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Performance Evaluation of Neural Network Based Pulse-Echo Weld Defect Classifiers

S. Seyedtabaii

Engineering Faculty, Shahed University, Tehran, P.O.Box 18155/159, Iran, stabaii@shahed.ac.ir

Pulse-echo ultrasonic signal is used to detect weld defects with high probability. However, utilizing echo signal for defects classification is another issue that has attracted attention of many researchers who have devised algorithms and tested them against their own databases. In this paper, a study is conducted to score the performance of various algorithms against a single echo signal database. Algorithms tested the use of Wavelet Transform (WT), Fast Fourier Transform (FFT) and time domain echo signal features and employed several NN's architectures such as Multi-Layer Perceptron Neural Network (MLP), Self Organizing Map (SOM) and others known to be good classifiers. The average performance of all can be viewed fair (90%) while some algorithms render success rate of about 94%. It seems that acquiring higher success rates out of a single fixed angle probe pulse-echo set up needs new arrangements of data collection, which is under investigation.

Keywords: Nondestructive testing, Pulse-Echo ultrasonic; neural network; radial basis function; self organizing map; Wavelet Transform

1. INTRODUCTION

THE WELD nondestructive testing (NDT) is well worth as welds may have defects [1]. There are on-line and off-line methods. Spectroscopic analysis of the plasma, analysis of the acoustic mission produced during the process and machine vision of the weld pool are some of the on-line proposals [2]. Off-line NDT methods include x-ray, ultrasound, penetrant liquids and some others [3].

Ultrasound is one of the favorite NDT methods used for assessment of weld conditions. The ultrasonic techniques that have been used are: (a) pulse-echo, (b) transmission, (c) resonance, and (d) a more sophisticated ultrasonic holography method. Among ultrasonic techniques, the pulse-echo method is the most commonly used one in industry, mainly due to its simplicity, small size of the equipment, and efficiency [4]. In this method, a single ultrasonic transducer sends a pulse and then collects the echo. Where the signal is reflected by a weld junction, the echo signal contains information about the uniformity and conditions of the weld.

Despite the advantage of the ultrasound in normal-defect weld detection [5], its potential in flaw classification is still frequently questioned, since the analysis and the identification of defects depend exclusively on the experience and knowledge of experts [6]. Moreover, it is still not clear whether a single echo-pulse signal conveys enough information to be adequate for accurate defect clustering or not.

Various set-ups have been worked out in devising an automated system equipped with the intelligence of weld defect experts. The system's three main blocks: 1) Measurement set up, 2) Echo signal feature selection and 3) Classification algorithms are all under vigorous investigations for the best arrangement. Echo signal features that have already been tried are: time domain echo signal [4], time domain echo pulse, Fast Fourier Transform (FFT) of the echo signal [7] and its various Wavelet Transform (WT) decompositions [7].

For the classification purposes, the classifiers of choice are NN's due to their ability in pattern recognition, especially in the case of nonlinear processes [8]. In a search for exploring an acceptable weld defect classifier, Multilayer Perceptrom (MLP) [9], Self Organizing Map (SOM) [10] and Radial Basis Function (RBF) have all been tested.

Unfortunately, there is not a standard weld defect database and necessarily, each researcher has generated their own. Hence, it is not possible to come to a conclusion and hand-pick the best. One of the missions of this study is to fill the gap and rank various algorithms against a fixed database. The classifiers are required to differentiate among four more common weld defects: Lack of Penetration (LP), Lack of Fusion (LF), Slag Inclusion (SL) and Excess Penetration (EXP).

The results show "fair" performance of around 90% success rate, in average. The best success rate mounts to about 94%, using echo-pulse and peak time as input of an RBF classifier. Ignoring "EXP" defect improves the algorithm performance considerably as it seems that EXP has more features in common with the others and therefore cannot be easily separated. The computation efficiency of each algorithm is also assessed. What remains in stake is how the algorithm performance may be raised to about just 1% false rate. It seems that some new ideas out of the current framework have to be utilized, which is still under investigation.

In section 2, the weld defects and their causes are briefly introduced. Section 3 gives introduction to the underlying processing and classification algorithms. Pulse-echo mode is discussed in section 4, experimental preparation in section 5 and Discussion comes in section 6. Lastly, Conclusion is presented in section 7.

2. WELD DEFECTS

Providing the correct welding conditions, techniques and standard quality materials, the arc welding process yields a good quality weld deposit. However, defect-free weld cannot be guaranteed and fault may occur. 26 types of defects are listed in [11]. The four most common of them that are usually encountered and used for classification studies, are lack of penetration, lack of fusion, slag inclusion and excess penetration [11].

1. Lack of Penetration

This type of defect occurs 1) When the weld bead does not penetrate the entire thickness of the base plate, 2) When two opposing weld beads do not interpenetrate, 3) When the weld bead does not penetrate the toe of a fillet weld but only bridges across it. Possible causes are: current too low, travel speed too high, incorrect weld preparation, root gap too small, incorrect torch angle and misalignment [11].

2. Lack of Fusion

Lack of fusion occurs when there is no fusion between the weld metal and the surfaces of the base plate. Possible causes are: current too low, travel speed too high, incorrect torch angle, oxide film on prepared surfaces, inadequate joint cleaning and too narrow weld preparation [11].

3. Slag Inclusion

The definition of inclusion is entrapping foreign solid material such as slag flux tungsten, or oxide in weld. Thus, the term inclusion includes both metallic and nonmetallic substances [11].

4. Excess Penetration (EXP)

Excess penetration describes conditions in which weld bead is in excess of the amount required to fill a joint. Current too high, travel speed too low, root gap too wide and root face too thin are the defect causes [11].

3. PREPROCESSING AND CLASSIFICATION METHODS

A. Discrete Wavelet Transform

In the discrete wavelet transform [12], the original signal *x(n)* is first passed through a half-band highpass filter *g(n)* and a lowpass filter *h(n)*. After the filtering, every other sample can be eliminated (down-sampled by 2) according to the Nyquist rule, since the signal now has highest frequency of π/2 radians instead of π. This constitutes one level of decomposition that yields lower band *cA1* and higher band *cD1* signals. The above procedure can be repeated for further disintegration. By this, cA1 is decomposed to a lower band cA2 and a higher band cD2 time domain signals. Now, signal can be reconstructed by cA2, cD1 and cD2 where their total length is equal to the length of the original signal. The degree of decomposition is entirely case dependent. By ignoring the coefficients that carry less relevant information, signal compression is attained. Wavelet is also used for signal denoising [13]. Denoising, on the other hand, is carried out by removing some portions of the lower cD coefficients' level.

B. Neural networks

What makes artificial neural network algorithms valuable is that they can be taught to perform a particular task, such as recognizing patterns inherent in an incoming data set, curve fitting, and data clustering [8]. In pattern recognition and curve fitting, network is trained based on a set of inputs and a set of desired outputs. This is called supervised learning against unsupervised learning where no desired output is introduced. Some architecture of NN used as a weld defect classifier is as follows:

1. Multilayer Perceptron Neural Network (MLP)

Fig.1 shows an MLP with *I* inputs, a hidden layer of *J* neurons and an output layer of *K* neurons [8]. Each layer has its own bias (-1). Neuron function is chosen from a list of several known nonlinear transfer functions. Error back-propagation learning method based on gradient descent approach of optimization has given the NN idea a push. Other training methodologies are evolutionary methods, simulated annealing and so on.

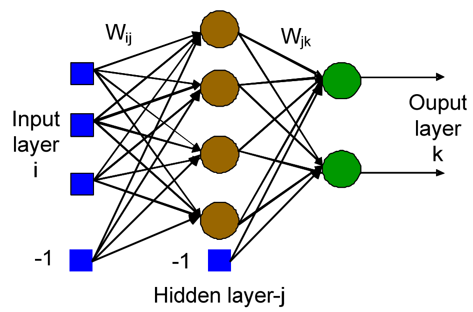

Fig.1. A MLP neural network configuration

2. Self Organizing Map (SOM) Network

Self organizing map is a single layer neural network which is often used to cluster datasets in an unsupervised manner [14]. The Kohonen learning rule allows the weights of a neuron to learn an input signal. The weights are updated after the presentation of each signal. To do this, the distance (usually the Euclidian) is computed between the input vector (signal) and each weight vector as in:

$$d_k = \|X(t) - W_k(t)\| \qquad k = 1...N$$

where *N* is the number of the output neuron. In the second step, the algorithm searches for the winning neuron d_w, i.e. the neuron that best matches the input neuron and is characterized by the minimum distance from the input vector.

$$d_w(t) = min(d_{k(t)}) \qquad k = 1...N$$

In the third phase the algorithm updates the weights of the winning neuron and of the neurons that lie in a user defined neighborhood as follows:

$$W_k(t+1) = W_k(t) + \alpha(t) h_{kw}(t) \|X(t) - W(t)\| \qquad k = 1...N$$

where α(t) is the learning rate that modulates the weights update and hkw is the neighborhood function that depends, given time t, on the winning neuron under consideration k.

3. *Radial Basis Function*

RBF is a two-layer network. The first layer has radial basis neurons with transfer function φ that calculates the distance between their centers and the inputs. The second layer has linear neurons. Both layers have biases.

4. *Probabilistic Neural Network*

"Probabilistic" Neural Network (PNN) is the name given to a RBF, modified for classification purposes. The linear output layer of RBF is followed by a competitive layer. The output layer produces a vector of probabilities. Then, the competitive layer assigns "1" to the class with the maximum probability, and "0" to the others. Only the first layer has biases.

4. PULSE-ECHO DEFECT TESTING

Ultrasonic testing utilizes sonic waves with higher frequency (1–6 MHz). Ultrasonic waves propagate quite easily in liquids and in solid materials, but not in gas. When the ultrasonic pulses reach the back wall of the test piece, they are reflected [15]. The pulses will also be reflected by inhomogeneity in the test specimen. The time taken for the sound to transverse the distance to a defect and return to the probe reflects the position of the defect. The principle of ultrasonic testing is shown in Fig.2. The acoustic pulses are both generated and detected by piezoelectric crystals. The most commonly used probes are normal probe, angle probe and the double crystal probe (separate transmitter and receiver).

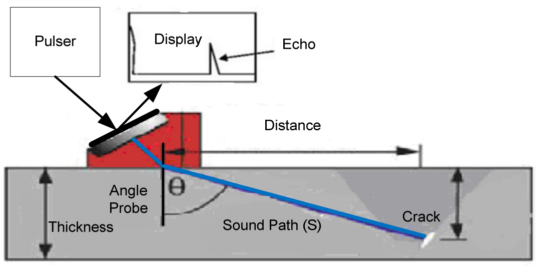

Fig.2. The Principle of Ultrasonic Testing using Pulse-Echo Technique and an angle probe [16].

Defect Types

Fig.2 shows the propagation of a sound wave beam at angle θ into a part. As the beam collides with the defect, the wave is reflected back to the probe and the signal is collected by the receiver. The distance that the wave travels, is twice the sound path (S). The superposition of backscattered signals from ideal reflectors in a material can be expressed in the time domain as:

$$s(t) = \sum_{k=1}^{K} \sigma_k e^{-\alpha\tau_k} s(t - \tau_k)$$

where s(t) is the ultrasonic pulse, τ_k is the delay associated with the k_{th} scatterer, K is the number of scatterers, α is the material attenuation coefficient and σ_k is the reflection coefficient of the k_{th} scatterer.

Extensive research for establishing a relationship between the types of defects and the echo-pulse shape has been conducted in [17] [18]. Unfortunately, it seems that there is not a decisive difference between echo-dynamics for volumetric and crack type of defects using a fixed angle probe. Therefore, the classical features, echo shape specification, are probably insufficient for the weld defect classification, which implies that a more sophisticated tool is needed for efficient feature extraction. On the other hand, defects with normal orientation to a beam angle produce a strong echo while those with 20 or 30 degrees deviation from the normal reflect small or even no signal [18]. This means that echo peak does not reflect a specific situation.

From the defects under study here, LOF, EXP and LOP are smooth type of cracks and SLAG is a volumetric type of one. As a result, occurrences of overlapping defect features may be unavoidable, making the classification process confusing.

5. EXPERIMENTAL SETUP

A. *Test Device and Samples*

The study has been conducted using 60° PZT angular probe of 4MHz central frequency. The pulse-echo ultrasound device is a PXUT-350-C model. The test set-up is shown in Fig.3.

Fig.3. Measurement set-up: the ultrasound device and a welded steel sample.

Test samples were 25 steel plates of 20 mm thickness, 250mm length, bevel level V with the gradient 60°, the root gap 2mm, and weld with the process SMAW (Shielded Metal Arc Welding) using E7018 electrodes. Four classes of defects deliberately embodied during welding process are: excess penetration (EXP), lack of fusion (LOF), Lack of penetration (LOP) and slag inclusion (SLAG).

B. *Data collection*

Data of each defect were taken individually from different welded plates, where the type of defect had earlier been identified using radiography. With the help of weld defect experts, echo waves have been verified to be recorded correctly. The ultrasonic device internally filters the signals and provides the envelope of the echo. An ensemble of 35 LOP samples, 32 LOF samples, 37 EXP samples and 37 SL samples constitute the final database. Fig.4 shows some samples of the collected signals.

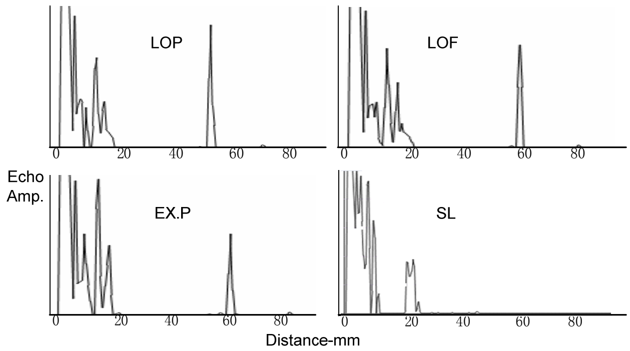

Fig.4. Examples of the collected pulse-echo signals for various defects.

C. Echo signal and echo pulse

The initial part of the received signals is associated with the probe-metal contact and is irrelevant to the type of defects; therefore, it is cleared by setting to zeros. Not all parts of the received signal engage with the primary reflection by the defects. Considering the thickness of the test plate, sound speed and probe angle, signal corresponding to 70 millimeter of sound path is considered more adequate for defect classification and therefore it is extracted and called “echo signal”. Echo signal contains a pulse that reflects scattering by the defects. This is named echo dynamics or “echo pulse”.

6. DISCUSSION

In the performance evaluation of NN based weld defect classifiers:

1. 14 algorithms are competing with each other. Some of the algorithms are the reproduction of the already investigated ones and the others are new suggestions.
2. For the classification of weld condition including normal situation, an effective approach, different from [16] where normal case is the fifth class, is adopted. It is well known that weld normal-defect detection can be done using pulse-echo ultrasonic technique with high probability. Therefore, a simpler fault detection section is employed that just checks the existence of an echo pulse in a predefined time slot. If there is not any, the weld is normal, otherwise it is faulty and the echo signal is passed to a more complex fault classification procedure where the echo signal shape is examined for fault clustering. The arrangement is both practically and theoretically attractive and efficient and outperforms the similar algorithms in [16].
3. Classification and feature extraction algorithms, wavelet and neural networks, are implemented using MATLAB.
4. 70 percent of the randomly arranged data of each class are assigned for training and the remaining 30 percent are set aside for test purposes.

1. The selection of signal features and classifier configuration (number of neurons, neuron function and learning method) is a search problem exploited by careful trial and error. Hence, the classifiers of the algorithms are the best of those tried.

A. Algorithms based on time domain echo signal features

1. Echo signal & MLP classifier

In [9] time domain signal has been used for flaw detection in materials. The performance of a big 512-128-6 network is good while the performance of a 128-128-6 network is shown poor.

Test done specifically for weld classification has been reported in [4] with fair results. Three types of defects are classified using a MLP network of one hidden layer with 26 neurons. The results indicate 100% training success rate and LOF (90%), LOP (70%) and Porosity (60%) test success rates.

In the algorithm, here, similar approach is undertaken and echo signals are used for classification. A MLP NN with Hyperbolic tangent sigmoid “tansig” transfer function, Resilient Backpropagation “rp” training algorithm and two hidden layers, each with 13 and 8 neurons, respectively, is used. The outputs are 4 classes of defects and the inputs are 70 samples of each echo signal. Thus, the network size is 70-13-8-4. Table1 (Alg.1) gives the results.

The test results show LOF (70%), LOP (80%) and SL (90%) that are more or less the same as in [4] while our databases are different. The only advantage here is that less input data has been used for classification. Results indicate that there is a room here for further investigation. The number of weight links, to be trained, is the total sum of $71*13+14*8+9*4=1071$.

Among the defects, the variance of excessive penetration correct pinpointing is very high, meaning that there is a high correlation between EXP and the other defects.

2. Echo pulse features & MLP classifier

In this algorithm, 21 samples of each echo pulse together with its peak time are used as NN input for classification. A MLP network of 22-6-4-4 is used. The neuron transfer function “tansig” and Levenberg-Marquardt “lm” training algorithm are used. The results are shown in Table1 (Alg.2). The variance of correct pointing to EXP test samples is high. It swings from 9% to 64% in various runs while the correct classification variance of the other three defects is low and acceptable. The number of NN weights to be calculated is $23*6+7*4+5*4=186$.

3. Echo pulse features & MLP classifier

Echo pulse features adopted for the classification algorithm are:

1. The peak time
2. The peak value
3. The echo pulse rising edge- 5mm interval average.
4. The echo pulse falling edge- 5mm interval average.

A MLP network of 4-5-3-4 is used. The overall weights incorporated are $5*5+6*3+4*4=59$. The results obtained are depicted in Table1 (Alg.3). Note that while the size of the network has been reduced remarkably, the performance decline is not so large, from 89% in test 1 to 87.5% here.

4. Echo signal & SOM classifier

In [9] a report on using SOM for flaw detection has been presented. Both time domain and its spectrum features have been adopted as SOM inputs. The results do not exhibit satisfactory outcome. The Kohonen network used in [10] has also rendered poor performance in comparison with what MLP does. Our investigation also shows poor performance from the adopted SOM in the case of weld defect classification as it is obvious from Table1 (Alg.4).

5. Echo signal & RBF classifier

Flaw detection using RBF has been investigated in [19] presenting a relatively fair outcome. Employing RBF with spread=1.5 and 99 neurons in the hidden layer gives the results depicted in Table1 (Alg.5).

6. Echo pulse & RBF classifier

In this algorithm, echo pulse and peak time drives a RBPF network of size 22-99-4. The results are presented in Table1 (Alg.6). The number of weights is mounted to about 2677. The best outcome belongs to this algorithm and this is the algorithm of choice.

7. Echo signal& PNN classifier

Using the PNN with spread=10 and 99 neurons in the hidden layer renders the results depicted in Table1 (Alg.7).

8. Echo signal & GRNN classifier

Generalized Regression Neural Networks (GRNN) is another RBF class neural network that subsumes both RBFNs and PNNs. It requires high "spread value" to pinpoint correctly "EXP" test samples. The results are presented in Table1 (Alg.8).

Table 1. Weld defect classification success rate using time domain features.

Alg No.	Network Specs	Feature		LOP	SL	EXP	LOF	Overall
1	MLP (70-13-8-4)	Echo signal	training	100	100	96	86	95.5
			test	90	91	46	70	74.25
			overall	97	97	81	81	89
2	MLP (22-6-4-4)	Echo pulse+ peak time	training	100	100	100	100	100
			test	90	91	46	70	74.25
			overall	97	97	84	91	92.25
3	MLP 4-5-3-4	Echo pulse TD features	training	100	100	96	90	96.5
			test	90	91	37	70	72
			overall	97	98	80	75	87.5
4	SOM	Echo signal	training	80	54	39	46	54.75
			test	80	36	0	50	41.5
			overall	85	49	27	47	52
5	RBF (70-99-4)	Echo signal	training	100	100	97	96	98.25
			test	80	90	100	70	85
			overall	94	97	97	87	93.75
6	RBF (22-99-4)	Echo pulse+ peak time	training	100	100	96	96	98
			test	80	91	100	70	85.25
			overall	94	97	97	88	94
7	PNN (70-99-4)	Echo signal	training	100	100	100	96	99
			test	90	90	45	70	73.75
			overall	97	97	83	87	91
8	8 GRNN (70-99-4)	Echo signal	training	100	100	97	96	98.25
			test	80	90	0	80	62.5
			overall	94	97	67	87	86.25

B. Algorithms based on frequency domain echo signal features

9. FFT of echo signal & MLP classifier

In [9], in addition to the time domain echo signal, its spectrum has also been examined as NN input. The result indicates that the same size network using signal spectrum relatively outperforms the one using the time domain signal.

In this attempt 70 points of each echo sample undergo an FFT process. Since the signal is pulse type, its spectrum is expected to be relatively flat. Due to the symmetric nature of the spectrum, half of the spectrum samples are used for classification. A network of 17 inputs, two hidden layers of each 6 neurons and a 4 neuron output layer, classify the faults. The number of weights to be trained is 178. The results are depicted in Table2 (Alg.9).

10. FFT of echo pulse+ peak time & MLP classifier

The FFT of 21 point echo pulse is calculated and 10 point FFT amplitude plus "peak time" is used as NN input. A MLP of size 11-6-4-4 is used for classification. The results are shown in Table2 (Alg.10). The number of NN weights is $12*6+7*4+5*4=120$.

11. FFT of echo pulse & MLP classifier

The FFT of 21 point echo pulse is calculated and 10 point FFT amplitude is used as NN input. A MLP NN of size 10-6-4-4 is used for classification. The results are shown in Table2 (Alg.11). By this arrangement a faster NN convergence speed is achieved. The number of NN weights is $11*6+7*4+5*4=114$.

The idea of adding the signal FFT phase to the NN input set, for better performance, has been suggested in [20] which has been tried for flaw detection. However, nothing special has been noticed employing the phase of FFT of echo signal in the experiments here. Therefore, its results have been excluded from the table.

Table 2. Weld defect classification success rate using frequency domain features.

Alg No	Network Specs	FFT of		LOP	SL	EXP	LOF	Overall
9	MLP (17-6-4-4)	echo signal	training	96	100	100	95	97.75
			test	90	90	63	70	78.25
			overall	94	97	89	87	91.75
10	MLP (11-6-4-4)	Echo pulse+ peak time	training	100	100	100	91	97.75
			test	90	91	28	80	72.25
			overall	97	97	78	87	89.75
11	MLP (10-6-4-4)	echo pulse	training	100	96	92	86	93.5
			test	90	91	64	70	78.75
			overall	97	95	84	81	89.25

C. Algorithms based on wavelet features of echo signal

Employing wavelet decomposition for extraction of signal features fit for classification purposes [21] is a well-known practice and has been tried in various fields. A wavelet flaw-detection algorithm has also been discussed in [7].

12. Wavelet feature of echo signal & MLP classifier

Echo signals are decomposed using a 9-level wavelet transform employing Daubechies “db2” mother wavelet. Then cA9 and cD4 to cD9 are used as signal features for classification purposes. Actually, this set of coefficients is equivalent to a 3 level decomposition keeping cA3 and cD3. Outcome of the classification has been reported to be better than the one using combined spectrum and time domain features.

The test is re-examined here using the available data set. The echo signals go through a 3 level decomposition using “db2” mother wavelet. cA3 and standard deviation of cD3, cD2 and cD1 constitute the 16 input samples. The classification network size is 16-8-8-4 that embodies 244 weights. Table3 (Alg.12) shows the results.

13. Wavelet of echo pulse & MLP

In this test, the echo pulses undergo a 3 level wavelet decomposition using Coifman “coif1” mother wavelet. Then “Peak time”, cA3 and the standard deviation of cD1, cD2 and cD3 form the 11 inputs of the network. The MLP network size is 11-7-7-4 with total number of 172 weights. The test results are introduced in Table3 (Alg.13).

14. Wavelet of echo signal & MLP

Using cA3 and cD3 components of wavelet decomposition of echo signal for classification has been suggested in [20]. Its mother wavelet of choice is Coifman “Coif2” which is fairly smooth and well-suited for the application. To classify the weld defects, an MLP network of size 26-7-7-4 is employed. This network constitutes 270 weights in total, their values have to be determined in the training steps. The performance of the algorithm is exhibited in Table3 (Alg.14).

In [22] an electromagnetic acoustic transducer (EMAT) generates the Lamb waves and a three-level wavelet decomposition using “Coifman” mother wavelet extracts signal features. “Coifman” is used because its shape is close to the shape of the peak of echo that is to be detected in an ultrasonic signal. The normalized mean and variance of cD3 forms two inputs of a MLP network classifier. Here, the algorithm is applied to the data base signal. The result of the experiment was poor to be placed in the table.

Table 3. Weld defect classification Success rate using wavelet decomposed features.

Alg No.	Network Specs	DW features of		LOP	SL	EXP	LOF	Overall
12	MLP (16-8-8-4)	Echo signal	training	100	100	96	96	98
			test	90	90	63	70	78.75
			overall	97	97	87	87	92
13	MLP (11-7-74)	Echo pulse	training	100	100	100	96	99
			test	90	90	46	70	74
			overall	97	97	84	88	91.5
14	MLP (26-7-7-4)	Echo signal cA3&cD3	training	100	100	96	91	96.75
			test	100	91	28	70	72.25
			overall	100	97	76	84	89.25

D. Summary

For the assessment of the algorithms, two merits are calculated and compared. The first one is the average success rate depicted in Fig.5. The other is the network complexity by the number of nodes involved in the training as it is shown in Fig.6. The best performance goes to algorithm 6, which uses the time domain echo pulse plus “peak time”, and the RBF classifier. This algorithm also enjoys the fast training speed of RBF. Algorithm 12, while it renders good outcome, benefits from the power of data compression of DW. This is the same for algorithm 9 that backs on the advantage of data compression acquired using frequency domain analysis.

While reshuffling the test and training data set is expected to affect the training and test success rate, less impact on the overall performance of the networks is noticed, which is great.

7. Conclusions

In this experiment, the performance of several already tried and some new intelligent algorithms for the classification of weld defects using single fixed angle ultrasonic probes are evaluated. The best performance goes to the one based on a RBF classifier using time-domain echo signal plus “peak time” as input. Its performance reaches to about 94% success rate or about 6% error rate. The overall average success rate of all is fair around 90%. The power of DWT in data compression, while preserving the main features of the signal, is also highly noticeable.

Attempts in lowering the error rate of the algorithms below 6% remained fruitless as some of the defects appeared to have features common with the others. This is more obvious in EXP and LOF types. It seems it would be very difficult to enhance the performance of the weld defect classifiers based just on the single echo signal. However, if more samples are collected for each case, e.g., 4 samples, it may be possible to obtain more precise results. While this may marginally increase the cost of evaluations, better performance may be acquired.

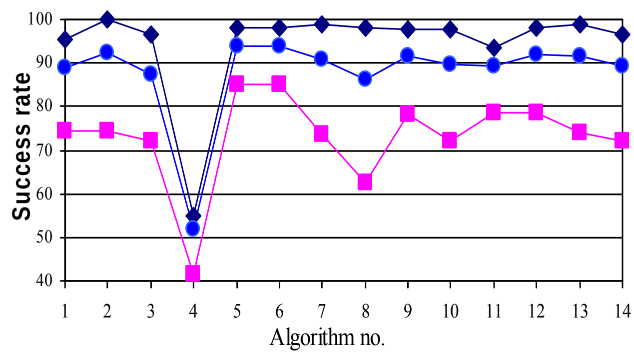

Fig.5. Performance of the all 14 algorithms; training (top), overall (middle) and test (bottom) average success rates.

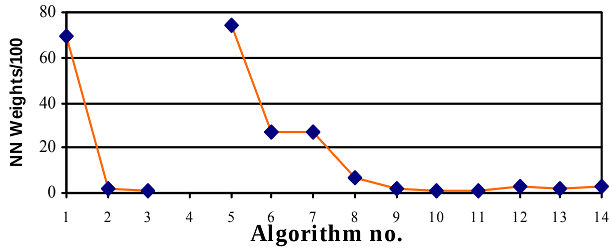

Fig.6. No. of network weights for each of the 14 classification algorithms.

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