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An intelligent approach based on adaptive neuro-fuzzy inference systems (ANFIS) for walnut sorting

Smail Khalifa*, Mohammad Hassan Komarizadeh

Department of Mechanical Engineering of Agricultural Machinery, Urmia University, Urmia, Iran,

***Corresponding author: smailkhalifa@yahoo.com**

Abstract

In the present paper**,** an efficient walnut recognition system was developed by combining acoustic emissions analysis, Principle Component Analysis (PCA) and Adaptive Neuro-Fuzzy Inference System (ANFIS) classifier. The system was tested later and classified walnuts into two classes. In order to produce sound signals, a 60^{o} inclined polished steel plate was used. This intelligent system had three phases (stages). In pre-processing phase, the data acquisition and pre-processing for impact signals performed and 281 sample data were used to evaluate the performance of the system. In feature extraction stage, some statistical parameters of impact signals in the time domain were selected as a feature source for sorting, and then the feature reduction was carried out using PCA. In classification phase, selected statistical features were used as the input of the ANFIS classifier. The classification accuracy of proposed PCA–ANFIS intelligent system was 100%.

Keywords: Walnut, Acoustic, Signal processing, Principle component analysis, ANFIS.
Abbreviations: ANN: Artificial Neural Network; ANFIS: adaptive network based fuzzy inference system; PCA: principle component analysis; MISS: Multi Impact Spiral Surface.

Introduction

The walnut is one of the most important agricultural products all over the world. The annual global walnut production is over 1,600,000 Mton. This product plays an important role in agricultural economy of Iran. The walnut is purchased in two types: kernel (shelled) and nut (shell separated). According to the FAO statistics, Iran produces 10 percent of world walnut production but only owns less than 1 percent of international export (FAO, 2010). One reason for low export value of Iranian walnut is the product's non-uniformity which is believed to be the issue of seedling planting and using of different genotypes. As a consequence, the product has a wide variety in size, weight, feature and quality properties. Presentation of new varieties offers a solution; however, the expansion of the grounds under cultivation of this species and long life span of walnut tree, methods of product grading may serve as an interesting field of study. One of the best solutions to eliminate non-uniformity of walnut products and increase export is classification of kernel (shelled) or nut (shell separated) preferably using a non-destructive method. Previous studies showed the importance of application of acoustics for classification of agricultural products (Pearson, 2001; Omid et al., 2009). Mahmoudi, (2006) used a device based on impact of acoustic emission to separate (sort) the closed pistachio shells from the open ones. The same impact acoustics-based system was later extended to separate empty hazelnuts from fully developed nuts (Onaran et al., 2004). Computerized analysis system has an advantage of acquiring and processing large numbers of data in a short time. Fuzzy set theory plays a key role in dealing with uncertainty of decision making in classification systems of defects.. Therefore, fuzzy sets have attracted a growing attention and interest in modern information technology, pattern recognition, diagnostics, data analysis and etc. (Übeyli, 2009; Tran et al., 2009). Ivani, (2006) used an advanced acoustic method named Multi impact spiral surface (MISS) for walnut classification. Outputs of system were walnut types, mass and density of kernels. The best ANN (Artificial Neural Network) structure was obtained from a three-layer multi layer perception (MLP) (463:23:5). The network precisely identifies the type of walnut from its sound response (99%). Although the accuracy of system was very reliable but the size of ANN was a defect for classification system. Khalifa et al. (2011) applied ANN and impact acoustic emission to classify walnuts into three different classes (empty walnut, average walnut, and filled walnut)**.** The optimized MFNN model was found a 326–12–4 architecture. Khalifa et al. (2011) reported that the CSR (Correct Separation Rate) percentages for fully developed, average and empty walnuts were 97.62, 80.00 and 93.33, respectively. In this study, an intelligent diagnosis system based on principle component analysis (PCA) and an adaptive network-based fuzzy inference system (ANFIS) was developed to classify fill walnuts and empty walnuts.

Result and discussion

The structure of the proposed system is shown in Fig 1. The data sets were divided into two separate sections and 185 samples (60%) of the impact signals were used to train ANFIS classifier. After training, 96 samples (40%) of testing data were used to validate the accuracy of the ANFIS model for classification of filled and empty walnuts. The detailed descriptions of data sets are given in Table 2. The confusion matrix, which shows the classification results of ANFIS model, is given in Table 3. In confusion matrix, the diagonal elements show the number of correctly classified instances. The other elements, those were off-diagonal in the confusion

matrix, showed misclassifications. In fact, none of the walnuts were wrongly sorted by the classifier system. The test performance of the classifiers can be determined by the computation of some criteria such as specificity, sensitivity and total classification accuracy. These criteria are defined as:
Specificity: number of true negative decisions divided to number of actually negative cases.
Sensitivity: number of true positive decisions divided to number of actually positive cases.
Total classification accuracy: number of correct decisions divided to total number of cases.
The ANFIS model classified both the filled and empty walnuts with the accuracy of 100. The total classification accuracy was 100%. The final membership function of each input is represented into high and low degrees. The variation of the membership functions was investigated after the training process. The results of this study showed that training data set and training process can change the membership functions according to the real condition. Fig 4 shows the final membership functions of each three inputs, which were used to determine their degree values in the classification process. The present FIS can then be retrained to be adapted to the other nuts. Once correctly trained, the coefficient packets from the monitored impact signal are input into the FIS to sort walnuts. A number of investigations have proved the capability of ANFIS in classifying data (Avci and Turkoglu, 2009; Tran et al., 2009; Ubeyli, 2009; Ebrahimi and Mollazade, 2010).Yet this method has not been applied to sort agricultural products and further research needs to be done to establish the accuracy of the present study. This study have some advantages such as requiring short signal durations and simple algorithm, small size feature vectors, etc. The capacity of classification in Ivani's (2006) study was less than 10 walnuts per minute, but the results of the present study indicated that system is capable to sort more than 100 walnuts at the similar time period. Results have a good agreement with findings of Khalifa et al. (2011) and show that acoustic signal processing is effective tool to sort the walnuts. The CSR of present study (100%) is higher than CSR reported by Khalifa et al. (2011) (95.38%); however, the ANFIS classifier could not classify walnuts in three classes.

Materials and methods

Sample preparation and data acquisition

The walnuts were selected from a farm in Boukan-Iran at the latitude of $36^\circ 54'$ North and longitude of $45^\circ 49'$ east. The walnut shells then dried in sun for one week. 281 samples were selected randomly for investigation. 174 of the walnuts chosen were filled and the remaining were empty walnuts. A stainless steel block was used as the impact plate. In order to minimize vibrations, the weight of impact plate was chosen more than that of the nuts (Ghazanfari et al., 1996; Omid et al., 2009). The apparatus work by dropping walnuts onto the impact plate and then collect the acoustic emissions by a microphone as shown in Fig 2. The microphone (Panasonic microphone, VM-034CY model) was installed inside an isolated acoustic chamber to eliminate environmental noise effects (Amoodeh, 2006). Detected sound signals were sent to a PC based data acquisition system. Signals were digitized at a sampling frequency of 40.0 kHz. Sound signals were saved by using

Table 1. Time domain features.

Features description	features
Maximum	$F_1 = \max\ x(n)$
Minimum	$F_2 = \min\ x(n)$
Average	$F_3 = \frac{\sum_{n=1}^{N} x(n)}{N}$
Standard deviation	$F_4 = \sqrt{\frac{\sum_{n=1}^{N} (x(n) - F_3)^2}{N-1}}$
Skewness	$F_5 = \frac{n}{(n-1)(n-2)} \sum_{n=1}^{N} (\frac{x(n) - F_3}{F_4})^3$
Sum	$F_6 = \sum_{n=1}^{N} x(n)$
Median	It is the number separating the higher half of signal point values from the lower half.
Kurtosis	$F_8 = \left\{ \frac{n(n+1)}{(n-1)(n-2)(n-3)} \sum_{n=1}^{N} (\frac{x(n) - F_3}{F_4})^4 \right\} - \frac{3(n-1)^2}{(n-2)(n-3)}$
variance	$F_9 = \frac{n\sum_{n=1}^{N} x^2 - (\sum_{n=1}^{N} x)^2}{n(n-1)}$

Where x(n) is a signal series for n = 1, 2, …, N. N is the number of data points.

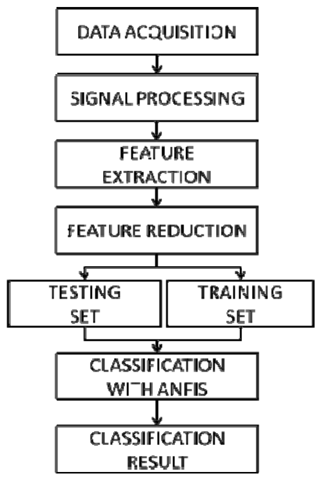

Fig 1. The block diagram of the intelligent diagnosis system used in this study.

MATLAB® (version of R2008a) data acquisition toolbox for subsequent analyses (Mathwork, 2008).

Feature extraction and feature reduction

The results of the classifier will be very successful, if features are chosen fit. Therefore, a feature extractor should reduce the pattern vector to a lower dimension that includes most of the useful information from the original signal (Turkoglu et al., 2003).

Table 2. Train and test sets.

Label of classification	Number of training sounds	Number of testing sounds	Total
Empty walnuts	71	36	107
Fill walnuts	114	60	174
Total samples	185	96	281

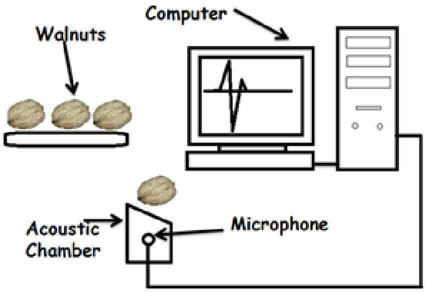

Fig 2. Apparatus used for data acquisition.

In this paper, features were extracted by using descriptive statistics from time domain values of impact signals. Other researches reported use of this method (Mollazade et al., 2009; Tran et al., 2009). The statistical parameters were Maximum, Minimum, Standard deviation, Skewness, Sum, Average, Median, Kurtosis and Sample variance. These statistical features are explained in Table 1. For feature reduction processes, PCA procedure using WEKA software was used. The feature reduction process using PCA can be explained as below. Supposed M is a t-dimensional data set. The n principal axes G_1, G_2,...,G_n here $1 \leq n \leq t$, are orthonormal axes, onto which, the retained variance is maximum in the projected space (Avci and Turkoglu, 2009). Commonly G_1, G_2,..., G_n can be given by eigenvectors of the sample covariance:

$$matrixC = (\frac{1}{L})\sum_{k=1}^{L}(x_k - m)^T (x_k - m) \quad (1)$$

Where, $x_k \in$ M. m is the mean of samples. L is the number of samples. According to this:

$$UG_k = v_k G_k , k \in 1,...,n, \quad (2)$$

Where, v_k is the kth largest Eigen value of U. The n principal components of given observation vector $x_k \in$ M are given as below:

$$q = [q_1, q_2, ..., q_n] = G_1^T x, G_2^T, ..., G_n^T] = G_x^T \quad (3)$$

Where, q is the n principal components of x.

Classification

According to the feature reduction results, three superior features have been selected by the PCA and then were fed to the ANFIS classifier. These three features are superior to the others in classifying the filled and empty walnuts. Fig 3. shows the topology of ANFIS designed for walnut classification.

Table 3. Confusion matrix of testing data

Type	Empty walnuts	Empty walnuts
Empty walnuts	36	0
Fill walnuts	0	60

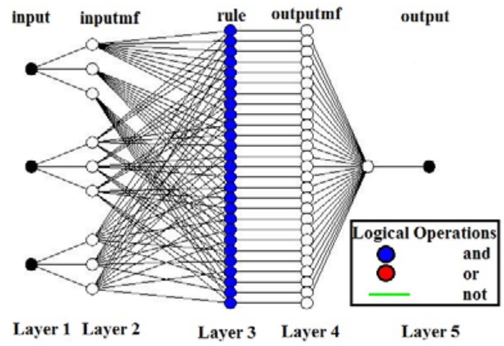

Fig 3. Architecture of ANFIS.

ANFIS is consisted of if-then rules and couples of input–output. Learning algorithms of neural network is used for ANFIS training (Avci and Turkoglu, 2009; Ebrahimi and Mollazade, 2010). This architecture is formed using five layers and twenty seven if-then rules:

In the first layer, all the nodes are adaptive. The outputs of this layer are the fuzzy membership grade of the inputs, which are given by following equation:

$$O_i^1 = M_i(x_i)$$

Where, $i=1, 2, 3,..., P$; x_i denotes the ith input of ANFIS and O_i^1 is the output of node i.

In the second layer, the nodes are fixed nodes. They are labeled with M, indicating that they perform as a simple multiplier. Here, to calculate the output of the layer, AND (min) operation is used:

$$O_i^1 = M_i(x_i) AND M_j(x_i)$$

In the third layer, every node is a fixed node, as well. Comparison between firing strength of the rules and the sum of all firing strength is done in this layer. The outputs of this layer can be calculated as:

$$O_i^3 = \frac{O_i^2}{\sum_i O_i^2}$$

In the fourth layer, every node is an adaptive node. The output of each node in this layer is simply the product of the normalized firing strength and a first order polynomial (for a first order Sugeno model). Therefore, the outputs of fourth layer are given by:

$$O_i^4 = O_i^3 \sum_{i=1}^{p} P_j x_j + c_j$$

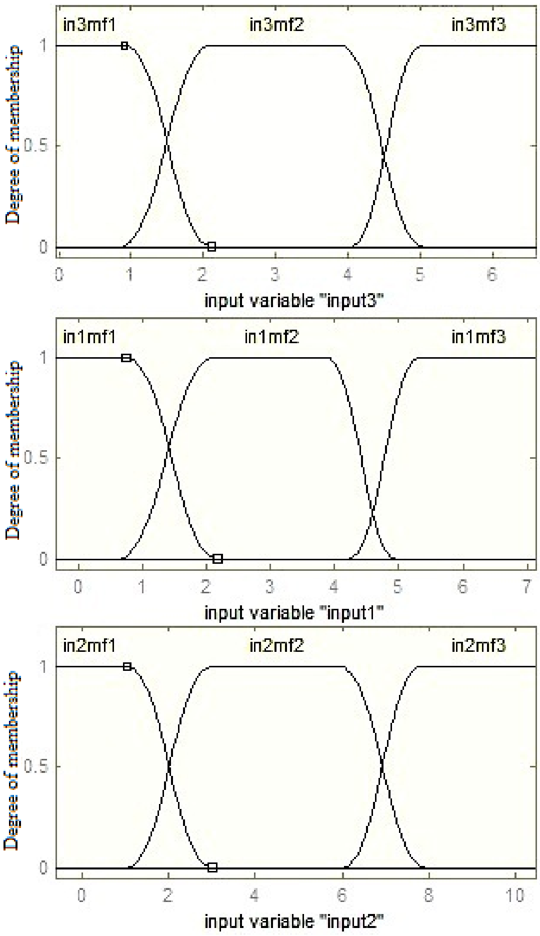

Fig 4. Membership function for inputs.

The parameters P_1, P_2, ...,P_n and c_1, c_2, …, c_n are consequent parameters set.

In the fifth layer, there is only one single fixed node that calculates the overall output as the summation of all incoming signals. Hence, the outputs of layer 4 are aggregated:

$$O_i^5 = \sum_i O_i^4$$

The 27 rules were obtained as follows:

Rule1: If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) then (output is out1mf1) (1)

Rule2. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf2) then (output is out1mf2) (1)

…..

Rule26. If (input1 is in1mf3) and (input2 is in2mf3) and (input3 is in3mf2) then (output is out1mf26) (1)

Rule27. If (input1 is in1mf3) and (input2 is in2mf3) and (input3 is in3mf3) then (output is out1mf27) (1)

which, input1, input2 and input3 are functions based on used features, mf1, mf2 and mf3 are the fuzzy sets, out1mf1, …, out1mf27 are the outputs within the fuzzy region specified by the fuzzy rule.

Conclusion

It seems that the feature reduction and adaptive network based on fuzzy inference system (ANFIS) have been very useful tools to sort walnuts. While the feasibility of this method has been proven in the present study, a sensitive study involving more cases is strongly suggested before the proposed method can be adopted in commercial applications.

Moreover, these statistical features were reduced using PCA method. In this way, the feature vector has a lower dimension that includes most of the useful information from the initial vector. The recognition performance of this PCA–ANFIS intelligent classification system showed that the present system has massive advantages such as high-speed operation, non-destructiveness and inexpensiveness. The final ANFIS model has 27 rules. The results indicated that the proposed system can provide a highly accurate walnut classification (100%). Further effort is needed, however, to verify these results and adapt the acoustic method for other varieties of walnuts and on-line operation.

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