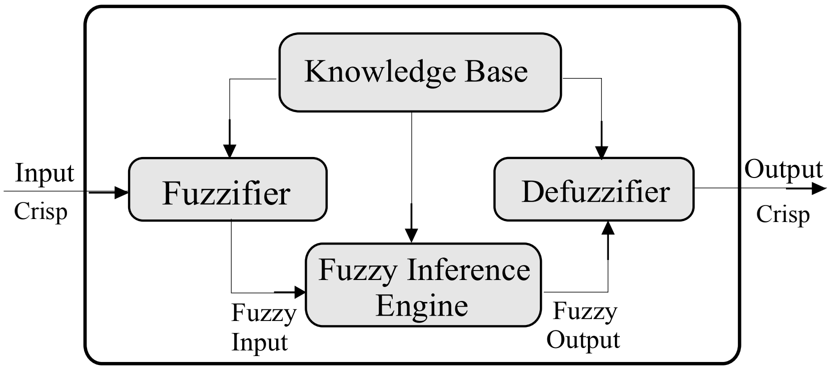

Fig. 1. Block diagram of a fuzzy inference system

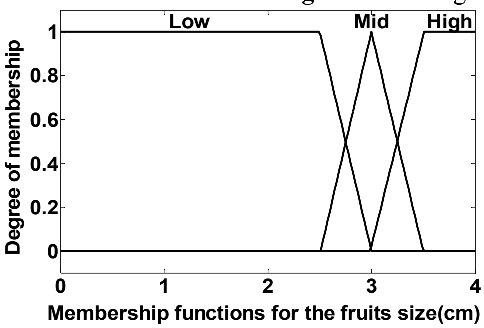

Fig. 2. Input 1.

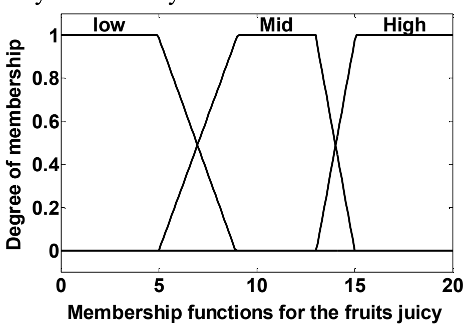

Fig. 3. Input 2

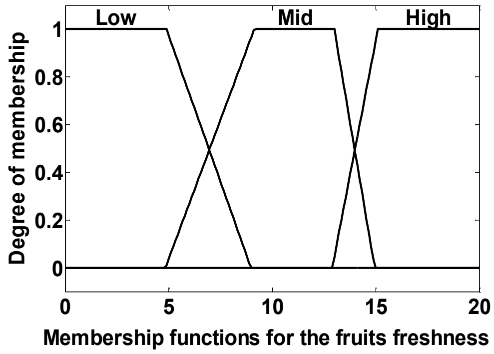

Fig. 4. Input 3.

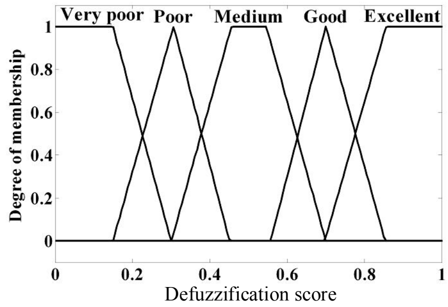

Fig. 5. Membership functions for the date grading.

Fuzzy rules determination

Many researchers have investigated techniques for determining rules, and expert knowledge is the one most commonly used. The expert is asked to summarize knowledge about the system in the form of a cause and effect relationship. From these the rules are formulated (Center and Verma, 1998). Yoshinari *et al*. (1996) discuss another method of fuzzy rule determination based on fuzzy classifier techniques. Neural networks have also been used to learn rules (Jang and Sun 1995). In this study the set of rules based on date growers' expert knowledge to construct the fuzzy model are given in Table 1. The MFIS used here has 3×3×3=27 rules based on the membership functions considered for inputs. An example of rule definition is. If fruit size is "High", fruit freshness is "High" and fruit juice quality is "High" then fruit is "Very good".

Table 1. Developed fuzzy rules

Fruit size	**Fruit freshness**		
	Low	**Mid**	**High**
(a) Fruit juice quality is 'Low' Good			
Low	Very bad	Very bad	Bad
Mid	Bad	Bad	Mid
High	Mid	Mid	Good
(b) Fruit juice quality is 'Mid'			
Low	Bad	Mid	Mid
Mid	Bad	Good	Good
High	Mid	Good	Very good
(c) Fruit juice quality is 'High'			
Low	Bad	Mid	Mid
Mid	Mid	Good	Very good
High	Mid	Very good	Very good

Results

For the different date varieties there was 86% general agreement between the MFIS results and the human expert. This result show fuzzy logic has been able to model human expertise successfully (Table 2). The level of agreement between the MFIS and human expert is not usually 100% because fuzzy logic gives 'class' membership degrees to dates (Mazloumzadeh *et al.*, 2009). Table 2 shows the analysed results after defuzzification process. Total predicted column shows the classification by the expert. For example the expert says 28 dates are very good but fuzzy system says from these 28 just 25 are very good, there are 2 good and 1 medium. The explanation is similar for the other rows. There are 14 percent of disagreements between the expert and the fuzzy system views. It shows the ability of fuzzy system to evaluate and compare 3 parameters at 3 levels as inputs and generate outputs in 5 levels simultaneously.

Table 2. Comparison of date quality between experts and fuzzy inference system

		Fuzzy system prediction						
	Class	Very good	Good	Medium	Bad	Very bad	Total predicted	%
Experts	Very good	**25**	2	1	0	0	28	89.3
	Good	2	**32**	2	0	0	36	88.9
	Medium	0	1	**14**	2	0	17	82.35
	Bad	0	1	2	**9**	0	12	75
	Very bad	0	0	0	1	**6**	7	85.7
Total observed		27	36	19	12	6	$\frac{86}{100}$	
	%	92.6	88.9	73.7	75	100		**86**

Discussion

To apply the MFIS to evaluate and classify date fruits in other regions of cultivation with different growing conditions, the membership functions would need to be tuned to obtain sensible evaluation results. For example, the average date fruit size of Porkoo and Karoot varieties is 3.5 and 4 cm, respectively (Anon, 2011), whereas it is 3 cm in the studied region. Therefore, membership functions of fruit length must be modified for different date varieties. Neuro-fuzzy systems such as NEFCLASS (Nauck and Kruse, 1995) enable this.

Fuzzy systems, including fuzzy rule-based systems and fuzzy set theory, provide a rich and meaningful addition to standard logic. Many systems may be modeled, simulated, and even replicated with the help of fuzzy systems, not the least of which is human reasoning itself . 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) and Alavi *et al.* (2010).

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 is a 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 fuzzy logic was successfully applied to serve as a decision making technique in grading dates. Grading results obtained from fuzzy logic showed a good general agreement with the results from the human experts, providing good flexibility in reflecting the expert's expectations and grading standards into the results. It was also seen that length, freshness and juice quantity are 3 important criteria in date fruit grading.

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. Moreover, the shape of the membership functions may be predicted by applying cluster or statistical analysis techniques to the sub-samples of the data to be sorted. This could result in membership functions that closely represent the output classes and, therefore, improve the classification success of the fuzzy rule-based classifier. Applying commonly used triangular or trapezoidal membership functions to the quality categories of agricultural produce may not work as it would for industrial operations. This may be due to the diversity and uniqueness of agricultural products. 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 creates the need for modeling systems that are robust, noise tolerant, adaptable for multiple uses, and are extensible. Fuzzy logic has these characteristics and is being examined for use in control and modeling in agricultural systems.

Conclusion

A new application of Mamdani fuzzy rule-based system to evaluate and classify date fruits was presented. The comparison between results of MFIS and experts shows that the overall classification accuracy of the MFIS model was 86%. This model demonstrated that, date fruit evaluation based on this method is more exact than experts, and provides a better representation of date grading. Results indicate that fuzzy rule-based modeling is a promising alternative to the traditional approach.

References

Abraham, A. (2005). Rule-based expert systems. In: P. H. Sydenham., & R. Thorn (Eds.) Handbook of Measuring System Design (pp. 909-919). Stillwater, OK, USA: Oklahoma State University.

Alavi, N. Nozari, V. Mazloumzadeh, S.M. and 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.

Anon (2011). Iranian ministry of agricultural statistics. http://www.agri-jahad.ir.

Center, B. and Verma, B. (1998). Fuzzy logic for biological and agricultural systems. Artificial Intelligence Review 12: 213-225.

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

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

Chua, S.C. Wong, E.K. and Koo, V.C. (2007). Performance evaluation of fuzzy-based decision system for pool. Applied Soft Computing 7: 411–424. doi:10.1016/j.asoc.2005.09.003

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

Herrera, F. and Lozano, M. (2003). Fuzzy adaptive genetic algorithm: design, taxonomy, and future directions. Soft Computing, 7: 545-562.

Jang, J. and Sun, C. (1995). Neuro-Fuzzy modeling and control. Proceedings of the Institute of Electrical and Electronics Engineers 83: 378–406.

Kavdir, I. and 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. and 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. (2008). Development of a machine vision system for automatic date grading using digital reflective near-infrared imaging. Journal of Food Engineering 86: 388–398.

Mamdani, E. and Assilian, S. (1975). An experiment in linguistic synthesis with a fuzzy logic controller. In International Journal of Man-Machine Studies 7: 1–13.

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. and 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

Mazloumzadeh, S.M., Shamsi, M. and 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.

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

Mirabbasi, R., Mazloumzadeh, S.M. and 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.

Nauck, D. and Kruse, R. (1995). NEFCLASS - A Neuro-Fuzzy approach for the classification of data. Proceedings of the 1995 ACM Symposium on Applied Computing. ACM Press, New York. pp. 461-465. http://citeseer.ist.psu.edu/nauck95nefclass.html.

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

Schmilovitch, Z., Hoffman, A., Egozi, H., Grinshpun, J. and 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., Zvi, R., Bernstein, Z. and Alchanatis, V. (1997). System and method for maturity determination of pre-harvested fresh dates by near infrared spectrometry. In: Proceedings of Sensors for Nondestructive Testing, pp. 111–121.

Schmilovitch, Z., Hoffman, A., Egozi, H., Zvi, R., Bernstein, Z. and Alchanatis, V. (1999). Maturity determination of fresh dates by near infrared spectrometry. Journal of the Science of Food and Agriculture 79: 86–90.

Schmilovitch, Z., Hoffman, A., Egozi, H., Zvi, R., Bernstein, Z. and Alchanatis, V. (2000). Machine for automatic sorting 'barhi' dates according to maturity by near infrared spectrometry. In: 4th International Conference on Postharvest Science.

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

Shahin, M.A. and 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 .

Takagi, T. and Sugeno, M. (1985). Fuzzy identification of systems and its application to modeling and control. Institute of Electrical and Electronics Engineers Transactions on Systems, Man and Cybernetics 15: 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. and Algazi, R.V. (1993). Defect sorting of dry dates by image analysis. Canadian Agricultural Engineering 35 (2): 133–139.

Yoshinari, Y., Pedrycz, W. and Hirota, K. (1996). Construction of fuzzy models through clustering techniques. Fuzzy Sets and Systems, 78. pp. 1–4
Zadeh, L.A. (1965). Fuzzy sets. Information and Control, 8: 338-353.
Zaid, A. (2002). Date palm cultivation, FAO publication No. 156, Rome.

(Published in July 2012)