Applying acoustic emission and neural network to classify wheat seeds from weed seeds

Smail Khalifahamzehghasem

(*Young Researchers and Elite Club, Boukan Branch, Islamic Azad University, Boukan, Iran*)

Abstract: In the present study, an expert weed seeds recognition system combining acoustic emissions analysis, Multilayer Feedforward Neural Network (MFNN) classifier was developed and tested for classifying wheat seeds. This experiment was performed for classifying two major important wheat varieties from five species of weed seeds. In order to produce sound signals, a 60^o inclined glass plate was used. Fast Fourier Transform (FFT), Phase and Power Spectral Density (PSD) of impact signals were calculated. All features of sound signals are computed via a 1024-point FFT. After feature generation, 60% of data sets were used for training, 20% for validation, and remaining samples were selected for testing. The optimized MFNN model was found to have 500-12-2 and 500-10-2 architectures for “101” and “Shiroodi” wheat varieties, respectively. The selection of the optimal model was based on the evaluation of mean square error (MSE) and correct separation rate (CSR). The CSR percentages for two wheat varieties were 100%. Considering the overall aspects of the results, it can be stated that the developed system was successful enough to correlate the acoustic features with wheat seed type.

Keywords: weed seeds, wheat seeds, classification, identification, acoustic emission, signal processing, neural network

DOI: 10.3965/j.ijabe.20120504.008

Citation: Smail Khalifahamzehghasem. Appling acoustic emission and neural network to classify wheat seeds from weed seeds. Int J Agric & Biol Eng, 2012; 5(4): 68－73.

1 Introduction

The analysis and classification of seeds are necessary activities which are performed at different stages of the global process, including seed production, cereal grading for industrialization purposes, and scientific research for improvement of weed species, etc. Specialized technicians are employed for these purposes, but the manual seed identification by these technicians is time-consuming and not enough accurate. In the past three decades, a number of researchers have sought to implement computer-based methods for reliable and fast seed identification and classification.

Wheat plays a key role in human nutrition and must be refined from any impurity before using. The previous studies showed that insect damaged kernels can be detected by using near–infrared (NIR)[1,2]. A number of researchers used successfully color images to establish seed quality and characterize damages and diseases[3,4]. Besides varietal identification and cereal grain grading, early identification of weeds from the analysis of strange seeds is also of the major interest in the agricultural industry. This can be performed in order to chemically control weed growth or it can be usually performed as a part of official requirements before a seed batch can be made commercially available. Petersen and Krutz[5] showed the key role of using color images instead of black and white to identify weed seeds to increase classification accuracy. More researchers investigated the potentiality of linear discriminant analysis and artificial neural networks (ANNs) to identify weed seeds from morphological and textural parameters[6-8].

Impact acoustic emission has the advantages of being a rapid, cheap and accurate method that can be adapted

Received date: 2011-11-17 **Accepted date:** 2012-08-24

Biography: Smail Khalifahamzehghasem, Young Researchers and Elite Club, Boukan Branch, Islamic Azad University, Boukan, Iran. Email: smailkhalifa@yahoo.com.

for non–destructive and automated detection. In recent years, there has been an increasing interest in using acoustic emission to identify and sort agricultural products. This method was used for the detection of damaged wheat kernel by Pearson et al.[9] and Ince et al.[10].

The major objective of this study was to propose the acoustic emission system for identification of wheat seeds from weed seeds. The structure of the proposed system is shown in Figure 1.

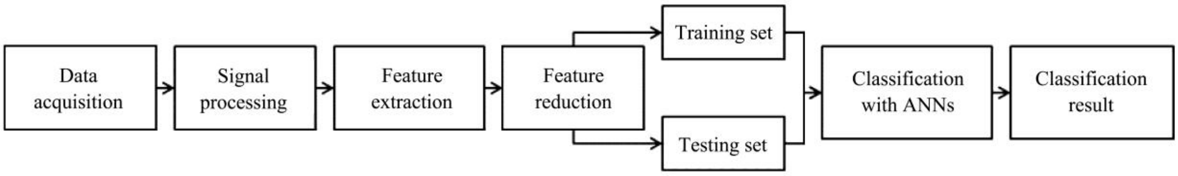


Figure 1 Block diagram of the intelligent diagnosis system used in this study

2 Materials and methods

2.1 Sample preparation and data acquisition

In this study, five spices of weed seeds and two varieties of wheat were used (Figure 2). The kernel moisture content for all weed seeds and wheat varieties was 14%. The impact plate was a block of glass. The acoustic emissions from the seeds were picked up by a microphone (a surface microphones 1.8 mV/Pa, 40LS) which was placed inside the insulated chamber. Seeds were falling freely onto the impact plate. The drop distance from the feeder to the impact plate was 10 cm and the glass plate was inclined at an angle of 30° above the horizontal[9,11]. A schematic of the experimental apparatus collecting the acoustic emissions from the impact plate is shown in Figure 3. Sound signals were saved by using MATLAB® data acquisition toolbox for subsequent analysis[12].

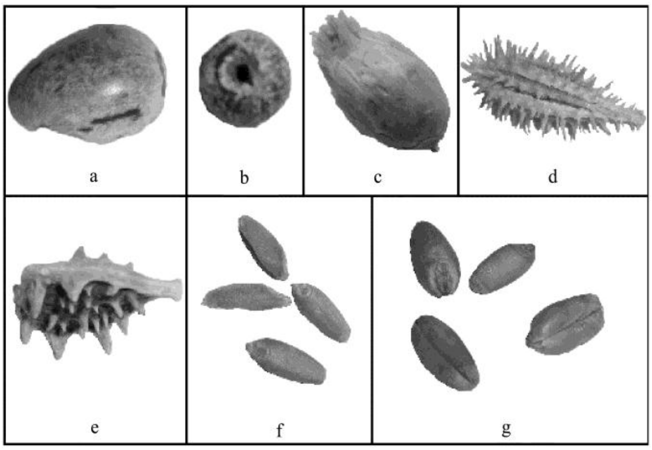


Figure 2 Five spices of weed seeds (a-e) and two wheat varieties (f and g)

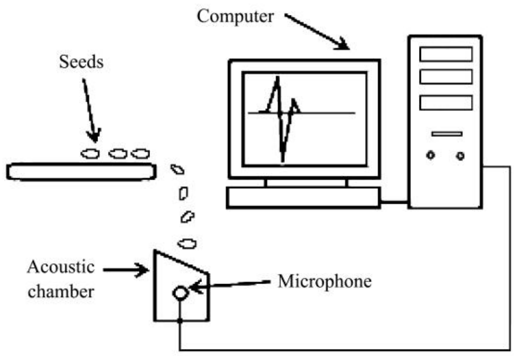


Figure 3 Apparatus used for data acquisition

2.2 Feature generation

One of the common signal analysis procedures to produce useful features is its transmission from time-domain to frequency-domain. A 1024-point Fast Fourier Transform (FFT), Phase and Power Spectral Density (PSD) of sound signals were calculated, respectively, by Equations (1), (2), and (3). Figure 4 presents an example of the computed impact signal, amplitude (A), phase angle (B) and PSD (C) for seeds. The FFT analysis produced 1024 sample data for each seed. These features are produced by MATLAB R2008 software. Due to the symmetry of PSD (phase), these features were halved. In addition, since PSD has FFT amplitude information in itself, it was not considered further.

$$X(k) = | FFT\{x(n)\}, (1024) | \tag{1}$$

$$phase = angle\ X(k) \tag{2}$$

$$PSD = \frac{X(k)X^*(k)}{1024} \tag{3}$$

A number of researchers applied Multilayer perceptron (MLP) as neural network topology in the classification of agricultural products[13,14]. Classical MLP algorithm was used for the models developed in this study. Each neuron has a weighted connection to every neuron in the next layer, and each performs a summation of its inputs passing the results through non-linear sigmoid transfer functions, $f(x)$ equals $\tanh(x)$, at the hidden and output layers[15]. A number of techniques such as Gradient Descent (GD), Levenberg–Marquardt (LM) and Conjugate Gradient (CG) can obtain error minimization in the feed forward networks. The standard BP (Back Propagation) uses the GD technique which is very stable when a small learning rate is used, but has slow convergence properties. In the present study, GDM learning rule which is an improvement to the straight GD rule in the sense that a momentum term is used to speed up learning, stabilizing convergence and avoiding local minima. Momentum makes the current weight change depend on the previous weight change as well as on the current error, which encourages weight changes to continue in the same direction. The MLP is trained with error correction learning (supervised), implying that the desired response for the system must be known a priori[15]. In this study, to minimize the training procedure, only one hidden layer is considered[11].

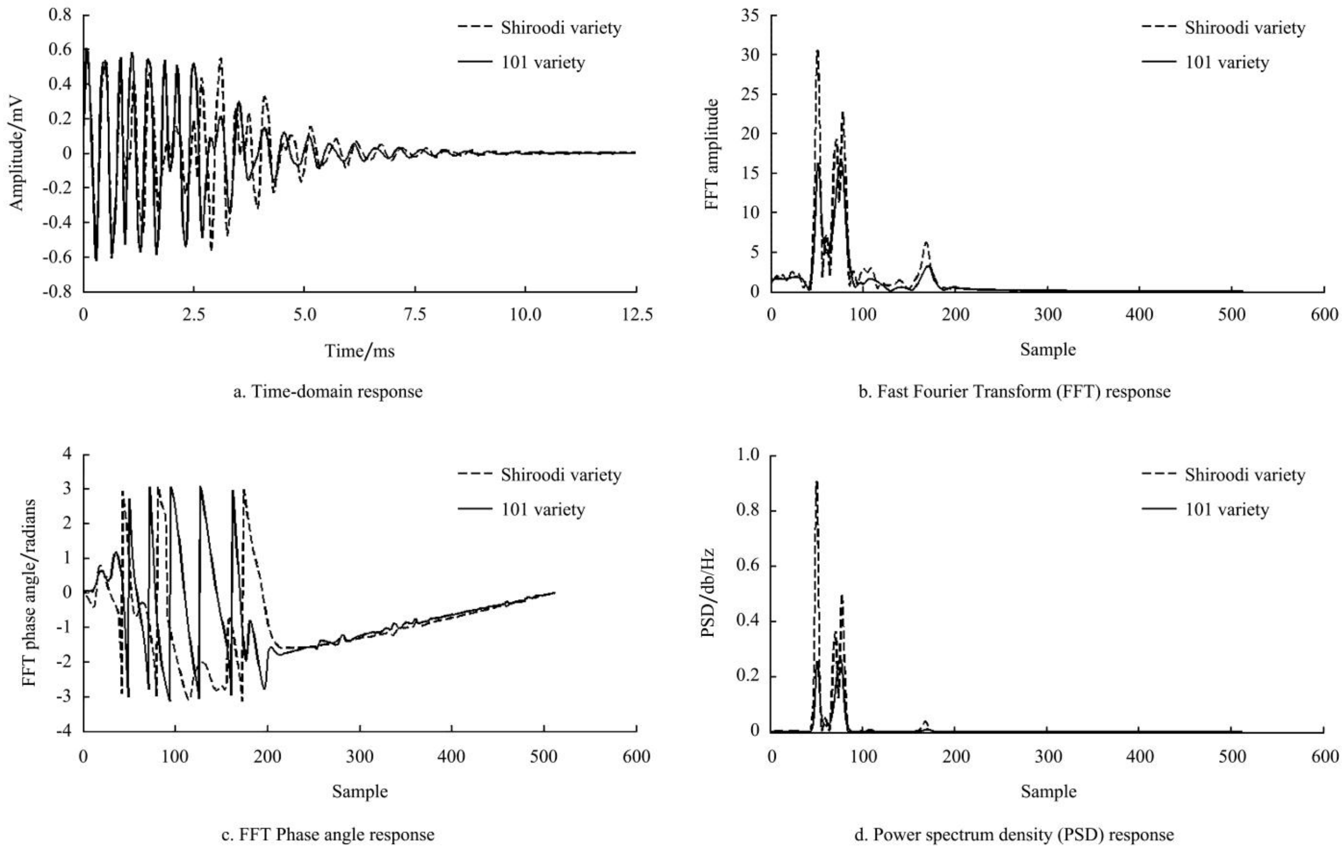


Figure 4 Typical impact sound signals and spectra of wheat seeds

2.3 Technical details

The data set on weeds and wheat were split into three categories: 60% for training, 20% for cross-validation (CV) and the remaining data points (20%) for testing MFNN models. After adequate training, the network weights are adapted and employed for validation in order to determine the MFNN model overall performance[16]. Normalization of data was performed for removing the variation existed among the data points. In order to build statistically sound MFNN topologies, the networks were trained three times and the average values were recorded for each parameter. All simulations were performed with a three-layer MFNN with GDM learning rule (Equation (4)) and the TANH (tangent hyperbolic) transfer function for all of the neurons in the hidden and output layers. Figure 5 depicts the schematic of the classifying weed seeds from wheat seeds.

$$\Delta_{ji}^{(n)} = \eta\delta_j^{(n)} o_i^{(n)} + \alpha \Delta w_{ji}^{(n-1)} \tag{4}$$

where, w_{ji} is the weight between the jth node of the upper layer and the ith node of the lower layer; δ_j is error signal of the jth node; o_i is output value of the ith node of the previous layer; and η and α are the learning rate and the momentum term, respectively.

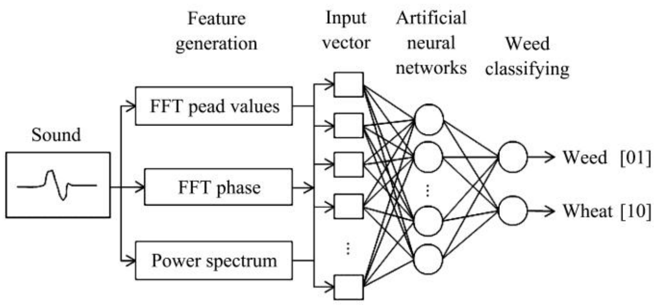


Figure 5 Back propagation neural networks (BPNN)-based scheme for classifying weed seeds from wheat seeds

3 Results and discussion

To find the best network of effective features and optimal MFNN configuration, nine different topologies for each varieties of wheat were tested by neural networks. Features with different structures were fed to the MFNN topologies and their performances were determined by evaluation of the mean square error (MSE) and correct separation rate (CSR). Performances of different MFNN models were compared based on MSE. The expression used to calculate the MSE is given by Equation (5):

$$MSE = \frac{1}{mn}\sum_{j=1}^{m}\sum_{i=0}^{n}(d_{ij} - o_{ij})^2 \tag{5}$$

where, m is the number of output neurons (two in present study); n is the number of exemplars in data set (180); and δ_{ij} and o_{ij} are the network outputs and the desired outputs for ith exemplar at jth neuron, respectively.

Table 1 summarizes the results of simulation which offers a great deal of importance. Among the different configurations examined, the 500-12-2 and 500-10-2 configurations were obtained for classifying weed seeds from “101” and “Shiroodi” wheat varieties, respectively. The highest accuracy and the least error on CV data set were gained (MSE=0.011164 for classifying weed seeds from “101” variety and MSE=0.003782 for classifying weed seeds from “Shiroodi” variety). The optimum MFNN has 500 features as the input vector for “101” variety, 12 neurons in its hidden layer and 2 neurons as the output vector (weed seeds and wheat seeds) also the optimum MFNN has 500 features as the input vector for “Shiroodi” variety, 10 neurons in its hidden layer and 2 neurons as the output vector.

Table 1 Summary of results for wheat seed classification from weed seeds using BPNN

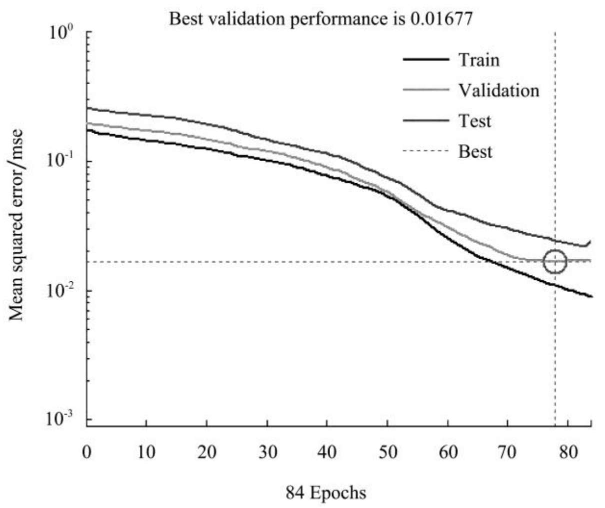
Cereal variety	Feature	Input layer	Hidden layer	MSE	Test/%
101 variety	FFT	500	10	0.01677	96.7
		500	12	0.011164	100.0
		500	15	0.030922	98.3
	PSD	500	10	0.01606	98.3
		500	12	0.029807	100.0
		500	15	0.047942	95.0
	ANG	500	10	0.025705	90.0
		500	12	0.013042	93.3
		500	15	0.056014	93.3
Shiroodi variety	FFT	500	10	0.0088984	98.3
		500	12	0.0066048	98.3
		500	15	0.013875	100.0
	PSD	500	10	0.003782	100.0
		500	12	0.042237	98.3
		500	15	0.014158	95.0
	ANG	500	10	0.03635	96.7
		500	12	0.030519	91.7
		500	15	0.02756	100.0

The results of this study showed that FFT and PSD are the dominant features in the classification of weed seeds from two wheat varieties, “101” and “Shiroodi”, respectively. Results showed that optimal responses were not necessarily conferred from complex topologies. This may be due to over-learning problems or randomly selection of data through training stages[17].

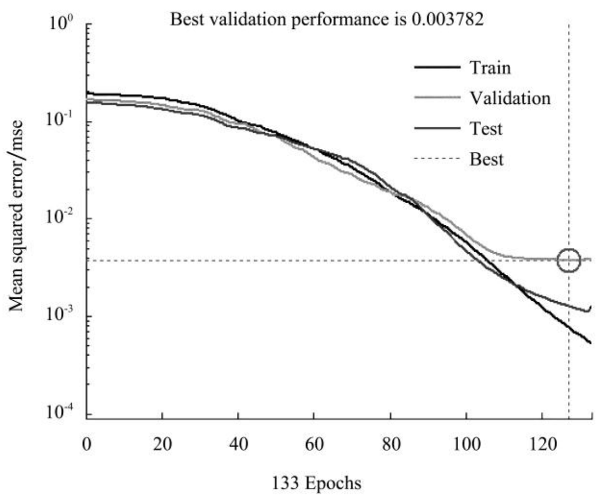
The CSR were calculated from the confusion matrix given in Table 2. The CSR percentages for weed, “101” and “shiroodi” wheat varieties were obtained to be 100%. The convergence of the MSE of the optimal network during training, cross-validation and testing is shown in Figure 6. This study have some advantages such as excellent accuracy, requiring short signal durations, simple algorithm and small size feature vectors, etc.

Table 2 Confusion matrix of testing data for both "101" and "Shiroodi" varieties from weed

Desired classification	Predicted classification	
	Weed	Wheat (101 variety)
Weed	46	0
Wheat (101 variety)	0	14
	Weed	Wheat (Shiroodi variety)
Weed	52	0
Wheat (Shiroodi variety)	0	8



a. Classification of weed from "101" wheat variety



b. Classification of weed from "Shiroodi" wheat variety

Figure 6 Learning curves with GDM algorithm

4 Conclusions

Several attempts have been made to classify weed seeds from wheat seeds by using image processing[7,8], but there was no research using acoustic emission to classify cereal from weed seeds and this study is the first work at this aim. In the present study, an innovative combined system, based on acoustic detection and neural networks was developed for classifying weed seeds from two major wheat varieties in Iran ("101" and "Shiroodi"). The method is based on classification using BPNN. The total weighted average in system accuracy was 100% for both wheat varieties. The procedure outlined here works on the basis of impact sound differences and it is therefore not restricted to a particular application. Moreover, because of non-destructivity, the developed system does not cause damages or defects to either weed seeds or wheat seeds. This may be highly advantageous for utilization in industrial sorting lines leading to enhanced quality and economic benefits.

Therefore, the results indicated that the proposed system can provide a highly accurate wheat classification from weed seeds. Further efforts are needed, however, to verify these results and to expand the acoustic method for more varieties of weed.

[References]

[1] Cheewapramong P, Wehling R L. A simplified near–infrared method for detecting internal insect infestation in wheat kernels. AACC Abstract Paper 368. St. Paul, Minn. AACC. 2001.

[2] Maghirang E B, Dowell F E, Baker J E, Throne J E. Automated detection of single wheat kernels containing live or dead insects using near–infrared reflectance spectroscopy. American Society of Agricultural and Biological Engineers, 2003; 46(4): 1277-1282.

[3] Jansen P I. Seed production quality in *Trifolium balansae* and *T. resupinatum*: the role of seed color. Seed Science and Technology, 1995; 23: 353-364.

[4] Ahmad I S, Reid J F, Paulsen M R, Sinclair J B. Color classifier for symptomatic soybean seeds using image processing. Plant Disease, 1999; 83: 320-327.

[5] Petersen P E H, Krutz G W. Automatic identification of weed seeds by color machine vision. Seed Science and Technology, 1992; 20: 193-208.

[6] Chtioui Y, Bertrand D, Dattée Y, Devaux M F. Identification of seeds by color imaging: comparison of discriminant analysis and artificial neural networks. Journal of the Science Food and Agriculture, 1996; 71: 433-441.

[7] Granitto P M, Navone H D, Verdes P F, Ceccatto H A. Weed seeds identification by machine vision. Computer and Electronics in Agriculture, 2002; 33: 91-103.

[8] M Granitto, Pablo F, Verdes Pablo, Alejandro Ceccatto H. Large-scale investigation of weed seed identification by machine vision. Computers and Electronics in Agriculture, 2005; 47: 15-24.

[9] Pearson T, Cetin A E, Tewfik A H, Haff R P. Feasibility of impact-acoustic emissions for detection of damaged wheat kernels. Digital Signal Processing, 2005; 17(3): 617-633.

[10] Ince N F, Onaran I, Pearson T, Tewfik A H, Cetin A E, Kalkan H, et al. Identification of damaged wheat kernels and cracked-shell hazelnuts with impact acoustics time-frequency patterns. American Society of Agricultural and Biological Engineers, 2008; 51(4): 1461-1469.

[11] Mahmoudi A, Omid M, Aghagolzadeh A, Borgayee A M. Grading of Iranian's export pistachio nuts based on artificial neural networks. International Journal of Agriculture & Biology, 2006; 8(3): 371-376.

[12] MathWorks 2008. MATLAB User’s Guide, the Math Works, Inc.

[13] Hosainpour A, Komarizade M H, Mahmoudi A, Shayesteh M. Feasibility of impact-acoustic emissions for discriminating between potato tubers and clods. Journal of Food, Agriculture & Environment, 2010; 8(2): 565-569.

[14] Ahmadi Moghaddam P, Hadad Derafshi M, Shayesteh M. A new method in assessing sugar beet leaf nitrogen status through color image processing and artificial neural network. Journal of Food, Agriculture & Environment, 2010; 8(2): 485-489.

[15] Howard D, Mark B. Neural Network Toolbox, Version 4. The MathWorks Inc. Natick, MA, USA. 2000.

[16] Hassoun M H. Fundamentals of Artificial Neural Networks. MIT Press, Cambridge, MA. 1995.

[17] Haykin S. Neural Networks: A Comprehensive Foundation, Mac-milan, New York. 1994.