Modelling of Long Wavelength Detection of Objects Using Elman Network Modified Covariance Combination

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Abstract: *The problem of spatially detection and imaging of closely separated buried objects is investigated. A high resolution modified covariance method is employed. A recurrent neural network is used as a preprocessing technique to decrease the effect of concealing media on the results. The in-line holography is applied to increase the signal to noise ratio. Different concealing media and different values of signal to noise ratio are used to investigate the performance of such combination experimental results show that pre-processing the noisy data with recurrent neural network improves the performance.*

Keywords: *Modified covariance method, recurrent neural network (RNN), in-line holography.*

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1. Introduction

The main attributes of neural networks processing are its nonlinear and adaptive learning capability, which enables machines to recognize possible variations of a same object or pattern and/or to identify unknown functions and mappings based on a set of training data, which can be noisy with missing information. Based on this training by example property with strong support of statistical and optimization theories, neural networks are becoming one of the most powerful and appealing nonlinear and adaptive data analysis tools for a variety of signal processing applications [1].

Neural Network (NN) techniques for noise reduction have been investigated [2, 3, 4, 5, 6, 7, 8, 9, 10], and the main design goal of these NN was to get a good approximation for some input-output mapping. In addition to obtaining a conventional approximation, neural networks are expected to generalize from the given training data. The generalization is to use information that NN learned during training period in order to synthesize, similar but not identical, input-output mapping [4]. In this paper, the NN to be designed and implemented will be considered as a preprocessing stage for the corrupted signal. This stage is used to enhance the noisy data signal; i.e., decreasing the effect of the noise as much as possible, before the application of the spectral estimation methods is performed to the resulted signal. A two layer recurrent back propagation, Elman Network, have been designed, trained, and tested. Unlike the standard back propagation algorithm, the network being considered here is permitted to have feedback connections among the neurons; that is, the network is recurrent. During training, the input sequences are presented to the network, and there outputs are calculated and compared with the target sequences (desired signals) to generate an error sequences. The input training sequences are assumed to be a composition of the desired signal plus an additive white gaussian noise. For each time step, the error is back propagated to find the gradients of errors. This gradient is then used to update the weights.

The network is expected to learn the noisy training data with the corresponding desired output and generalize the model. Thus, care must be taken to prevent the system from over learning (i.e., modeling the details of the noise rather than the desired signal) [11]. The Recurrent Neural Network (RNN) has been chosen because they are computationally more powerful than other adaptive models such as hidden markov models (no continuous internal states), feedforward networks and supper vector machines (no internal state at all).

The problem of spectral estimation has been receiving considerable attention in the signal processing community since it arises in various fields of engineering and applied physics, such as spectrometry, geophysics, biomedical doppler echography, radar, *etc.* [12]. When the problem at hand is the restoration of Smooth Spectra (SS), basic nonparametric methods based on the Discrete Fourier Transform (DFT) such as period grams are often taken up. Such techniques usually involve a windowing or an averaging step, which requires a sufficiently large data set. By contrast, estimation of Line Spectra (LS) is more often dealt with in parametric methods, which are known as high-resolution methods [12]. A modified covariance method is one of these. It is a high resolution and stable method, so it has been widely used in many applications [13, 14]. It generates frequency component estimates for a signal based on linear prediction modeling and minimization of the forward and backward errors in linear predictors. The buried object is illuminated by acoustic (ultrasound) waves, and the reflected (backscattered) waves are recorded. A transmit/ receive ultrasonic transducers are scanning over a synthetic aperture. The interest in acoustic waves for detection and imaging stems from its properties as highly coherent waves [15]. The ability of ultrasound waves to penetrate many media that are optically opaque makes them very important for detecting and imaging targets that cannot be imaged by light waves [16, 17].

The received signal is added electronically to a reference signal, of the same frequency, to generate the in- line holography. The recorded signal is sampled and is known as a hologram. Holography was initiated as an interferometric technique for recording the amplitude and phase of a coherent wave, whether it is electromagnetic or acoustic wave. A recording of this interference pattern is called a hologram, a term coined by Dennis Gabor in 1948 [18]. Holography has received considerable attention since more than three decades. It has been applied in the fields of optical, acoustical, and microwave radiations [19, 20, 21]. The holographic soundfield imaging technique combines the ultrasonic wave with the holographic interferometry. Holography [22] is one of a two major source 'localization' tools. The other one is a beamforming.

The in-line holographic data are modeled as an AutoRegressive (AR) process where the prediction coefficients are calculated by the modified covariance method. The use of holography enables improvement of the signal-to-noise ratio by coherently cumulating the acoustic field on the ultrasonic transducers when scanning the field [23]. The combination of high resolution and holographic techniques improves the performance of the problem [24]. The imaging process consists of two steps: the recording of the hologram and the image reconstruction of the object.

Our contribution is as following:

- The Elman neural network is designed and implemented as a preprocessing technique to reduce the noise in the corrupted signal.
- The combination of neural network with holographic imaging.
- Using a high resolution technique (modified covariance method) for holographic imaging.

The rest of the paper is organized as follows. Section 2 presents the architecture of recurrent neural network and describes the method used in the training process of the designed NN. Section 3 presents the principles of the field propagation from the object under imaging process and in-line holography. Section 4 presents a principle of modified covariance method. Our contribution is summarized in section 5. In section 6, the experimental results are presented and discussed. Section 7 presents the final conclusions of our paper.

2. Recurrent Neural Network

2.1. Architecture

Elman networks have been constructed in this paper to perform the required extraction of the knowledge from a noisy training set to achieve better signal enhancement. The architecture of the RNN constructed is shown in Figure 1 [25].

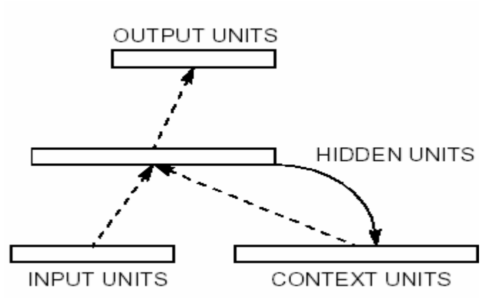

Figure 1. The architecture of Elman network.

The Elman network is a two-layer network with feed back from the first-layer output to the first layer input. It performs the following [25]:

1. The input units receive the first input.
2. Both the input units and context units (group of units that receives feedback signals from the previous time step [26]) activate the hidden units.
3. The hidden units also feedback to activate the context units (copying the content of the hidden unit).
4. The output units is compared with a teacher input (desired output) and backpropogation of error is used to incrementally adjust the connection strength.

The Elman network constructed has *tansig* neurons in its hidden layer, and *purline* neurons in its output layer. This combination is special in that two-layer networks with these transfer functions can approximate any function (with a finite number of discontinuities) with arbitrary accuracy. The only requirement is that the hidden layer must have enough neurons. More hidden neurons are needed as the function being fit increases in complexity. The recurrent connections allow the network's hidden units to see its own previous output, so that the subsequent behaviour can be shaped by previous responses. These recurrent connections are what give the network memory. The context units are also "hidden" in the sense that they interact exclusively with other nodes internal to the network, and not the outside world [25].

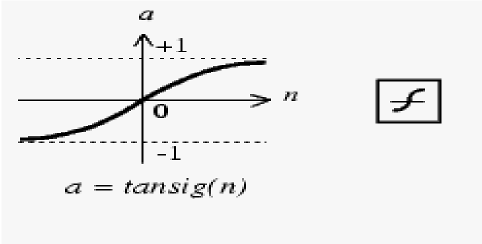

Figure 2. Tansig transfer function.

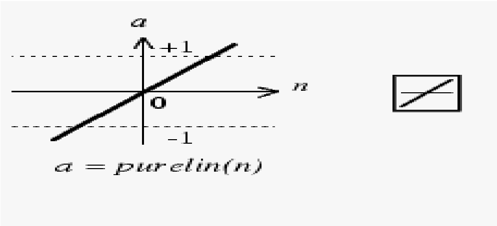

Figure 3. Purline transfer function.

2.2 Training Process

The distinction between training and generalization accuracies lies in the test patterns adopted. Good training accuracy can be achieved by forming complex decision boundaries, which in turn requires a large network size [8]. Also, good generalization accuracy needs not to push too hard on the training accuracy; the overtraining may result in degraded generalization. This is happened if too many hidden units are used [8].

A number of network architectures have been designed and tested with different noisy data samples. The aim was to have good training process, to avoid overtraining problem, and to have better Mean Square Error (MSE) goal during the training process. The research results declare that for the given model, with a reasonable number of training samples, 10 neurons in the hidden layer was sufficient to achieve the required aims. It has been proven [6] that the addition of random noise to the desired signal during the training process of the neural network can improve the generalization of the network and can take the learning process from getting into local minimum.

Assume a neural network such that, x_k denotes one element of an input vector; y_i is the i^{th} output of the output layer. Let $d_i(t)$ denote desired response for output neuron i at time t, where t is the discrete time index. The error signal is defined as the difference between the target response $d_i(t)$ and the actual response $y_i(t)$ as shown below:

$$e_i(t) = d_i(t) - y_i(t) \tag{1}$$

The aim of learning is to minimize a cost function based on the error signal $e_i(t)$, with respect to network parameters (weights), such that the actual response of each output neuron in the network approaches the target response [6]. A criterion commonly used for the cost function is the MSE criterion, defined as the mean-square value of the sum squared error [27]:

$$J = E[\frac{1}{2}\sum_i (e_i(t))^2] \tag{2}$$

$$J = E[\frac{1}{2}\sum_i (d_i(t) - y_i(t))^2] \tag{3}$$

where E is the statistical expectation operator and the summation is over all the neurons of the output layer. Usually the adaptation of weights is performed by using the desired signal $d_i(t)$ only. Figure 4 shows the idea of the adaptation procedure used to optimise the selection of the weights [27].

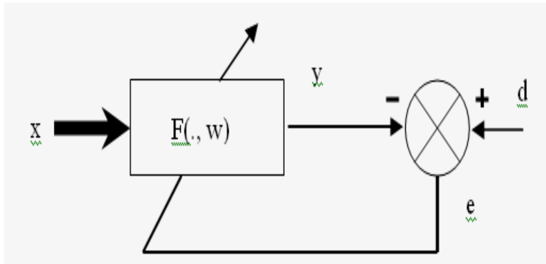

Figure 4. Neural network model for weight adaptation.

In [6] it is stated that a new $d_i(t)+n_i(t)$ signal can be used as a desired signal for output neuron i instead of using the original desired signal $d_i(t)$, where $n_i(t)$ is a noise term. This noise term is assumed to be white gaussian noise, independent of both the input signals $x_k(t)$ and the desired signals $d_i(t)$. With the new desired signals, the MSE of equation 3 can be written as:

$$J = E[\frac{1}{2}\sum_i (d_i(t) + n_i(t) - y_i(t))^2] \tag{4}$$

It is shown in [6] that equation 4 is equal to:

$$J = \frac{1}{2}E[\sum_i (y_i(t) - E\{d_i(t) + n_i(t) | x(t)\})^2] + \frac{1}{2}E[\sum_i var((d_i(t) + n_i(t)) | x(t))] \tag{5}$$

where the symbol $|$ means conditional probabilities and *var* is an abbreviation of variance. The second term in the right hand side of equation 5 will contribute to the total error J and in learning progresses, but it does not affect the final value of the weights because it is not a function of the network weights, while the first term will decide the optimal value of the weights [6]. Since the noise is zero mean and it is independent of both desired and the input signals, thus:

$$\{E\{d_i(t) + n_i(t) | x(t)\} = \{E\{d_i(t) | x(t)\} \tag{6}$$

It is clear from equations 5 and 6 that the final weight values can be determined without the existence of noise in the Equation. Thus, learning with noisy desired signal will yield in the mean the solution for the original optimization problem, i.e., without the noise added to the desired signal.

3. Holographic Imaging (Detection)

3.1. Field Analysis at the Receiver [18, 28]

The object, under imaging (detection) process, is assumed to have a field distribution *D(p)*. The distribution is caused by reflecting the incident ultrasonic waves on the object. This distribution propagates to the recording axis *X* where it produces the field distribution *S(x)*, given by:

$$S(x)=\frac{B}{Z_o\lambda}\int_p D(p)\exp(jkr(p,x))dp \tag{7}$$

This is the paraxial approximation to the huygens-fresnel principles. B is a complex constant, k is a propagation constant (wave number), Z_o is the distance between the object and recording (observation) planes, and r is the distance from a typical point on the object to a typical point on the recording axis X. r is given as:

$$r(p,x)=\sqrt{Z_o^2+(x-p)^2} \tag{8}$$

According to a paraxial approximation, where

$$((x-p)^2/Z_o^2)<<1 \tag{9}$$

Then equation 8 is written as:

$$r(p,x)=Z_o+\frac{(x-p)^2}{2Z_o}-\frac{(x-p)^4}{8Z_o^3}+\dots \tag{10}$$

In fresnel region, r can be approximated by the first two terms of equation 10, hence

$$r(p,x)=Z_o+\frac{p^2}{2Z_o}+\frac{x^2}{2Z_o}-\frac{px}{Z_o} \tag{11}$$

Substituting equation 11 into equation 7 yields

$$S(x)=B_1\exp(\frac{jkx^2}{2Z_o})\int_p D(p)\exp(\frac{jkp^2}{2Z_o})\exp(\frac{-jkxp}{Z_o})dp \tag{12}$$

where B_1 is a complex constant resulting from equations 7 and 11.

3.2. Analysis of In-Line Hologram

Analysis of in-line holography can be found in many references [29, 30]. Figure 5 shows the geometry of recording the in-line hologram with a plane-wave reference. This type of wave can be easily synthesized in an experimental recording system by simply introducing a constant reference signal in the receiver.

Assuming that the synthesized plane-wave reference is $A_r \exp(j\Phi)$ where A_r and Φ are constants. The in-line hologram *h(x)* is given by

$$\begin{aligned} h(x) &= \left|S(x)+A_r\exp(j\phi)\right|^2 \\ &= A_r^2+\left|S(x)\right|^2+A_r\exp(j\phi)S^*(x)+ \\ &\quad A_r\exp(-j\phi)S(x) \end{aligned} \tag{13}$$

where * is a conjugate symbol (operator).

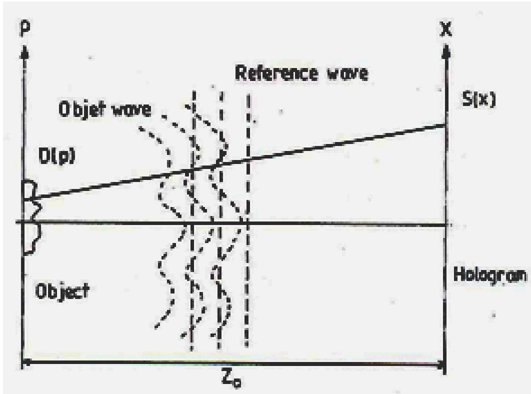

Figure 5. Hologram recording geometry.

An image can be extracted from the recorded hologram *h(x)* through its multiplication by either one of the focusing phase factors $\exp(\pm\frac{jkx^2}{2Z_o})$ and subsequent either Fourier Transformation (FT) (a classical method [31]) or one of the modern high resolution spectral analysis, like modified covariance method. A positive phase factor produces an in-focus image from the third term of *h(x)* and defocused image from its fourth term while the negative phase factor achieves the opposite result. For both signs of the phase factor, the second term produces a defocused autocorrelation function of *D(p)* and the first term generate a fresnel diffraction pattern related to the hologram boundary. Thus, while only one term of *h(x)* produces an in-focus image, the other three terms generate interference that obscure the wanted image. It has been shown [31] that the effect of these interfering terms can be considerably reduced. The first term A_r^2 *is* constant and can be subtracted from the recorded hologram prior to reconstruction [23, 31].

The training of RNN was made to follow the model described by the following equation:

$$dp = A_r^2+S^2+2A_rSCos\theta \tag{14}$$

where θ is a phase difference between A_r and S. This is equivalent to equation 13.

4. Modified Covariance Method

The derivation of this method can be found in many references [32, 33]. The modified covariance method for estimating the autoregressive parameters of order p (*AR(p)*) can be viewed as least-squares method , based on the minimization of the forward and backward errors in linear predictors. The hologram *h(x)* is sampled, and the distance between each two samples is Δx. The number of samples is *N*. The resultant hologram is then *h(n)*; *n*= 0, 1,….., *N-1*. To derive the estimator, let us consider the forward and backward linear prediction estimates of order *p,* given as

$$\hat{h}(n) = -\sum_{k=1}^{p} a(k)h(n-k) \tag{15}$$

$$\hat{h}(n) = -\sum_{k=1}^{p} a^*(k)h(n+k) \tag{16}$$

where *a*(*k*)'s are the *AR* filter parameters. In either case the minimum prediction error power is just the white noise variance σ^2. The modified covariance method estimates the *AR* parameters by minimizing the average of the estimated forward and backward prediction error powers, or

$$\hat{\rho} = \frac{1}{2}\left(\hat{\rho}^f + \hat{\rho}^b\right) \tag{17}$$

where

$$\hat{\rho}^f = \frac{1}{N-p}\sum_{n=p}^{N-1}\left|h(n) + \sum_{k=1}^{p} a(k)h(n-k)\right|^2 \tag{18}$$

$$\hat{\rho}^b = \frac{1}{N-p}\sum_{n=0}^{N-1-p}\left|h(n) + \sum_{k=1}^{p} a^*(k)h(n+k)\right|^2 \tag{19}$$

A least-square solution is used for minimization of (17). The result is [32, 33]

$$\begin{bmatrix} c_{hh}(1,1) & c_{hh}(1,2) & \cdots & c_{hh}(1,p) \\ c_{hh}(2,1) & c_{hh}(2,2) & \cdots & c_{hh}(2,p) \\ \vdots & \vdots & \ddots & \vdots \\ c_{hh}(p,1) & c_{hh}(p,2) & \cdots & c_{hh}(p,p) \end{bmatrix} \begin{bmatrix} \hat{a}(1) \\ \hat{a}(2) \\ \vdots \\ \hat{a}(p) \end{bmatrix} = -\begin{bmatrix} c_{hh}(1,0) \\ c_{hh}(2,0) \\ \vdots \\ c_{hh}(p,0) \end{bmatrix} \tag{20}$$

where

$$c_{hh}(i,j) = \frac{1}{2(N-p)}\left(\sum_{n=p}^{N-1} h^*(n-i)h(n-j) + \sum_{n=0}^{N-p-1} h(n+i)h^*(n+j)\right) \tag{21}$$

Solving equation 20 will give the values of *a(k), k= 1, 2,…p*. Then the power spectral density can be estimated using the values of *a(k), k= 1, 2,…p*. The estimate of the white noise variance is

$$\hat{\sigma}^2 = c_{hh}(0,0) + \sum_{k=1}^{p} \hat{a}(k)c_{hh}(0,k) \tag{22}$$

The power spectral density is:

$$P_{hh}(f) = \frac{\hat{\sigma}^2}{\left|1 + \sum_{k=1}^{p} \hat{a}(k)e^{-j2\pi fk}\right|^2} \tag{23}$$

The advantages of the modified covariance method for estimating the parameters of the AR model are (1) it yields statistically stable spectral estimates with high frequency resolution [14, 32], (2) the usual shifting of the peaks of an AR spectral estimate from the true frequency locations due to additive observation appears to be less pronounced for many of the other AR spectral estimators, and (3) spectral line splitting in which a single sinusoidal component gives rise to two distinct spectral peaks has never been observed [32].

The algorithm steps are as followes:

1. *A pre-processing of the measured data using elman neural network.*
2. *Averaging the samples.*
3. *Subtracting the average value from the hologram, i.e. removing an approximation value of the first term of (13).*
4. *Multiplication the hologram (observed samples) by one of the quadratic factor:*

$$\exp\left(\frac{\pm jkx^2}{2Z_o}\right) \tag{24}$$

5. *Application of modified covariance algorithm on the resulting data.*

5. Experimental Results

In this paper, a test object consisting of two steel rods of 2.5 cm diameter was used. The separation between the two rods was 7 cm. The object was located at a distance Z_o cm from the recording (hologram) plane. A different concealing opaque media were used. The object was illuminated by ultrasound waves using ultrasonic transmitting transducer of 40 kHz. The reflected wave from the object that impinging the receiving transducer is added electronically to a reference signal to form the in-line hologram. The transmit/receive transducers scan the hologram aperture to record the received signal at uniformly spaced (Δx) positions. The total number of samples is *N*. In order to enhance the received signal, or in other words, to decrease the effect of the relatively high background that caused by the opaque media; a RNN is designed and used as a pre-processing technique.

Two experiments were made, with two different concealing media. In the first experiment a sheet of a paper was used as a concealing medium. The distance Z_o was 90 cm. Image reconstructions was performed using modified covariance method. In the second experiment, a concealing styrofoam plate of 3 cm thickness was used instead of the sheet of paper. The object was located 50 cm instead of 90 cm from the recording plane. Figure 6 shows the image of the object. Where the two peaks A_1 and A_2 are corresponding to the two rods, and they are clearly defined.

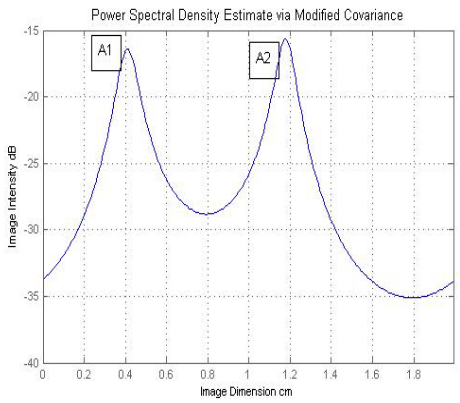

Figure 6. Reconstructed image of two rods concealed by a styrofoam of 3cm thickness.

The combination of RNN techniques and in-line holography try successfully to decrease the effect of concealing medium which contribute itself as a background noise that degrade the signal to noise ratio and also the resolution.

It is worthwhile to mention that, the resolution formula for FT method is given as [31].

$$\beta = \frac{\lambda Z_o}{b} \quad (25)$$

Where 2b is the hologram length, and

$$b = \frac{(N-1)\Delta x}{2} \quad (26)$$

In [34], where FT technique was used to image a same 2-point object concealed by a sheet of paper, a degrading effect of the performance was noticeably greater. The separation between the two points was made greater by more little than two times of the separation given by equation 26, in order the object (two rods) to be resolved.

In order to study the problem more deeply, and to compare the performance between the two cases, with and without using the neural network, a white noise was added to the hologram and its effect on the results has been investigated. Two points are taken into account. These are the deviation from the true value of separation between the two rods *(dv)*, and the difference between the intensity of the two peaks, symboled *as* A_1 and A_2. Theoretically, it is expected that the received signals from the two rods are of the same values because the two rods are similar.

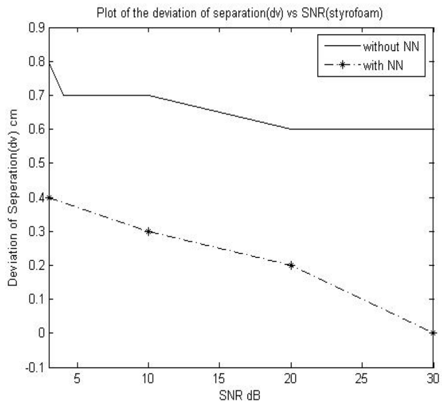

Figure 7. Difference in intensity of the two rods as a function of SNR-sheet of paper.

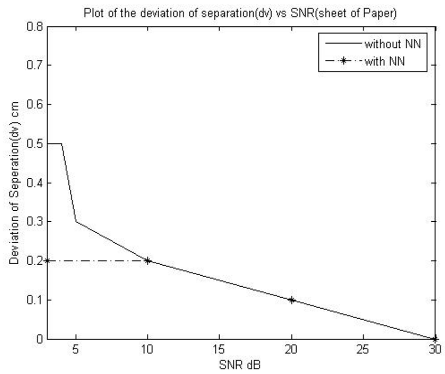

Figure 8. Separation between the two rods as a function of SNR-sheet of paper.

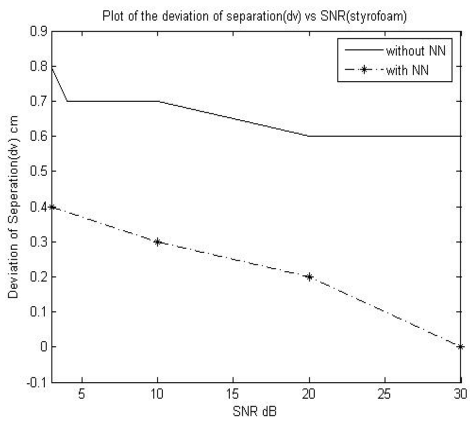

Figure 9. Separation between the two rods as a function of SNR-styrofoam.

Figures 7 and 8 show the performance with and without using the neural network on the separation between the two roads as a function of Signal-to-Noise Ratio (SNR) for both concealing medium. It is clear that as the SNR decreases, the performance degrades. The degradation is not so severe when SNR decreases to about 0 dB. This is because the addition of a reference wave, in recoding the in-line hologram, will result in a coherently cumulating the acoustic field on the ultrasonic transducers when scanning the field. However, the implementation of neural network improves the performance noticeably especially for the case of styrofoam medium.

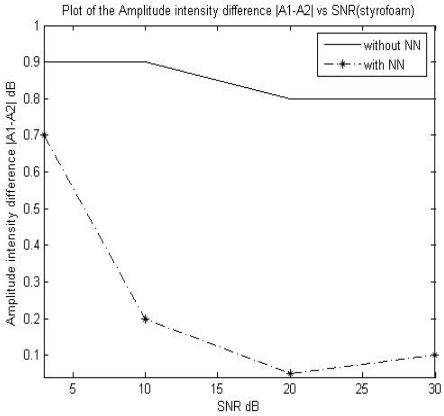

Figure 10. Difference in intensity of the two rods as a function of SNR-styrofoam.

Similar results are noticed for the difference of intensities of the two peaks that are corresponding to the two rods, as shown in Figures 9 and 10. Hence it is clear that the performance is better for the case of using neural network as a pre-processor before applying the spectral estimation method.

6. Conclusion

It is demonstrated that the modified covariance method can be used to detect and image a concealed object of closely separated points, and to find the required parameters such as the amplitude and the separation between a two adjacent points. Experimental results show that a pre-processing the noisy data with RNN to decrease the effect of noise as much as possible and then applying the enhanced data to spectral estimation methods can improve the tracking of the model parameters. Also the use of holography enables an improvement of the signal-to-noise ratio by coherently cumulating the acoustic field on the ultrasonic transducers when scanning the field.

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