Recognition of filled walnuts and empty walnuts using acoustic signal processing

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Abstract: An intelligent walnut recognition system combining acoustic emissions analysis, decision tree and fuzzy inference system (FIS) was developed and tested. In data acquisition part, Fast Fourier Transform (FFT) of impact signals was measured. Feature was extracted in two ways: using time domain and FFT of impact signal. The 66% of samples were used for training and the remains were used for testing. In selection feature part, the most important feature selected was: average and the second frequency amplitude of FFT. The method is based on the feature generation by FFT and time domain, produce decision tree with J48 algorithm and classification by fuzzy rules. The output of J48 algorithm was employed to produce the crisp if-then rule and membership function (MF) sets. The structure of FIS classifier was then defined based on the crisp sets. The results showed that the total classification accuracy was 94.7%, and the proposed FFT-J48-FIS model can be used in separation of filled walnuts from empty walnuts.

Keywords: walnut recognition system, fuzzy inference system, acoustic emission, decision tree, signal processing

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1 Introduction

Based on FAO statistics, annual Iranian Walnut production is 168 320 Mt, which is 11% of total world's production. In Iran, average of product performance is 0.188 kg/m^2[1]. Unfortunately, despite having 11% of world production, Iran only owns less than 1% of international export[2]. One reason of low export value of Iranian walnut is its vast non uniformity which is an issue of planting seedling and using of different genotypes. This subject causes products' wide varieties in size, weight, feature and quality properties. The best solution to eliminate non-uniformity of products and increase export is classification of crops. Using of a non-destructive method to classify walnut related to be filled or hollow is an important topic.

Impact acoustic emission was used as basis for a device that separates pistachio nuts with closed shells from those with split-shells[3]. Onaran et al.[4] developed a prototype system that was set up to detect empty hazelnuts by dropping them onto a steel plate and processing the acoustic signal generated when kernels impact the plate. In their research, 98% of filled developed kernels and 97% of empty kernels were correctly classified. Knowledge-based techniques[5,6] become a suitable strategy towards automatic fault detection (AFD). Fuzzy logic is among the knowledge-based techniques to address the fault detection

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problem. Several researchers[7-10] have proposed fault detection and diagnosis approaches based on fuzzy system. Typically, fuzzy rules are generated by intuition and experts' knowledge. Researchers have continuously tried to find efficient and effective methods to generate these fuzzy rules. Decision Trees have been proposed to solve the problem[11] as shown in Figure 1.

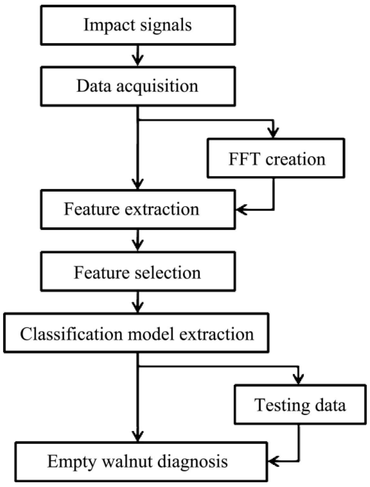


Figure 1 Flowchart of the proposed system

Studies showed that, research in this area was not developed. Perhaps the most important reason was the sensitivity of this method to external noise, which made the method ineffective under field operating conditions. The objective of this research was to propose the intelligent system for recognition of empty walnuts and filled walnuts.

2 Materials and methods

2.1 Experimental works and data acquisition

All walnuts were selected from single tree in the city of Bukan in West Azerbaijan, Iran. Then, walnuts were dried in the sun for a week. Two hundred and eighty-one walnuts were selected for testing randomly. The impact plate is a polished block of stainless steel and it is much heavier than that of the nuts in order to minimize vibrations from the plate interfering with acoustic emissions from nuts[3,12]. Walnuts fell freely onto the impact plate. The acoustic emissions from the walnuts were picked up by a microphone (VM-034CY model of Panasonic). The microphone was installed inside an isolated acoustic chamber to eliminate environmental noise effects[12]. Detected sound signals were sent to a computer based data acquisition system[13]. A schematic of the experimental apparatus for singularing walnut is shown in Figure 2. Walnuts were dropped onto the impact plate and the acoustic emissions from the impact, were collected. Sound signals were saved by using MATLAB® data acquisition toolbox for subsequent analysis[14]. Figure 3 showed the peak value of walnut recorded with the data acquisition system.

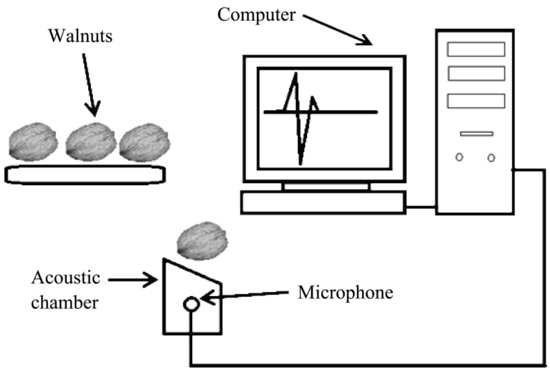


Figure 2 Schematic of walnut classifier based on acoustic emissions

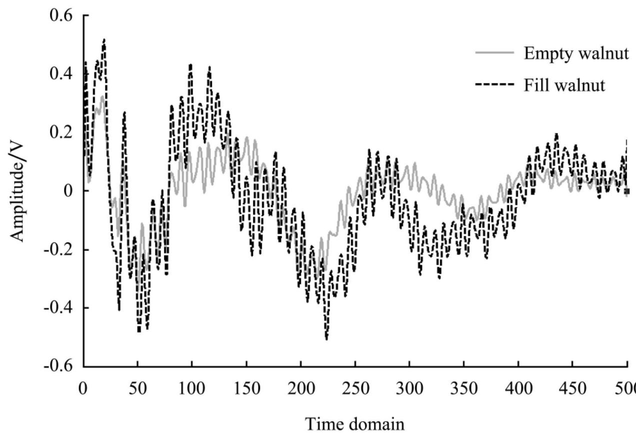


Figure 3 Walnut signals in time domain

It can be seen that signal amplitudes are not similar and amplitude of filled walnut is higher than empty walnut, this fact attracted our minds to this issue, the signal amplitude could be a good way to separate the empty walnuts from filled walnuts. The frequencies of sound emanating from filled walnut and empty walnut were slightly different.

2.2 FFT creation

Several researchers have been demonstrated capability of the Fast Fourier Transform (FFT) to solve complex problems[15]. The FFT is simply a class of special algorithms which implement the Discrete Fourier

Transform (DFT, Equation (1)), with considerable savings in computational time.

$$X(k)=\sum_{n=0}^{N-1}x(n)e^{-jk2\pi n/N},\quad k=0,1,\cdots,N-1 \tag{1}$$

$$X(k)=FFT\{x(n)\}\leftrightarrow x(n)=FFT^{-1}\{X(k)\} \tag{2}$$

where, $X(k)$ represents the Fourier coefficients of $x(n)$, and the integer N is the number of time (or frequency).

2.3 Feature extraction

The accuracy of feature extraction is of great importance since it directly affects the final diagnosis results. In this study, the feature extraction using descriptive statistics from time domain values and FFT values of impact signals were used. Research works reported the use of this method[16]. The time domain parameters were Average, Standard deviation, Median, Sample variance, Kurtosis, Skewness, Minimum, Maximum, and Sum; and FFT parameters were situation of the first, second and third frequencies and amplitude of these frequencies.

2.4 Feature selection and classification model extraction

In this research, J48 algorithm (A WEKA implementation of c4.5 Algorithm) was used to construct decision trees[17]. Input to the algorithm was the set of statistical features extracted from time domain and FFT values of impact sound signatures. In this research, two-thirds of samples were employed for training process and the remaining samples for testing purposes. The detailed descriptions of those data sets were given in Table 1. Based on the output of J48 algorithm, various statistical parameters were selected for the various types of walnuts. Selected statistical features were used as membership functions (MFs) and the values appearing among various nodes in the decision tree were used for generating the fuzzy rules to classify the walnuts.

Table 1 Training and testing sets

Label of classification	Number of training sounds	Number of testing sounds	Overall
Empty walnuts	72	35	107
Filled walnuts	116	58	174
Total samples of train and test	188	93	281

2.5 Walnut diagnosis using fuzzy inference system

The general fuzzy logic inference engine is given in Figure 4. In the fuzzy logic inference engine, "x" is the input value, $\mu(x)$ is the fuzzified value, $\mu(u)$ is the result of the inference operation, and "u" is the output value. The fuzzifier unit converts crisp data in the input of the inference engine to the format of linguistic variables. The knowledge base represents two basic data: the database and the rule base. While, the database includes definition of each system variable using the fuzzy set, the rule base covers inspection rules that are necessary to obtain a real output. The inference unit is a unit that performs fuzzy inference on fuzzy rules. This unit performs the operation resembling the way that people think. Finally, the defuzzification unit converts the fuzzy values obtained from the output of the inference unit to numerical values. This operation is called defuzzification[18].

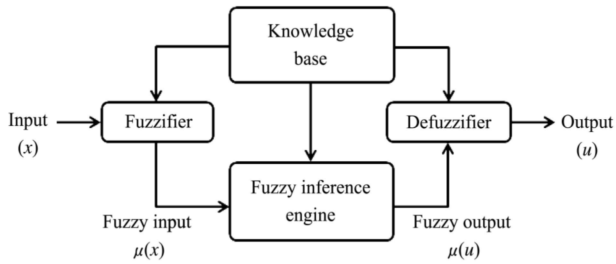


Figure 4 Block diagram of Mamdani fuzzy inference system

After defining MFs and generating the if-then rules by J48 algorithm, the next step is to build the fuzzy inference engine. The fuzzy toolbox available in MATLAB® was used to build fuzzy inference engine.

3 Results and discussion

3.1 FFT-frequency domain

Figure 5 shows the samples of FFT-frequency diagram of impact signals acquired for filled and empty walnuts. It is obvious that in filled walnut, amplitude is higher than that in empty walnut.

3.2 Decision tree

The outcome of J48 algorithm is shown in Figure 6. Decision tree shows the relation between features and the types of the walnut (filled or empty). Tracing a branch from the root node leads to a condition of the walnut and decoding the information available in a branch in the form of if-then statement gives the rules for classification using fuzzy for various types of the walnut. Hence, the usefulness of the decision tree in forming the rules for fuzzy classification is established. The top node of decision tree is the best node for classification. The other features appear in the nodes of decision tree in descending order of importance. It is emphasized that only features contributing to the classification appear in the decision tree and others do not, because they increase the error. The level of contribution is not the same and all statistical features are not equally important[17].

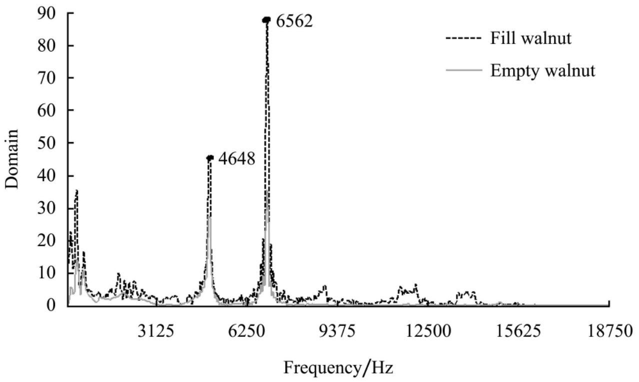


Figure 5 FFT diagram of empty walnut and filled walnut at frequency domain

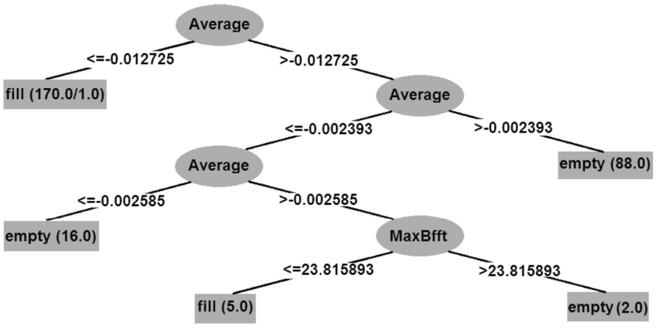


Figure 6 Decision tree from J48 algorithm for classifies walnut

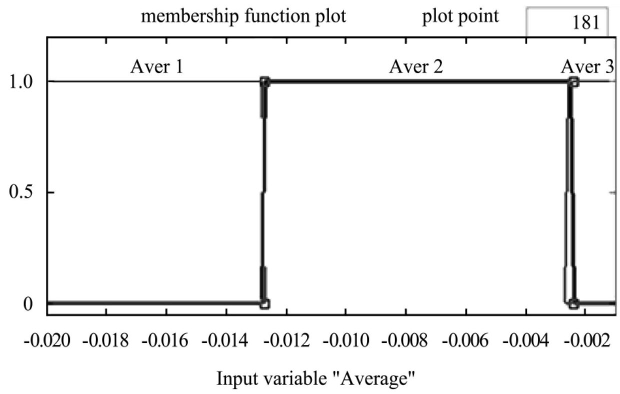
The level of contribution by individual feature is given by a statistical measure within the parenthesis in the decision tree. The first number in the parenthesis indicates the number of data points that can be classified using that feature set. The second number indicates the number of samples against this action. If the first number is very small compared to the total number of samples, then the corresponding features can be considered as outliers and hence ignored. Features that have less discriminating capability can be consciously discarded by deciding on the threshold. This concept is used in selecting good features. The algorithm identifies the good features for the purpose of classification from the given training data set and thus reduces the domain knowledge required to select good features for pattern classification problem[17].

3.3 Membership functions

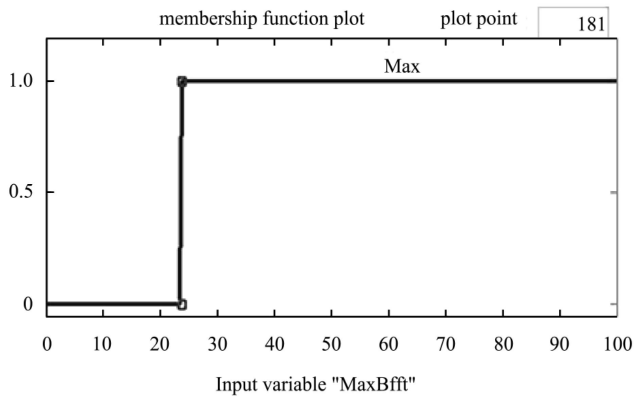
An MF is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between “0” and “1”[19]. Through observing the values of the feature, based on which the branches of the decision tree are created for empty walnuts and filled walnuts, MFs for the corresponding features are defined.

From Figure 6 we can see that Average and amplitude of second frequency of signal (MaxBfft) play a decisive role in classification of walnut types (filled and empty). This output of the decision tree is used to design the MFs for fuzzy classifier as shown in Figure 7. In the present study, trapezoidal MF is used. The selection of this MF is to some extent arbitrary. However, the following points were considered while selecting MF. Observing the values of the feature, based on which the branches of the decision tree is created, the MFs for the two features are defined for Average and MaxBfft, respectively.

From Figure 6, it is obvious that -0.012 725 is a threshold for membership value of Average. Up to this threshold value, the MF generates the value “1” and afterwards it decreases linearly (assumption). The trapezoidal MF suits this phenomenon and hence it was selected to map each point in the input space to a membership value (Figure 7a). To review, the threshold values are given by decision tree and the slope is defined by the user through heuristics. The threshold value is defined based on the representative training dataset. If Average value is lower than or equal to -0.012 725, an MF which is defined on a 0-1 scale gives a value of “1”, which means that it is an Average. If threshold value is higher than -0.012 725, the MF generates a value of “0”. Similarly, MFs for other features are designed accordingly and shown in Figure 7. There are two possible outcomes from a fuzzy classifier, namely filled and empty.



a. Average



b. MaxBfft

Figure 7 Membership Function (MF) for Average and MaxBfft

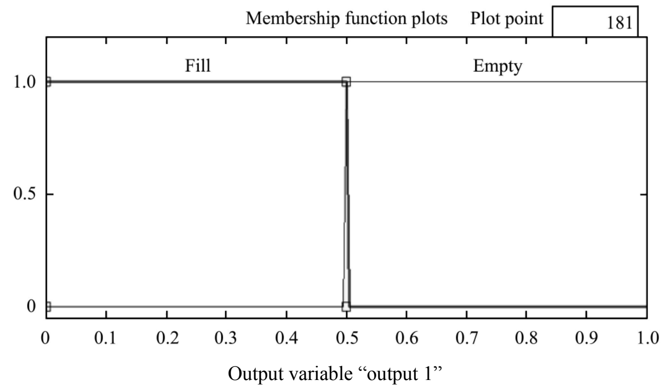


Figure 8 Membership Function (MF) for output ("Output1")

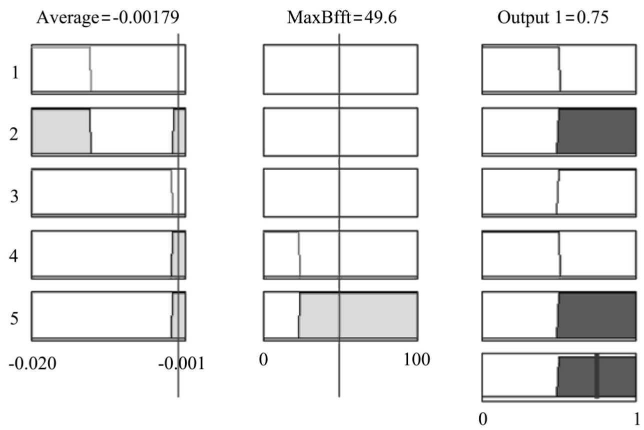


Figure 9 Rule viewer of Fuzzy Inference System (FIS)

3.4 Fuzzy rules

Using Figure 6, fuzzy rules were designed with if-then statements for walnut types. All rules are evaluated in parallel. (1) If (Average is Aver1) then (output1 is Filled); (2) If (Average is not Aver2) then (output1 is Hollow); (3) If (Average is not Aver3) then (output1 is Hollow); (4) If (Average is Aver3) and (MaxBfft is not Max) then (output1 is Filled); (5) If (Average is Aver3) and (MaxBfft is Max) then (output1 is Hollow)

Figure 8 illustrates the application of the rules designed. Here, each row corresponds to each rule was discussed in this section. The first two blocks in rows represent the MF of Average and MaxBfft, respectively. The sixth block corresponds to the MFs for output was shown in Figure 9. With the help of sample inputs for Average and MaxBfft, the rules are tested as follows, for a sample input Average as -0.00 179 and MaxBfft as 49.6, which satisfies the third rule completely and the corresponding output is empty walnut.

3.5 System accuracy

The classification results are calculated using a 10-fold cross-validation evaluation, where the data set to be evaluated is randomly partitioned so that 66% of samples are used for training and 34% of samples are used for testing (Table 1). The process is iterated with different random partitions and the results are averaged[17]. The confusion matrix is given in Table 2. In confusion matrix, each cell contains the number of samples that was classified corresponding to actual algorithm outputs. The diagonal elements in the confusion matrix showed the number of correctly classified instances.

Table 2 Confusion matrix

Type	Empty walnuts	Filled walnuts
Empty walnuts	30	2
Filled walnuts	3	59

The performance of the classifier can be checked by computing the statistical parameters such as sensitivity (number of true positive decisions/number of actually positive cases), specificity (number of true negative decisions/number of actually negative cases) and total classification accuracy (number of correct decisions/total number of cases)[18].

The values of statistical parameters are given in Table 3. Results showed that the total classification accuracy for walnuts is 94.7%. It is to be emphasized here because rules and MFs for fuzzy logic inference system were extracted from J48 algorithm directly; accuracy of fuzzy system is closely equal with that of decision tree built by J48 algorithm. Therefore, it is true to say these amounts show the accuracy of fuzzy inference system and also FFT-J48-FIS model.

Table 3 Value of statistical parameters

Type	Sensitivity /%	Specificity /%	Total classification accuracy/%	Total
Empty walnuts	93.8	95.2	94.7	32
Filled walnuts	95.2	93.7		62

4 Conclusions

1) The results showed that using of walnut sound intensity could be effective for separation of empty walnuts from filled walnuts.

2) Although FFT feature was used for classification of walnuts, the results revealed that FFT feature has a little effect on separation of empty walnuts from filled walnuts. Since FFT was directly proportional to the natural frequency of product, probably the hard shell of walnut prevents from kernel effect on the output signals saved by microphone.

3) The total accuracy of the classification was 94.7%. The results indicated that the proposed FFT-J48-FIS model could be used in separation of empty walnuts from filled walnuts.

4) 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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