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Feasibility of applying acoustic and ANN in date separating

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ABSTRACT

In distinguishing two sizes of three Iraniandry date cultivars, the acoustic system and artificial neural network was combined for the first time. Various features obtained from sound analysis were entered as ANN input set. Appropriate features have significant effect in final result of the network. Frequency features of sound signals are computed via a 1024-point FFT. Fast Fourier Transform (FFT), Phase and Power Spectral Density (PSD) of impact signals were calculated. Several combinations of selected and extracted features were used as input set in a multilayer perceptron neural network with a back propagation algorithm, with 60%-25%-15% of data astraining, validation and testing sets.The optimized MFNN was distinguished Dayiri sizes with 93.687Correct Detection Rate (CDR), Piarum sizes with 81.035 CDR and Zahidisizes with 91.

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Introduction

In date separating, most of the researches have been reported so far are focused on mechanical and machine vision methods. Incorporation of machine vision and artificial neural network has impressive influence in date separation(Al Janobi, 2000; Hobani, 2003; Hobani& Ahmed, 2006; Al Ohali, 2011)

Combining acoustic system and artificial neural network in sorting and grading agricultural products was used in several researches. One of the most important researches of utilizing this combination was done in feasibility of impact-acoustic emissions for detection damaged wheat kernels. The acoustic system used in mentioned research was based on Pearson research on detect closed and open shells pistachio nuts. The system was designed to feed pistachio nuts to an impact surface, acquire the sound signal upon impact. Kernels were impacted onto a steel plate and the resulting acoustic signal analyzed to detect damaged nuts. The microphone signal magnitudes, frequency spectra magnitudes and combinations of magnitude and gradient used. Both linear and non-linear discriminant analysis was used as the classification procedures(Pearson, 2001). For detection of damaged wheat kernels the acquired acoustic signal was processed using four different methods: modeling of the signal in the time-domain, computing time-domain signal variances and maximums in short-time windows, analysis of the frequency spectrum magnitudes and analysis of a derivative spectrum. Features were used as inputs for a neural network (Pearson, Cetin, Tewfik &Haff, 2007). In a similar approach an intelligent system was developed for Iranian pistachio nuts sorting. The system was combining acoustic emissions analysis, Principal Component Analysis (PCA) and Multilayer Feed forward Neural Network (MFNN) (Omid, Mahmoudi &Omid, 2009). The method is based on data reduction by PCA and classification using back-propagation neural networks (BPNN). Features of pistachio nut varieties were extracted from analysis of sound signals in both time and frequency domains by means of Fast Fourier Transform (FFT), power spectral density (PSD) and principal component analysis (PCA) methods (Mahmoudi, Omid & Aghagolizadeh, 2006). A similar acoustic system was developed for detection of Iranian Walnut Varieties (Khalesi, Mahmoudi, Hosainpour&Alipour, 2012),in detection Iranian Almond Varieties (Reshadsedghi &Mahmoudi, 2013), in grading walnuts(Khalifa, Komarizadeh, Tousi, &Nikbakht, A.M., 2011) and to classify wheat seeds from weed seeds (Khalifahamzehghasem, 2012).

Neural networks (NNs) have been used for a wide cultivar of agricultural applications like classification problems. The neural field considered to begin with Warren McCulloch and Walter Pitts from 1943 (McCulloch and Pitts1943,Sima, J. 1998). A neural network is composed of a number of nodes (units), connected by links. Each link has a numeric weight associated with it.To build a neural network it should be decided how many units are to be used, what kind of units are appropriate, and how the units are to be connected to form a network. One then initializes the weights of the network, and trains the weights using a learning algorithm applied to a set of training examples for the task (Sima 1998).

Procedure

An identification system with the combination of acoustic technique and artificial neural network (ANN) for recognizing two size of three different cultivar of Iranian dry dates were investigated. Three different cultivars of Iranian dry date, named Zahidi, Piarum and Dayiri were considered. Two size, big and small, were choseby visual. For eachsize300samples were randomly chose.

Laboratory system

Alaboratory system (fig. 1) consisting of hardware and software partswas designed. The hardware part was included a computer, an acoustic and a transfer mechanism. The software part was combined of an artificial neural network (Neuro Solutions 5) and Matlabsoftware (R2013b).

The transfer mechanism has the ability to change the angle and height and its base was a 35 cmPVC tube that was oriented 20˚ toward the horizontal.

The acoustic mechanism was an acoustic chamber (Omid, Mahmoudi&Omid, 2009), isolated from external sounds and has the ability to obtain a clear sound without any external noise. The microphone was installed inside the isolated acoustic chamber to eliminate environmental noise effects. The impact plate was placed at top of the acoustic chamber. Itwas a polished block of stainless steel(Amoodeh, Khoshtaghaza, &Minaei,

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2006) with a heavy mass that roles a damper. The large thickness was required to minimize vibrations the bar during the impact (Pearson, 2001).

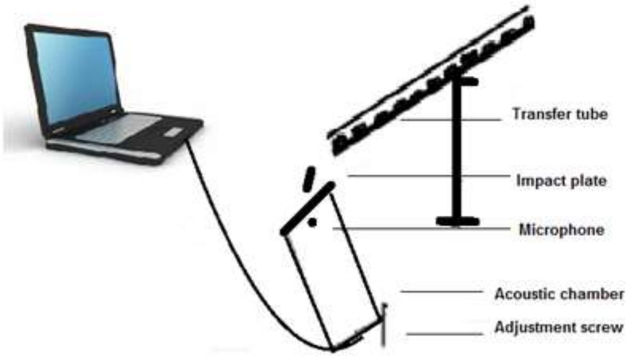

Figure 1.Laboratory system

Data acquisition

Data acquisition of all samples of three cultivars of dry date was carried out in a uniform condition that was determined with trial and error. 20˚slope for the 35length pipe, 15 cm ashigh of dates fall, 14×14 cm^2 as slide of impact plate with 1 cm thickness and gradient of 14˚ andtotal high of acoustic chamber was 50 cm.

Passing the pipe, collision of dates with plate was created a longitudinal wave that could be storage as sound wave in time domain with data acquisition toolbox in Matlab (Matlab users' guide). Emitted sound signals of 300date samples fromonesize of a cultivarare shown in Fig. 2(a).Sound signals were sent to a PCsystem and digitized at a maximum samplingfrequency of 44.1 kHz. In addition,in order to eliminate the data acquisition error, in total time of collecting data, the settings of data acquisition toolbox of Matlab was uniform too. The range of output voltage (output signal) was specified from -1 to 1 v, data acquisition threshold was 0.05 v and the number of data points (the number of data acquisition)for each contact of a single date was 1000.This number of data pointfor sampling in each contact and maximum sampling frequency of sound card caused a 22 ms sampling after triggering.

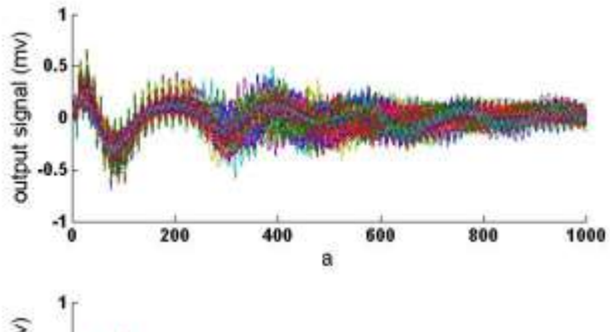

Figure 2.Emitted sound signal in time domain

Signal processing

Considering the figure (fig. 2,b) the first 6.8 ms (equal to 300 data point) seems to be useful, because of its uniformity, and was selected for subsequent analysis and 700 data point was disregarded. In other word the standard deviation of output signal values for 300 date sample in mentioned range is lower, that caused the capability of elimination the last 700 data point.

In signal processing, determination of the frequency of a signal is necessary. Fast Fourier Transform technique is applied to convert obtained signal in time domain to frequency domain. It converts a signal into magnitudes and phases of the various sine and cosine frequencies making up the signal. The Fourier transform decomposes a signal intoorthogonal trigonometric basis functions. A fast Fouriertransform is an efficient algorithm to compute thediscrete Fourier transform and it's inverse. The reduction in the number ofintervals makes FFT very fast (Roshni, Niranjan, Das Prakash&SrinivasRao, 2012).

Theamplitude of the signals in time domain is a feature represents the loudness of the audio signal(Richel, D.R).The frequency of a sine wave reagent the sound's pitch and the amplitude of that represents the sound intensity (Hartmann 1996). Pitch is a feature represents the vibration rate of audio signals, which can be represented by fundamental frequency(Richel, D.R). Features of sound signals in frequency domain were computed by means of a 1024-point FFT.

The magnitude of signal in frequency domain, FFT phase angle and Power Spectral Density (PSD) of impact signals were calculated(Omid, Mahmoudi&Omid, 2009).A huge amountof potential features were extracted from signals in time and frequency domain:

Amplitude of signal in time domain (A): 1000
Amplitude of signal in frequency domain (fft A):1024
Phase of signal in frequency domain (ANG): 1024
Power spectral density in frequency domain (PSD): 1024

Because of the symmetry of signal in frequency domain(fig. 3), the possibility of removing half of data points in frequency domain (1024 to 512) was provided(Omid, Mahmoudi&Omid, 2009).

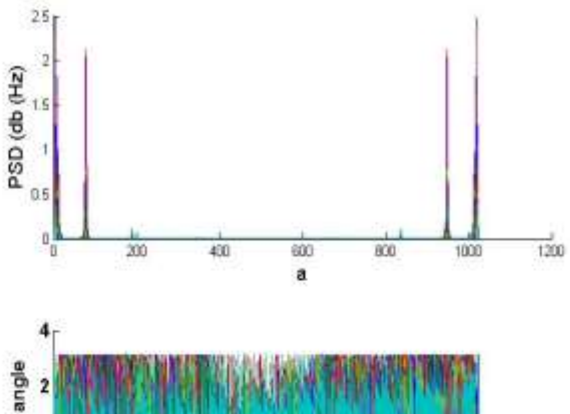

Figure 3.Symmetry of signal in frequency domain

Power spectral density (PSD) is multiplied of frequency amplitude and it's conjugate. This multiply provides a powerful feature for identification. In fact the amplitude of signal in frequency domain is hidden in PSD and has the waiver capability. So features were reduced as follows:

Amplitude of signal in time domain: 300

Phase of signal in frequency domain: 512

Power spectral density in frequency domain: 512

Feature reduction

A huge data amount will complicate the identification process and increase the error. Even after removing this amount of data, the dimension was large yet. So the reduction was done in the manner of feature extraction and selection.

There are two main reasons to keep the dimensionality of the number of features as small as possible: measurement cost and classification accuracy. Consequently, the resultingclassifier will be faster and will use less memory. Moreovera small number of features can alleviate thecurse of dimensionality when the number of training samples is limited (Jain, Duin& Mao, 2000).

Feature extraction

Feature extraction is the transformation of the original data to a data set with a reduced number of variables.Principal Components Analysis (PCA) is linear combinations of the original variables thatis uncorrelated to each other(Webb, 2002). The PCA transform applied for variables such as amplitude signal in time domain,Phase and Power Spectral Density (PSD). As shown in table2, applying the PCA transform, in five surface of variance (eliminates those principal components that contribute less than the applying variance to the total variation in the data set),reduced the dimension of thedatasignificantly.

Feature selection

The other technique for dimension reduction is selecting a feature. It selects those variables that contain the most discriminatory information. Feature selection want to remove redundant or irrelevant information to obtain a less complex classifier (Webb, 2002).

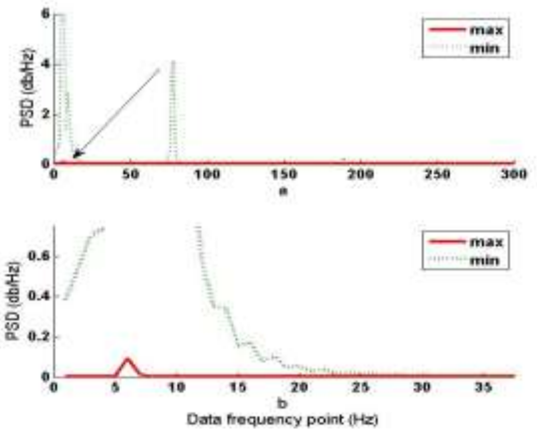

Figure 4.PSD maximum and minimum plot

With regards to maximum and minimum of PSD, it was appeared that there is a limited range of data frequency points that seems to be useful for date sizeidentification (fig.4). Computing the variances of PSDfor each data frequency point(correlates to a specificcultivar) could show differences. At first, for each size of a cultivar the variance of quantity of PSD in each data point (512 data point for each date cultivar) for 300 dates was calculated (fig.5 and 6). Based on the goal (compared cultivar sizes) variance of each size was calculated. Bigger differences was shown the better frequency data point that could be regent the distinguishing feature of date size. This variance was computed for each cultivar size separately. Computing the variance of computed variances (fig. 7) was observed the best range of frequency data point that is suitable for recognition cultivar sizes. This manner was used for reduction dimension of PSD and FFT phase angle and is illustrated as an instance in result and discussion part (3-3).

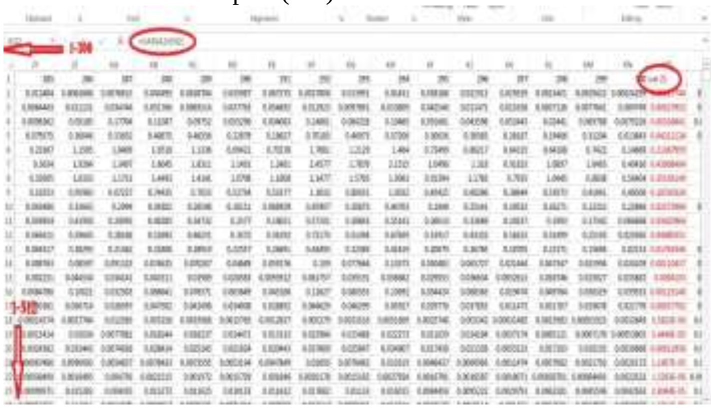

Figure 5.PSD varianve of big size of zahidi

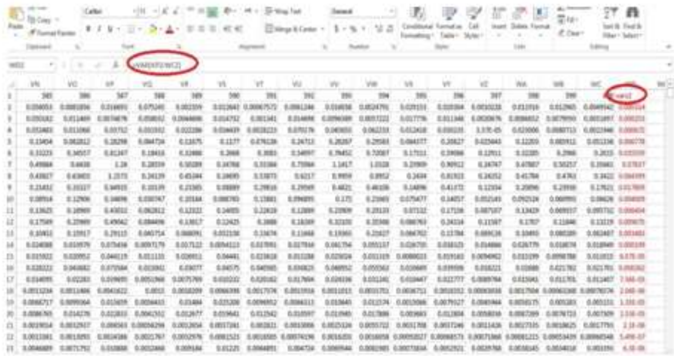

Figure 6. PSD varianve of small size of zahidi

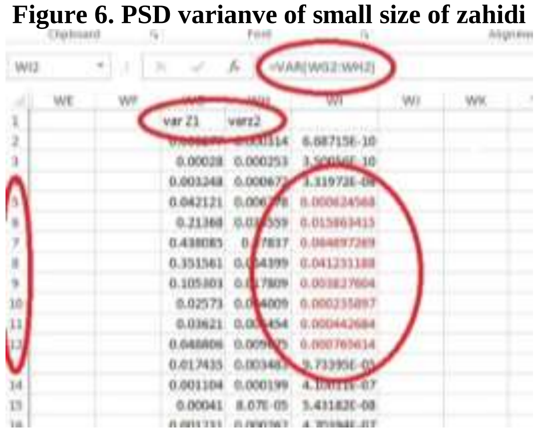

Figure 7.Total variance

In addition to feature selection among the 512 PSD features, the value of mean, maximum and minimum (statistical) of signal in time domain, angle of signal in frequency domain and power spectral density was calculated and was used as selecting feature manner (Haff, Jackson and pearson, 2005).

Recognition

Pattern recognition is the study of how machines can observe the environment, learn to distinguish patterns of interest from their background, and make sound and reasonable decisions about the categories of the patterns (Webb, 2002). Artificial intelligent is a manner of pattern recognition (Jain, Duin& Mao, 2000).

The main characteristics of neural networks are that they have the ability to learn complex nonlinear input-output relationships, using sequential training procedures, and adapting themselves to the data (Webb, 2002).

Several combination of features wereloaded as input set in ANN software, named neural solution. But before do this it should be determine what kind of network, transfer function and learning rule with how many hidden layer and neurons in hidden layer should be chose.

The type ofthe network was specified before determining the number of hidden layer and neurons. Some networks such as MLP, RBF, GFF, PCA and SVM have been usedfor classification in researches.

Among different types of neural networks, the most generally used one is the multilayer feed forward neural network (Balas, Koç&Tür, 2010). Without considering the best combination of input setall of networks were loaded with a unit inut set. Different networks with different topologies were run with a unit input set and unit ratio for train, test andvalidation set. In the base of network outcome and according to the value of percentage ofoutput classified correctly (Correct Detection Rate (CDR)), linear correlation coefficient (CC) and mean squared error (MSE), the valid judgment was done. With the chosen topology, networks were running with different transfer functions like TanhAxon, Sigmoid Axon and Bias Axon. After transfer function identification,the next parameter was gradient descent method like Momentum and Levenberg-Marquardt. Between multiplicity oftransfer function and learning rule these methods were tested because of their ordinary usage in classification problems in the researches. A single hidden layer was exerted for obstruction of increasing network train time. Inputs have an important role in ultimate result. The input set has chosenbetween variables as described before. With determining the number of neurons the final network was completed.

The number of neurons in the input layer corresponds to the number of input features and the number of neurons in the output layer corresponds to the number of classes. The classifier is trained, validated and tested using several combination ofobtained features.

Results and discussions

All three stepswas very important and had a critical role in final results. Data acquisition of all samples of three cultivars of dry date was carried out in a uniform condition. The extraction and selection feature was take place carefully. At the end,the best ANN was chose for recognition of three cultivars.

Properties of signal in time domain:

The difference between signal amplitude mean (in time domain) for different Zahidisizes are obvious (fig. 8). So it was appeared that it could be a suitable feature for separation. These differences are inserted in table 1.

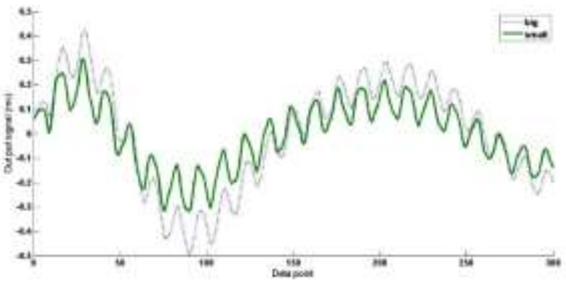

Figure 8.Average signal amplitude of two size of Zahidi cultivar in time domain

Properties of signal in frequency domain:

The power spectral density, signal phase and signal amplitude in frequency domain was computed by means of MATLAB. According to curve of average size signal (amplitude) at frequency domain (fig.9) different values for peaks provided recognition possibility. The value of these peaks and their differences is observable in table 1.

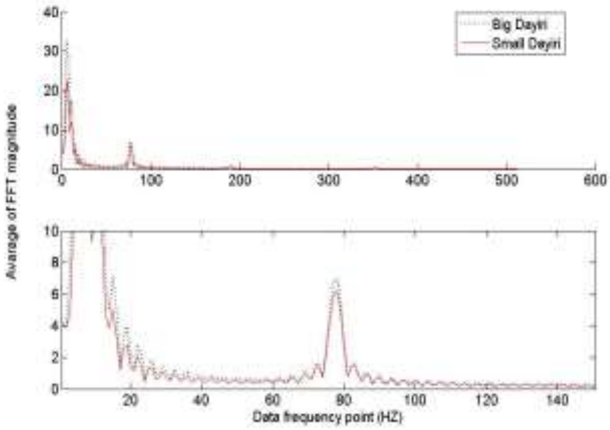

Figure 9.The amplitude in frequency domain for Dayiri

Table 1.The difference between amplitude of signal in both, time and frequency domain

cultivar	AMP(mv)	absfft first peak	absfft second peak	absfft third peak
Big Dayiri	0.32	33	7	1
Small Dayiri	0.21	22	6	1
Big Piarum	0.44	50	6	1
Small Piarum	0.30	40	6	1
Big Zahidi	0.32	38	16	3.5
Small Zahidi	0.22	24	16	3.5

Feature reduction:

As previously mentioned, feature reduction manners were reduced features in time domain and frequency domain dramatically. Results shows that how much the feature extraction and selection manners has been successful in feature reduction (table 2). For example PCA transformation with 0.01 variance surface applied reduced 300 feature of A to 8 and feature selection reduced that to three.

In order to clarify the mentioned manner of feature selection for identifying two size of Zahidi cultivar, the steps is expressed and illustrated with fig 5 to 7. According to (fig 5 and 6) computation steps of variances for each size and in each frequency data point in PSD matrix is observable.The manner of computing variances of each 512 data frequency point for 300 samples of big size of Zahidi has shown in fig. 5. And the variances of each 512 data frequency point for 300 samples of small size has shown in fig. 6. Also, the variance of these two variances for each 512 data frequency point was computed, that has shown in fig. 7. Whatever this value is much bigger it seems the correlated data frequency points are more suitable features for distinguishing two size. These variances was computed in EXELL software.

In identifying two size of Zahidi, regarding to table. 2eightdata frequency points has the biggest variance and was selected between 512 data frequency point. So the PSD matrix (512×300) reduced to (8×300).

Completing the previous example 25 feature were selected. Eight feature from the 512 PSD features, five from phase and 12 other is mean, maximum and minimum of signal amplitude in time and frequency domain, angle of signal in frequency domain and power spectral density.

Recognition

Recognition of neural network depends on several factors like network type, transfer function, leaning rule, the number of layers and neurons and input set.

Table 2.The number of features after applying feature reduction manners

Compared variaties	Feature extraction Sequence of applied variances:															Feature selection			
	A					PSD					ANG					PSD	ANG	A	FFTA
	0.05	0.02	0.01	0.008	0.005	0.05	0.02	0.01	0.008	0.005	0.05	0.02	0.01	0.008	0.005				
Dayiri	4	6	8	9	9	*1*	*1*	*2*	*2*	*3*	1	3	5	7	11	4+3[a]	8+3	3	3
Piarum	5	7	7	7	8	*2*	*3*	*5*	*6*	*6*	1	1	4	5	7	8+3	6+3	3	3
Zahidi	4	5	8	9	11	*1*	*1*	*2*	*3*	*4*	2	4	8	7	12	8+3	5+3	3	3

Table 3. Recognition steps

(a)

Piarum big	Piarum small	Diagnostic criteria	Network type
84 0.801 0.0939	93.055 0.801 0.0939	CDR CC MSE	MLP
75 0.747 0.172	89.385 0.747 0.179	CDR CC MSE	RBF
79.486 0.752 0.108	87.366 0.754 0.106	CDR CC MSE	GFF
81.818 0.732 0.199	83.561 0.718 0.122	CDR CC MSE	PCA
79.538 0.651 0.153	80.350 0.63 0.153	CDR CC MSE	SVM

(b)

Piarum big	Piarum small	Learning rule	Transfer function
82.168 0.749 0.126	92.735 0.79 0.125	Momentum	Tanh Axon
65.966 0.685 0.128	85.735 0.658 0.128	Monentum	Sigmoid Axon
85.428 0.63 0.136	90.566 0.63 0.147	LevenbergMarguardt	Tanh Axon
87.54 0.64 0.186	84.23 0.67 0.187	LevenbergMarguardt	Sigmoid Axon

Table 4.Results of selecting suitable network topology

Compared cultivars	Network type	Transfer function	Learning rule	Neurons of input layer	Neurons of hidden layer
Dayiri	MLP-2L[a]	Tangent Hyperbolic	LevenbergMarquadt	13	10
Piarum	MLP-2L	Tangent Hyperbolic	LevenbergMarquadt	20	9
Zahidi	MLP-2L	Tangent Hyperbolic	LevenbergMarquadt	26	4

Table 5.Final result of input set and ANN conclusion

<table>
<tr><td></td><td colspan="2">(Zahidi)
Big-Small</td><td colspan="2">(Piarum)
Big-Small</td><td colspan="2">(Dayiri)
Big-Small</td></tr>
<tr><td>Input set</td><td colspan="2">AMP.ANG[a]
min,max,mean[b]</td><td colspan="2">PSD[c]
min,max,mean</td><td colspan="2">PSD(0.01)[d]
min,max,mean</td></tr>
<tr><td>CDR</td><td>89.743</td><td>93.055</td><td>69.863</td><td>92.207</td><td>90.361</td><td>97.014</td></tr>
<tr><td>CC</td><td>0.841</td><td>0.838</td><td>0.687</td><td>0.665</td><td>0.860</td><td>0.859</td></tr>
<tr><td>MSE</td><td>0.0741</td><td>0.075</td><td>0.134</td><td>0.140</td><td>0.066</td><td>0.066</td></tr>
</table>

a.selected feature from AMP and ANG
b.statistical feature selected from AMP, PSD , ANG and absfft
c.selected feature from PSD
d.extracted feature from PCA transformation with applying 0.01 as variance in PSD

As mentioned before, in this paper as first step, the network type was selected between several networks(table 3. A). Specifying the transfer function and learning rule(table 3. B), the input set was selected(table 3. C). Apart from the last step all of them were tested with a unit input set regardless of different combinations and with the member of neurons in hidden layer that was suggested with software (without any alter). Huge member of different combination features were tested as input set.To follow a specified manner for all compared cultivar sizes, after trying different combinations of obtained features, it was decided to select between extracted and selected features separately and then combine them and select the best input set between them as the last step. Between too many tested input sets, just a few combinations are shown in table 3. C.

After selecting the best combinationthe last step was selecting the number of neurons(fig. 10).In all steps,the optimal model was selected after many evaluations based onminimizing of mean square error (MSE) and increasing CDR and CC (Diagnostic criteria). The lowest MSE, the highest CDR and CC were desired. These steps were repeated for each compared cultivars' sizes.

The best member of neurons in hidden layer are shown in table 4 and the final result are shown in table 5.

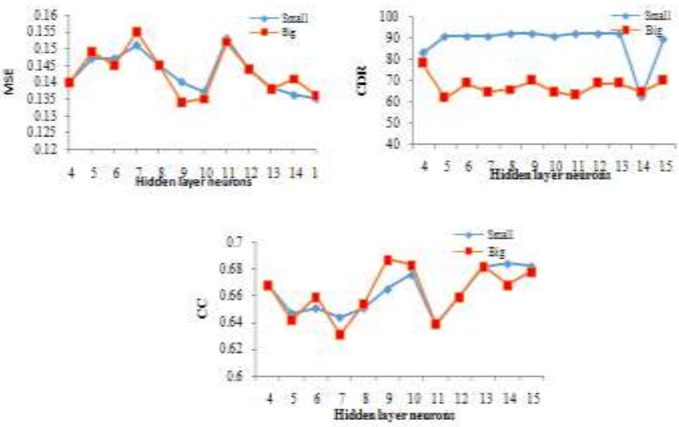

Figure 10. Steps of hidden layer neurons selection

Conclusions

An acoustic-based system combined with neural network was developed for identifying two size of three Iranian dry date cultivars for the first time. A multilayer perceptron neural network with a back propagation algorithm was used as recognition system. It was understood that combining the feature selected and extracted as input set in ANN has acceptable effects in final results. The result achieved in this paper isnotice:

1. A 2 layers MLP network with 13 neurons as input set and 10 neurons in hidden layer recognized small size of Dayiri from big size 97% correctly, 90% big size from small size with 0.08 mean square error and 0.6 correlation coefficient. Between a lot of combination of feature selected and extracted, the combination of extracted feature from PCA transformation in PSD with applying 0.005 as applied variance and 12selected features consisting of minimum, maximum and mean of amplitude signal in time and frequency domain PSD and ANG as input set caused the best result in ANN response.

2. A 2 layers MLP network with 20 neurons as input set and 9 neurons in hidden layer recognized big size of Piarum69% correctly, 85% small size with 0.06 mean square error and 0.1 correlation coefficient. Eight selected features of PSD in variance manner and 12 statistical feature containing min, max and mean of signal in time domain and frequency domain, PSD and ANG as input set caused the best result in ANN response.

3. A 2 layers MLP network with 26 neurons as input set and 4 neurons in hidden layer recognized big size of Zahidi89% correctly, 93% small size with 0.07 mean square error and 0.8 correlation coefficient. 14selected featuresof PSDand ANG in variance mannerand 12 statistical feature containing min, max and mean of signalin time domain and frequency domain, PSD and ANG as input set caused the best result in ANN response.

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