Grading of empty walnut using signal processing and artificial neural network techniques

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ABSTRACT: Walnut is one of the most important dried nuts products in Iran, which has the third area under cultivation after pistachios and almond. Due to the low quality of Persian walnut in Iran, traders prefer to buy nuts from other countries. One of the main reasons may be lack of suitable technology for classification of the quality. In this paper an intelligent separation system is presented based on artificial neural networks (ANNs) for separating empty walnuts without breaking them. The components of signal processing system include signal production and recording of its reflections. The produced sounds should be due to twirling of the walnuts and not slipping, therefore the spiral surface of the produced sounds has been designed in a way that walnut can rotate in all direction on its axis. After running the recorded sounds in MATLAB software, the results are investigated by Neural Network toolbox. The optimal model is selected after several evaluations based on minimizing of mean square error (MSE). A 12-11-1 multi-layer perceptron neural network was used for separation of empty walnuts. Accuracy of BP and LVQ neural network for separation walnuts was 99.7 % and 97.5 % respectively.

Keywords: Blank, sound analysis, separation, artificial neural networks, walnut.

INTRODUCTION

Various genotypes of Persian walnut (Juglans regia L.) widely distributed at the cold and temperate climate of Iran with latitude, 35° to 50°. Walnut is the edible fruit of every approximately 15 species of walnut trees belonging to the Juglandaceae family. Walnut is a highly appreciated nut because of its unique organoleptic characteristics (Lopez et al., 1995), high levels of fatty acids (Crews et al., 2005 & Zwart et al., 1999) and hypocholesterolemic (Abbey et al., 1994), and antihypertensive effects (Sabaté and Fraser, 1994).

In order to have a good market, a more uniform product, inspection and classification of mixed nuts into uniform shape and size is desirable. Visual inspection is usually performed by human operators and its output is affected by several factors, such as age of operators, their concentration and motivation, fatigue and visual acuity, room conditions (lighting, heating, ventilation, and noise) and so on; for these reasons, automated systems are especially being considered. In recent years, computer-generated neural classifiers which are apt to mimic human decision makings for product quality have been studied intensively. Combination high-technology handling systems, is the most important advantage of artificial classifiers provided in classification of agricultural products (Kavdir and Guyer, 2008).

Combined image analysis and neural classifier were used for the classification of lentil, apple and sweet onion (Shahin and Symons, 2001 & Shahin et al., 2001 & Shahin et al., 2002). The online lentil color classification using a flatbed scanner with a neural classifier has been developed and achieved an overall accuracy of more than 90% (Shahin and Symons, 2001). Various techniques including optical, mechanical, electrical and acoustical have also been used for classification and/or sorting of pistachio nuts. Machine vision was introduced for detection of stained and early split pistachio nuts (Pearson, 1996). Later, the feasibility of an automated food inspection system for pistachio defects detection based on X-ray imaging and statistical characterization was demonstrated (Pearson et al., 2001). Ghazanfariat et al. (1997a & b) utilized Fourier descriptors and gray level histogram features of 2D images to classify pistachio nuts into one of three USDA size grades or as having closed-shells. Impact acoustic emission was used as the basis for a device that separates pistachio nuts with closed-shells from those with split-shells (Pearson, 2001 & Cetin et al., 2004a & b).
The sorter system included a microphone, digital signal processing (DSP) hardware, material handling equipment and an air reject mechanism. The same impact acoustics based system was later extended to separate cracked hazelnuts shells from undamaged ones (Kalkan and Yardimci, 2006), underdeveloped ones from full hazelnuts (Onaran et al., 2006) and wheat inspection for detection of IDK (insect damaged kernel) from undamaged kernels (Pearson et al., 2007). Although the mechanical structure was similar, the authors reported that the signal features used for pistachio classification did not work well in wheat inspection. The results obtained by these works emphasized the importance of signal processing methods of the impact acoustic signal to achieve higher accuracies in food inspection. A multi-structure neural network (MSNN) classifier was proposed and applied to classify pistachio nuts (Ghazanfari et al., 1996). The performance of MSNN classifier was compared with that of a Multilayer Feed forward Neural Network (MFNN) classifier. The average accuracy of the MSNN classifier was 95.9%, an increase of over 8.9% of the performance of the MFNN, for the four commercial varieties of nuts tested. In another research, Fourier descriptors and the projected area of the individual nuts were extracted from their 2D images and used as recognition features to classify pistachio nuts into four grades (Ghazanfari et al., 1997a).

The Fisher criterion in conjunction with Gaussian classification method for feature selection was used. The results of this feature selection indicated that seven harmonics were sufficient for this classification task. The selected Fourier descriptors and the area of each nut were subsequently used as inputs to two classification schemes: hybrid decision-tree classifier and artiﬁcial neural networks (ANNs). The average classiﬁcation accuracy obtained for the decision-tree classiﬁer was 87.1%, whereas the ANNs resulted in an average classiﬁcation accuracy of 94.8%. In pistachio processing plants, image-based sorting devices using visible light have largely been replaced with X-ray devices, and the commercially available image-based sorters (Pearson et al., 2001) are in fact no longer in production. Casasent et al., (1998) obtained promising results by X-ray imaging and neural grid processing to classify pistachio nuts. X-ray image histogram features and their spatial derivatives were used for detection of insect–infested nuts. Therefore the aim of this study is to design and to present a suitable algorithm for classifying full walnuts from empty walnuts, without breaking.

MATERIALS AND METHODS

In this study, walnuts prepare from harvested walnuts in 2012 from one of the gardens in province of ChaharmahalvaBakhtiari. Samples were selected from thin skinned walnuts. Sincet is difﬁcult to identify the full and healthy walnut from empty walnut according to their appearance, they have been separated according to their weights in the laboratory and were considered as reference. To measure walnuts mass, a digital scale with Accuracy 0.1g was used. 1500 full and empty walnuts were weighed, numbered and recorded independently. The components of signal processing system include signal production and recording of its reﬂections. The produced sounds should be due to twirling of the walnuts and not slipping, (Eivani, 2008 & Rath, 2003), therefore the spiral surface of the produced sounds has been designed in a way that walnut can rotate in all direction on its axis.

The recorded sounds were run at the MATLAB software Ver(2007) and results of sound analysis were investigated by the neural network toolbox. The optimal model was selected after many evaluations based on minimizing of mean square error (MSE). For separation multi-layer perceptron neural network was used. About two seconds of walnut collision sound recorded by microphone and transferred to the PC and converted to digital signals by using sound card installed on computer. A schematic of the experimental setup for simulating walnuts, dropping them onto the impact plate, collecting the acoustic emissions from the impact is shown in Figure 1.
Sounds send in real-time to a PC based data acquisition system via a sound card. Feature extraction is performed on the collected data. The objective of feature extraction block was chosen the significant features in signal with reference to the subsequent differentiation of various system states to be performed in the classifier. The input signal for the block “feature extraction” represents the digital sound signal in time domain with the output from this stage being the feature vector. Signal analysis procedures from time domain (e.g. peak values) and frequency domain (e.g. Fast Fourier Transform (FFT), Power Spectral Density (PSD) & Phase) are used for feature extraction. These features are fed to classification system. The classification was performed with ANNs.

There are several types of ANNs, each with its own advantages and drawbacks. Neural networks are procedures for statistical specimen recognition. In a training process, the classifier is given specimen signals, and then sets its weight coefficients in the training phase so it is able to reproduce the classification results as adequate as possible. The individual system states are represented at the input of the stage for knowledge based interpretation by a class statement based on available expert knowledge. This expert knowledge was then fed to the system in the training phase. The system was designed to feed walnut nuts to an impact surface, catch the sound signal upon impact, process the data and divert product into four streams.

Microphone output was connected to the sound card in a Pentium IV personal computer (PC). PC was used for acquiring, saving and processing of data. Data acquisition Toolbox from MATLAB software Ver(2007) was used for data collection. Since the maximum frequency (sampling rate) of used sound card was equal to 42.0 kHz, data acquisition continued for 6.00 ms after triggering. This produced 252 data points for each nut. The Fast Fourier Transform (FFT) is an algorithm for calculating the Discrete Fourier Transform (DFT). FFT utilizes sharp algorithms does as DFT, but in much less time. DFT is extremely important in the area of spectral analysis because it takes a discrete signal within the time domain and transforms that signal into its discrete frequency domain representation. Without a discrete-time to discrete frequency transform one would not be able to compute the Fourier transform with a microprocessor or digital signal processing based system.

Feature extraction from impact sound is the first step for designing a successful nut classification system. Good features can be extracted for input vector to ANN model (Figure 2), by considering signal amplitude in time domain and calculation of magnitude, phase and power spectral density (PSD) of FFT components in frequency domain. The Learning Vector Quantization (LVQ) neural network and Feed forward neural network was used for separation.

The 1500 nut data were divided to three sets: 70% of data were used for training, 15% for testing and the remaining 15% were used for cross validation. In order to minimize ANN training time, only one hidden layer was considered. If the number of hidden neurons be too small, the model will not be flexible enough. On the other hand, if there are too many layers, the model will over fit the data. The algorithm calculates amount of error in output layer. The weight values in the hidden layer were adjusted to reduce output error. After training various algorithms, it clears that back propagation (BP) training algorithm and gives better results. Therefore feed forward back propagation network used in this study and tansig nonlinear transfer function and purelin linear function was used in hidden and output layer, respectively. Appropriate numbers of neurons in primary and middle layers were determined by trial and error method. 5 to 20 neurons were studied in first and intermediate layers. Only one neuron was used to represent filled or empty walnut. To select the best network in terms of minimum error and the regression curve, the number of hidden neurons and layers, number of repetitions, training speed, training model, momentum value and the transfer function were corrected. By consideration of simplest structure, minimum network error was in network with three layers. Schematic of the designed network is shown in Figure2.
Figure 2. The structure of back propagation neural network model to identify empty walnut

Since in LVQ models each of the outputs is a class, in this network model design, outputs should be divided into two classes (one for empty walnut and two for filled). After learning, LVQ network gets inputs and refer to the vector with the class that is nearest to it. Network inputs are 11 characters of sound signal. To determine the appropriate number of neurons in competitive layer, neural networks trained with different neurons and the sum of mean square error were considered as a criterion to select the appropriate number of neurons in the hidden layer. Numbers of competitive layer neurons were switched from $5 \times 5$ to $25 \times 25$ to obtain the best network and also one neuron was considered for final layer. The designed structure of the LVQ network is shown in Figure 3.

Figure 3. Typical structure of the LVQ neural network model for detecting osteoporosis walnuts

RESULTS AND DISCUSSION

A sample of digital signal in the frequency domain is shown in Figure 4 for empty and full walnuts, respectively. It was seen that the difference between two sound signals is in their amplitude, that is clear for frequency range from 0-4000 Hz, but above these differences are negligible, therefore walnuts classification were done under 4000 Hz.
According to previous researches on the voice recognition with neural networks, appropriate network is back propagation neural network and the number of neurons per layer should be selected by trial and error method (Shahinet al., 2001). As shown in figure 2, a three layer network incorporating a single hidden layer of processing elements was selected. Based on already discussed reasons 11 features selected as input of network. The number of neuron in the hidden layer was varied according to the number of inputs and network performance. Considering walnut nut varieties, output layer had one Neuron. By using mean square error (MSE) information for different ANN models, the number of neurons in hidden layer was selected. To this end MSE cross validation for different numbers of hidden neurons at various epochs were investigated. Based on data of network with 11 neurons in hidden layer, this network had the least standard deviation error as well as high stability. Therefore optimal selected model had 12-11-1 structure for classification. As an example of the results table 1 is given in order to select the best neural networkstructure back propagation, with the number of neurons and the middle. 

Table 1. Results of the lowest error values for BP neural network

<table>
<thead>
<tr>
<th>Neuron(1)</th>
<th>Neuron(2)</th>
<th>RMSE</th>
<th>Epoch</th>
<th>Regression</th>
</tr>
</thead>
<tbody>
<tr>
<td>99.6</td>
<td>11</td>
<td>0.0055</td>
<td>7</td>
<td></td>
</tr>
<tr>
<td>99.2</td>
<td>0.0071</td>
<td>0.0078</td>
<td>11</td>
<td>12</td>
</tr>
<tr>
<td>99.7</td>
<td>0.040</td>
<td>0.0077</td>
<td>11</td>
<td>12</td>
</tr>
<tr>
<td>99.1</td>
<td>8</td>
<td>0.0053</td>
<td>13</td>
<td>12</td>
</tr>
<tr>
<td>99.2</td>
<td>8</td>
<td>0.0077</td>
<td>11</td>
<td>13</td>
</tr>
<tr>
<td>98.7</td>
<td>8</td>
<td>0.0077</td>
<td>15</td>
<td>11</td>
</tr>
</tbody>
</table>

According to Table 1, the best value of regression for back propagation neural network is related to 12-11-1 configuration and confirms optimal selected model had 12-11-1 structure. Table 2 showed the number of competitive layer neurons in term of the lowest error values for LVQ neural network.

Table 2. Results of the lowest error values for LVQ neural network

<table>
<thead>
<tr>
<th>Neuron</th>
<th>Error</th>
<th>RMSE</th>
<th>Train%</th>
</tr>
</thead>
<tbody>
<tr>
<td>5-11-13-15-16-20-21-22</td>
<td>0.014</td>
<td>2.5</td>
<td>97.5</td>
</tr>
<tr>
<td>6-7-10-12-14-17-19-24</td>
<td>0.017</td>
<td>7.5</td>
<td>92.5</td>
</tr>
</tbody>
</table>

The best network with least squares error and best learningcoefficient to achieve the goal is related to the network have 0.014 mean square error. Changes of mean square error were drawn in different repetitions for both networks. Fig 5 show curves led to the highest accuracy and lowest error in separation for the two networks. As shown in figure, error of BP neural network is less than LVQ neural network which agrees to Eivani(2008) research.

Figure 5. Optimum mean square error curves for different repetitions per BP neural network (left) and LVQ neural network (right)
Figure 6 shows the regression diagrams of training, testing and evaluation data used in the 12-11-1 configuration BP neural network model. Also it can be seen that highest accuracy of separation in the BP neural network is 99.7%.

Figure 7 shows receiving operating characteristic curve for LVQ neural network. This diagram related to 5 x 5 competitive layer neurons, the RMSE value is 0.014 with separation accuracy of 97.5.

Study of tables and graphs related to BP and LVQ neural network show that separation accuracy of walnuts for BP neural network is 99.77 % and noticeable in comparison to LVQ neural network (97.5). It is should be noted Mahmoodiet al. (2010) predicted a 47-18-2 multi-layer perceptron neural network structure with accuracy 99.64 %. Therefore BP neural network model with structure type 12-11-1 is recommended for separation of empty walnuts.

CONCLUSION

This research was done to present a suitable algorithm for classifying full and empty walnuts, without breaking. Results show that signal parameters in frequencies lower than 4000 Hz are more suitable for neural network. A 12-11-1 multi-layer back propagation neural network with accuracy of 99.77 % is the best network configuration classifier of full and empty walnuts.

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REFERENCES


LebensmittelWissenschaft & Technologie, 31(2):122-128.