Weed detection using ultrasonic signal processing employing artificial neural network (ANN) with efficient extracted features

Danial Gandomzadeh, Abbas Rohani*, Mohammad Hossein Abbaspour-Fard

(Biosystems Engineering, Faculty of Agriculture, Ferdowsi University of Mashhad, Mashhad, Iran)

Abstract: In this paper, in addition to reviewing the conventional methods of weed detection, an alternative method based on processing of ultrasonic signals is introduced. In this regard, with the aid of a proper setup with the capability of sending and receiving 40 kHz ultrasonic waves, five weed species namely Portulacaceae, Chenopodiumalbum L., Tribulusterrestris L., Amaranthusretroflexus L. and Salsolaiberica were identified. The continuous 40 kHz ultrasonic waves are sent to weed canopy and received back by an ultrasonic receiver. These signals are then transferred to a laptop (DELL INSPIRON 5010) and stored in MATLAB 2013a software for several signal features extraction, using artificial neural network (ANN) to discriminate the weeds and ultimately weed classification. Overall, the results showed that by eliminating about 20% of the inefficient signal features, the maximum detection accuracy of the ANN performance could be reached as high as 80%. According to these satisfactory results, it is suggested that the performance of this system, which will be equipped with a height measurement module, be evaluated in motion.

Keywords: ANN, detection, signal, weed, ultrasonic

Citation: Gandomzadeh, D., A. Rohani, and M. H. Abbaspour-Fard. 2022. Weed detection using ultrasonic signal processing employing artificial neural network (ANN) with efficient extracted features. Agricultural Engineering International: CIGR Journal, 24 (3):52-58.

1 Introduction

The persisting problems such as climate changes, lack of water resources and arable lands and also infestation of pest, diseases and weeds should be efficiently considered. Weeds are in competition for water, nutrition and sunlight consumptions with crops. Without effective weed control, the quality and quantity of crops will be decreased (Wang et al., 2019). Because some weed seeds are toxic and cleaning these seeds from crops is difficult (Bahnas, 2018). In such situations, the mechanized mechanical weeding can be utilized but row cropping is a MUST for feasible and low cost operations, otherwise additional detection modules should be included.

Received date: 2021-03-21 **Accepted date:** 2021-10-30

* **Corresponding author: Abbas Rohani,** Ph.D., Associate professor of Biosystems Engineering, Faculty of Agriculture, Ferdowsi University of Mashhad, University campus, Azadi square, Mashhad, Iran. Email: Iran, arohani@um.ac.ir. Tel: +985138805819.

Chemical weed control is another method of eliminating weeds but need huge amount of herbicide liquids throughout the field to be sprayed uniformly. Increasing cost and environmental concerns are the results of this method (Wang et al., 2019). Fortunately, the variable rate applicators are now being developed that can be used for targeted spraying which is known as site-specific weed management (SSWM). However, the weed species and their density should be determined (Jeon et al., 2011). For weed discrimination and elimination, four steps are usually considered: (1) providing real-time weed map using sensors (2) decision making for eliminating weeds based on the achieved information (3) weeding operation (4) and eventually evaluating the process. The data acquisition step by sensors is the most important step, as it directly affects the accuracy of weed detection.

There are different methods of weed discrimination such as machine vision (Sedighi et al., 2021), visible and near infrared spectroscopy (Shirzadifar et al., 2018), multi-/hyper-spectral imaging (Sa et al., 2018), fluorescence imaging (Su et al., 2019) and height-measurement based detection with ultrasonic. These methods are classified in two groups: airborne sensitization i.e. deploying sensors in balloon and ground based methods. In ground based methods, information is processed promptly (Wang et al., 2019).

Along with machine vision and image processing technique, ultrasound technology plays an important role in improving the quality of fruits and vegetables, by increasing the speed and accuracy of monitoring (Mizrach, 2008). Various studies have been done on the application of ultrasound, especially in the area of weed detection. In a research an ultrasonic distance sensor was employed to distinguish the weeds within the cereal crops by measuring weed height (Chang et al., 2017). Ultrasound sensors were also used to calculate leaf area density of target trees (Nan et al., 2019), identifying crop biomass yield (Buelvas et al., 2019), distinguishing the crop canopy from other plant leaves (Li et al., 2020), and measuring wild blueberry plant height during harvesting (Chang et al., 2017).

By comparing the two methods of weed detection within crops (i.e. image processing and ultrasonic) it can be said that with two dimensional images the target detection is hardly achieved, mainly due to limitations of variable light conditions and storage space. On the other hand, if the output signals of an ultrasonic device are processed and different features of ultrasonic waves are extracted by employing some artificial intelligence techniques (e.g. artificial neural network, ANN), a higher detection efficiency may achieve. In this approach by introducing some efficient characteristics of ultrasonic waves the speed and accuracy of object detection may increase. Therefore, this research deals with a combined method of ultrasonic/ANN approach for quick object detection, especially crop plants in fields.

2 Materials and methods

2.1 Weed detection

This study was performed on the research farm of Ferdowsi University of Mashhad in June 2014. The longitude and latitude of this site are 59˚45′ and 10˚50′ meters, respectively. Based on the objective of this investigation, five weed species, namely *Portulacaceae*, *Chenopodiumalbum L*, *Tribulusterrestris L*., *Amaranthusretroflexus L*. and *Salsolaiberica* were considered. These weeds are categorized into broad-leaf and narrow-leaf weed species. The selected weeds were in the vegetative stage.

2.2 Ultrasonic system design

According to Figure 1, The ultrasonic device includes an ATMega32 microcontroller, a TLO74 amplifier, an ICL 232 serial communication, a NOT gate, a 40 kHz receiver and a transmitter transducer with a 20 ° playback angle and a 12 MHz piezoelectric crystal. The amplifier is responsible for amplifying the signals received by the receiver. The serial communication transmits the amplified signals to the computer. In addition, the NOT-gate increases the intensity of the transmitted signal.

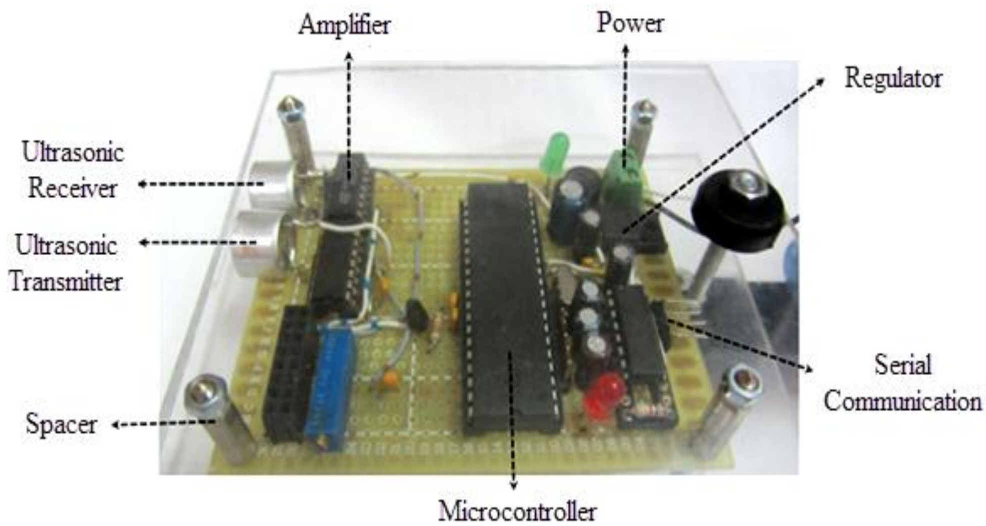
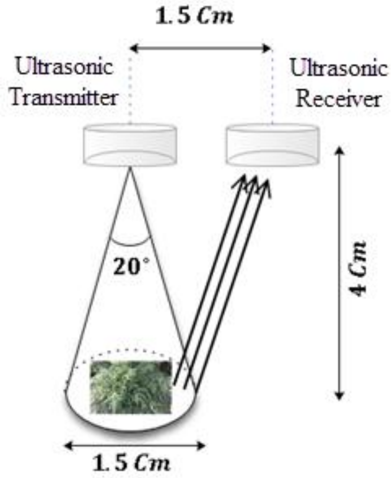


Figure 1 Components of the ultrasonic device made for weed detection

The ultrasonic device is mounted on a tripod. It has the ability of adjusting the ultrasonic device position along the X, Y, and Z axis (Figure 2a). Such a setting would allow the device to be positioned at an appropriate height and angle at each location of a weed. During sampling, the ultrasonic device was placed at a height of 4 cm vertically. The beam angle of the ultrasonic transmitter and receiver were 20 degrees and the distance between the ultrasonic transducers was 1.5 centimeters. Given these values, the disturbance of sent and received waves is minimized (Figure 2b).



(a) Suitable height for ultrasonic device according to the beam angle and distance between the ultrasonic transducers

(b) Tripods and clamps mounted to adjust ultrasonic equipment at a suitable height and angle

Figure 2 Principles and equipment used in sampling weed species

A continuous 40 kHz ultrasonic signal produced by microcontroller, piezoelectric crystal and ultrasonic transducer was sent to weed canopy. After the collision with the canopy of the weed plant, the waves were reflected into the ultrasonic receiver. After passing through the TLO74 amplifier and the ICL 232 serial port, the signal was stored on a DELL INSPIRON 5010 laptop.

2.3 ANN and feature extraction from ultrasonic signal

Considering Figure 3, signals are firstly transferred to MATLAB 2013a for wave features extraction, using ANN and subsequently weed classification. The Multilayer perceptron (MLP) neural network can work both in forward and backward phases. In this research, the backward phase was used. The MLP can estimate any continuous function. Input nods receive the input values. These values enter the hidden nodes after passing the input nodes. They are then multiplied by connection weights and added with bias (Senthilnath et al., 2012). This value is transformed by means of a transfer function. Before applying the neural network in actual classification, the weight network and bias value should be fixed by a learning algorithm and input-output known pattern. This process continues until the error between network generated output and real output is minimized. The Back-Propagation with Declining Learning-Rate Factor (BDLRF) employed in this study. The BDLRF algorithm is a modified version of Back-Propagation algorithm. This training algorithm starts with large step size of training rate and momentum term (Rohani et al., 2011). For each epoch, these values are monotonously decreased with progressive of algorithm. But this progress continues just before instability of network or reduction of convergence.

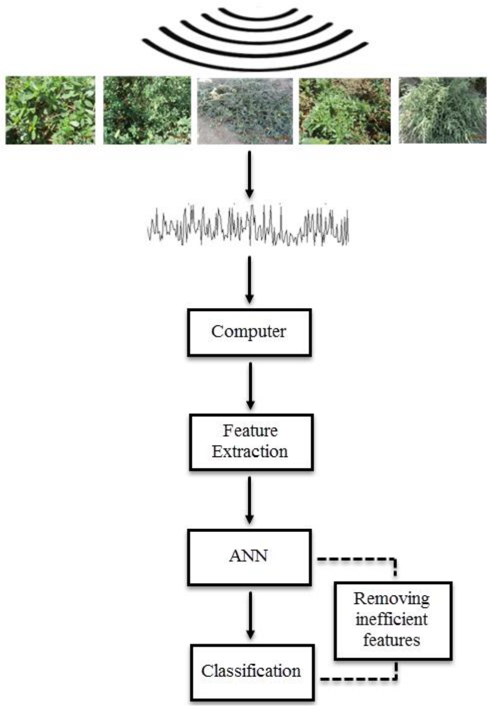


Figure 3 The flow chart of weed species classification in MATLAB software, based on ultrasonic signals

According to Figure 4, by considering the learning rate (η) and momentum term (α) from 0.1 to 0.99 with increment of 0.1, it is seen that the minimum error for Total-Sum-Squared-Error (TSSE) occurs in a certain value. This value for classification of five weed species, which are considered in this research, was 0.3. In other words, the learning rate (η) and momentum term (α) were the same and equal to 0.3.

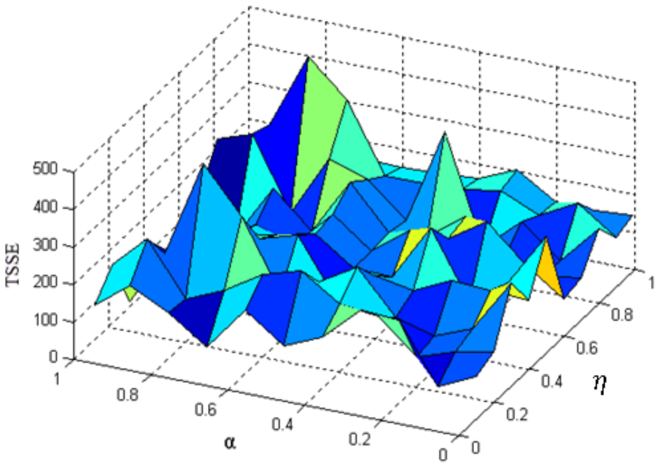


Figure 4 TSSE value for different values of learning rate (η) and momentum term (α) to classify the five weed species of this study

Using the factorial method, which is used to determine the optimal parameters of neural network, two hidden layers were employed for the ANN of this study. The first layer and the second layer have 15 and 10 neurons, respectively. For the first layer a log activation sigmoid function and for the second hidden layer a hyperbolic tangent sigmoid function were used, respectively. Also, for the outer layer, a linear function was chosen. Then by applying the optimal parameter for the neural network, the effective extracted ultrasonic wave features were selected to classify the weed species. For this purpose, any of the features (one by one) was eliminated from the total extracted features of 33. Then the MLP executed for 10 repetitions in MATLAB software. This step was repeated 10 times for each feature (i.e. total repetitions of 330 for all features). The extracted ultrasonic wave features are shown in Table 1.

For performance analysis of the classification models, the classification accuracy of the five weed species, which is the ratio of the number of correct predictions to the total number of evaluated patterns, was calculated as:

$$ClassificationAccuracy = \frac{n_p + n_n}{n_p + n_n + n_{mp} + n_{mm}} \times 100 \qquad (1)$$

where n_p and n_n are the number of correctly classified positive and negative samples, respectively. n_{mp} and n_{mn} show the number of misclassified positive, and negative samples, respectively (Miraei et al., 2020).

Table 1 The extracted time domain features of ultrasonic wave used in MATLAB software for weed classification

Feature No.	Explanation	Feature No.	Explanation
1	IU (Integrated Ultrasonic)	18	WAMP (Willison Amplitude)
2	MAV (Mean Absolute Value)	19	SSC (Slope Sign Change)
3	MAV1 (Modified Mean Absolute Value type 1)	20	MAVS_1 (Mean Absolute Value Slope type 1)
4	MAV2 (Modified Mean Absolute Value type 2)	21	MAVS_2 (Mean Absolute Value Slope type 2)
5	SSI (Simple Square Integral)	22	HIST (Histogram of Ultrasonic Wave)
6	VARU (Variance of Ultrasonic)	23	Auto-Regressive Coefficients
7	TM3 (The Third Moments)	24	MPV (Maximum Value or Maximum Peak Value)
8	TM4 (Fourth Moments)	25	VAR (Variance)
9	TM5 (Fifth Moments)	26	STD (Standard Deviation)
10	RMS (Root Mean Square)	27	SKEW (Skewness)
11	V3 (V-Order)	28	KUR (Kurtosis)
12	LOG (Log Detector)	29	MAD (Mean Absolute Deviation)
13	WL (Waveform Length)	30	IR (Interquartile Range)
14	AAC (Average Amplitude Change)	31	Q1 (The 25th Percentile)
15	DASDV (Difference Absolute Standard Deviation Value)	32	Q2 (The 50th Percentile)
16	MFL (Maximum Fractal Length)	33	Q3 (The 75th Percentile)
17	MYOP (Myopulse Percentage Rate)		

3 Results and discussion

At the first stage, the inefficient features including 17, 12, 20, 21, 27, 24, 31, 30, 33, 15, 14, 25, 18, 2, 23, 11, 7 and 32 were removed. The screening procedure was performed through one by one removing of any features. At each stage, by removing any of the features, the so-called k-fold method was used and the program was run for 10 times. By removing the aforementioned features, the overall weed detection performance of the neural network was slightly more than 70%. By removing these features at various stages, the detection accuracy of *Chenopodiumalbum L.*, *Salsolaiberica* and *Portulacaceae* was approximately more than 70%. This implies that the whole features are effective for recognizing these weed species. For detection of the *Amaranthusretroflexus L*., eliminating the features including 17, 12, 20, 21, and 33 decreased the recognition accuracy to less than 70%. In other words, these features are very important for recognition of *Amaranthusretroflexus L*. But by removing other features, the detection accuracy was more than 70%. Eliminating feature 11, which is the effective feature, the recognition accuracy of *Tribulusterrestris L*. was always less than 70%. By removing the features 12, 24, 31, 30, 25, 2, 7, and 32, the detection accuracy of *Chenopodiumalbum L*. was more than 80%. Thus these features are ineffective for detection of this weed species. Also, by removing feature 12, the recognition accuracy of *Portulacaceae* weed species was more than 80% (Figure 5). In other words, the feature 12 is the least important feature for recognition of *Portulacaceae* weed species. Based on the results, removing unnecessary data and features minimizes the dimension of the data as well as increases the accuracy of the ANN analysis (Joseph et al., 2018).

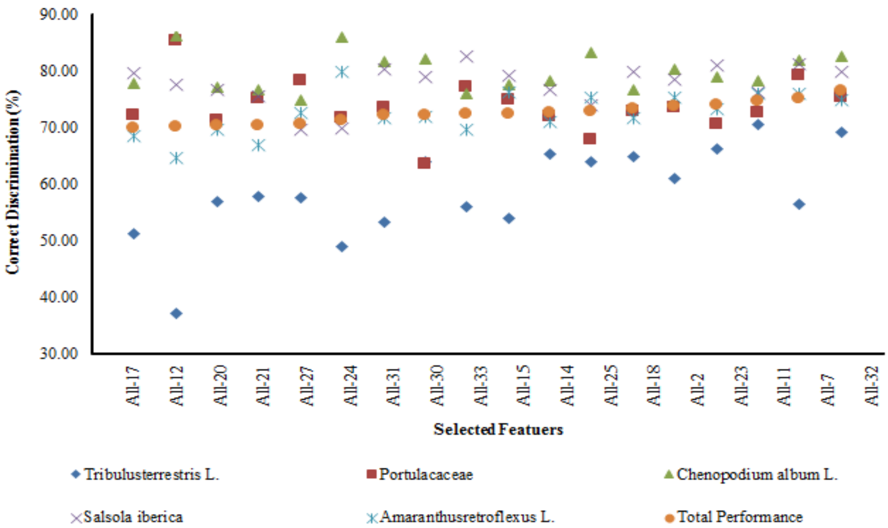


Figure 5 Detection of weed species with accuracy of more than 70% after any of the features was individually removed

Table 2 Sorted data based on their importance in recognition of the five weed species

	Average							Average					
	Class 1	Class 2	Class 3	Class 4	Class 5	Total		Class 1	Class 2	Class 3	Class 4	Class 5	Total
All-32	69.33	75.33	82.67	80.00	75.00	76.46	**All-17**	51.33	72.33	78.00	79.66	68.66	70.00
All-7	56.66	79.33	82.00	81.33	76.00	75.06	**All-5**	60.66	72.00	81.66	66.66	65.33	69.26
All-11	70.66	72.66	78.33	76.33	76.00	74.80	**All-4**	54.00	70.00	75.33	72.00	74.66	69.20
All-23	66.33	70.66	79.00	81.00	73.33	74.06	**All-16**	65.00	66.67	76.33	64.66	73.33	69.20
All-2	61.00	73.67	80.33	78.66	75.33	73.80	**All-28**	64.66	69.67	72.33	58.33	80.33	69.06
All-18	65.00	73.00	76.66	80.00	71.66	73.26	**All-29**	65.00	57.66	78.33	81.66	62.33	69.00
All-25	64.00	68.00	83.33	74.00	75.33	72.93	**All-8**	58.66	71.33	71.66	65.00	76.66	68.66
All-14	65.33	72.00	78.33	76.66	71.00	72.66	**All-6**	58.00	73.33	69.00	75.00	63.00	67.67
All-15	54.00	75.00	77.67	79.33	76.33	72.46	**All-1**	57.66	60.00	75.66	73.00	71.33	67.53
All-33	56.06	77.33	76.00	82.66	69.67	72.34	**All-22**	53.33	61.00	73.33	75.33	72.33	67.06
All-30	64.00	63.67	82.33	79.00	72.00	72.20	**All-19**	56.33	64.66	70.33	71.33	72.00	66.93
All-31	53.33	73.66	81.66	80.33	71.66	72.13	**All-10**	55.66	67.00	70.00	70.33	69.33	66.46
All-24	49.00	71.66	86.00	70.00	80.00	71.33	**All-13**	52.00	60.33	83.33	69.66	64.00	65.86
All-27	57.66	78.33	75.00	69.66	72.66	70.66	**All-26**	47.66	59.63	76.67	73.00	69.33	65.26
All-21	58.00	75.26	76.66	75.66	67.00	70.52	**All-9**	58.00	61.66	65.66	78.00	62.33	65.13
All-20	57.00	71.33	77.33	76.67	69.66	70.40	**All-3**	56.66	70.00	57.00	61.00	74.66	63.86
All-12	37.33	85.33	86.33	77.66	64.66	70.26							

Note: Class 1: *Portulacaceae*, Class 2: *Chenopodiumalbum L*, Class 3: *Tribulusterrestris L*., Class 4: *Amaranthusretroflexus L*. and Class 5: *Salsolaiberica*

Table 2 shows the sorted features based on their influence in recognition of the five weed species. In other word, the effective features, that by removing them, the detection accuracy decreases, was placed at the end of this table. To increase the detection accuracy of the weed species, in three stages, 20%, 40% and 60% of ineffective features were removed from the top of Table 2.

According to Figure 6, by removing 20% of the features, the highest detection accuracy was achieved. With this feature removing, the overall performance of the neural network was equal to 85.33%. Furthermore, the recognition accuracy of *Tribulusterrestris L*., *Portulacaceae*, *Chenopodiumalbum L*., *Salsolaiberica* and *Amaranthusretroflexus L*. were 83.33%, 80%, 90.3%, 93.33% and 80%respectively. In other words, the detection accuracy for each of the five weed species was more than 80%. Also by removing 40% of the features, the total performance of the neural network and recognition accuracy was still more than 80%. But in such circumstances the detection accuracy of the *Tribulusterrestris L*. was much lower than the other features and was equal to 73.33%. At the last stage, 60% of ineffective features were removed. For this condition the total performance of the neural network and the detection accuracy of the weed species were 78% and more than 80% respectively. But the recognition accuracy of the *Tribulusterrestris L*. and the *Salsolaiberica* weed species were as less as 66.66%. As mentioned, in this study, weed species were identified based on the features of the received ultrasonic wave. But the results of other research based on the discrimination of the weed height showed that the accuracy of weed detection for grasses and broad-leaved weeds were 81.1% and 98.5% respectively (Andujar et al., 2011). Also the accuracy of the grass and broad-leaved weeds detection in winter wheat field was 92.8% (Andủjar et al., 2012).

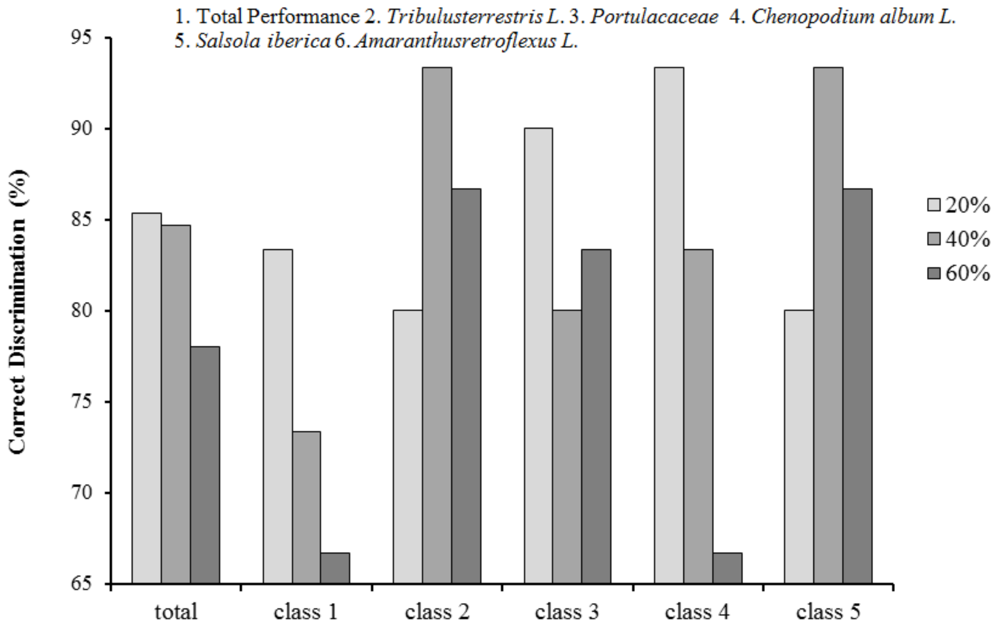


Figure 6 The percentage of detection of weed species and the total performance of the neural network when removing 20%, 40% and 60% of inefficient features

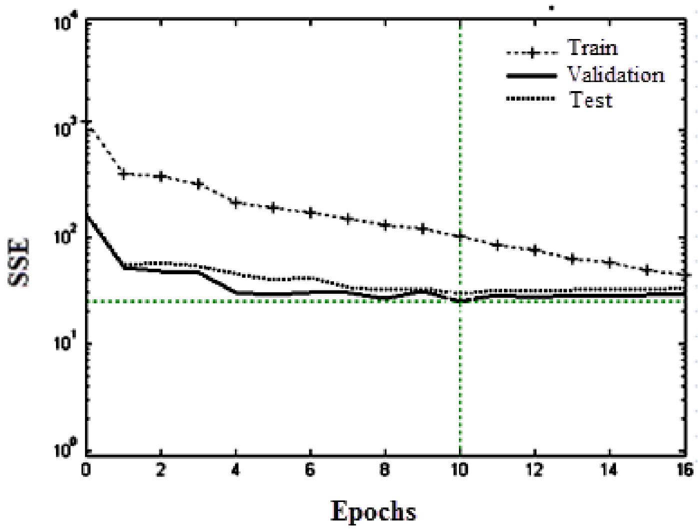


Figure 7 SSE versus the epoch number (number of learning runs) for the BDLRF algorithm for classifying five weed species

Figure 7 demonstrates SSE versus the epoch number (number of learning runs) for the BDLRF algorithm, while the number of execution was 16. According to this figure, the convergence started from epoch 10. It can be concluded that the BDLRF training algorithm has a good performance for classifying these five weed species especially when 20% of ineffective features were removed. Because the convergence rate was very fast.

4 Conclusion

Using the so-called k-fold method, each feature was individually removed, the detection accuracy of *Chenopodiumalbum L.*, *Salsolaiberica* and *Portulacaceae* was approximately more than 70%. Moreover, by removing 20% of the features, the highest detection accuracy was achieved. With this feature removal, the overall performance of the neural network was equal to 85.33%. Furthermore, the recognition accuracy of *Tribulusterrestris L.*, *Portulacaceae*, *Chenopodiumalbum L.*, *Salsolaiberica* and *Amaranthusretroflexus L.* were 83.33%, 80%, 90.3%, 93.33% and 80% respectively. In other words, the detection accuracy of the five weed species was more than 80%. This implies that the whole features are effective for recognizing these weed species. However, the lowest detection accuracy was observed for the *Tribulusterrestris L*. This is mainly due to the fact that the texture of leaves, stems and flowers of this weed species are morphologically very different.

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