Filtering Random Noise from Deterministic Underwater Signals via Application of an Artificial Neural Network

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Abstract

In this study, we examine the applicability of an artificial neural network(ANN) for filtering underwater random noise and for identifying underlying signals taken from noisy environment. The approach is to find a way of compressing the input data and then decompressing it using an ANN as in image compressing process. It is well known that random signal is hard to compress while ordered information is not. The use of a limited number of processing elements(PEs) in the hidden layer of an ANN ensures that some of the noise would be removed in the reconstruction process. Two types of the signals, synthesized and measured, are used to examine the effectiveness of the ANN-based filter. After training process is completed, the ANN successfully extracts the underlying signals from the synthesized or measured noisy signals. In particular, compared with the results from without filtering or moving averaged, the ANN-based filter gives much better spectrograms to identify underlying signals from the measured noisy data. This filtering process is achieved without using any kind of highly accurate signal processing technique. More experimentation needs to be followed to develop the ANN-based filtering technique to the level of complete understanding.

I. Introduction

In underwater environment, acoustic wave is the most powerful tool to detect targets. Although all other methods such as MAD(magnetic anomaly detection), IR(infra-red) and radar play their parts in detecting underwater targets, the only really successful and well proven method to date is by the use of sound.[1] There are four principal phases against targets: detection, classification, localization and strike. Among these, classification relies primarily on highly accurate signal processing techniques to filter random noise and to retain consistently recurring patterns. The most useful clue in classifying the target is the frequency information of the signal existing usually in the lower frequency. Hence, the low pass filter is often applied to filter out the higher frequency signal in classification phase.

Many kinds of algorithms have been developed to filter noise from deterministic signals. Most general type of optimal filtering is known as Wiener filtering. Specifically, it is desired to use the present value, and the previous values of some length, to estimate the desired value. This is to be done for all values by a linear filter designed to minimize the mean-square error.[2] The estimating process inevitably introduces errors and various other complications and brings up the whole issue of estimation of the model parameters. The Wiener filter requires a priori knowledge of the spectral properties of the noise-free signals.[3] The popular linear models are the autoregressive(AR), moving average(MA), and autoregressive moving average(ARMA). Other non-linear filters have been developed which outprtforms the Wiener filter and filters random noise with a priori knowledge of the signal characteristics.[4] However, these filters would be applied to a signal that is corrupted with random noise of known strength and completely random.

An ANN-based filter has been partially applied to filter random noise from underlying signals.[5] However, few attempts have been made to deal with underwater acoustic signals which are corrupted with noise other than of random. The underwater signals need to be processed before the ANN-based filter is applied to filter random noise.

In this study, we consider applications of an artificial neural network(ANN) based on the back-propagation learning scheme to filter underwater random noise and to identify underlying signals taken from noisy environment. Unlike the conventional filters, an ANN-based filter requires no parameter estimation or priori knowledge of noise strength. As one of the learning schemes of an ANN, the back-propagation is a powerful adaptive technique for ap-

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proximating relationships between several continuous valued inputs and one (or more) continuous valued output.[5]

The approach is to find a way of compressing the input data and then decompressing it as in image compression.[6] The main goal of image compression techniques is to store or transmit an image with a reduced number of bits and a limited distortion in the retrieval or reception. It is well known that random noise is hard to compress whereas ordered information is not. We use this property to filter random noise from noisy underwater signals. The compressing process removes portions of the input data, which represent small or nonrecurring features.

We consider an ANN having a limited number of processing elements(PEs) in the hidden layer to filter random noise. The use of a limited number of PEs ensures that some of the information (preferably the noise) would be removed during the reconstruction. We expect that the ANN-based filter would function as a low pass filter. Through this study, the noise is assumed to be random and of a higher frequency than the underlying signal. Two types of signals are used in this study. One is synthesized signal and the other is measured one using acoustic sensors in shallow water. In order to examine the effectiveness of the ANN-based filter, spectrograms are presented for the measured signals.

Ⅱ. Characteristics of Signal and Noise

We use two kinds of signals: synthesized and measured ones. The synthesized signals are sequences of constant and variable amplitudes contaminated by the white Gaussian noise. The two synthesized signal sequences are generated using

$$x_1[n] = \frac{1}{3}\,[0.3\sin(2\pi n/100) + 0.4\sin(2\pi n/200) + 0.3\sin(2\pi n/400) + 0.2\cos(2\pi n/150) + 0.3\cos(2\pi n/300) + \eta_1[n] + 1.5] \tag{1}$$

and

$$x_2[n] = \frac{1}{3.5}\,[n\sin(6\pi n/1024) - n\cos(40\pi n/1024) + \eta_2[n] + 2.0], \tag{2}$$

where $x_1[n]$ = noisy signal sequence of 5 tones and constant amplitude,

$x_2[n]$ = noisy signal sequence of 2 tones and variable amplitude,

$\eta_1[n]$ = noise sequence of mean of zero and variance of 0.1 or 0.5,

$\eta_2[n]$ = noise sequence of mean of zero and variance of 0.1, and $n = 0, 1, 2, \cdots, 1023$.

The noise is assumed to be random and of a higher frequency than the underlying signals. So, it is clear that the contribution of the noise to the signals will tend to be random or nonstationary with respect to other larger features. As a result, the noise will most likely be one of the features removed in the compressing process.

The measured signals have been collected in shallow water, where the depth is around 150 m.[7] The sound source, transmitting 4 tones in the frequencies of 204, 216, 229, and 240 Hz, was towed at speed of 10 kts and depth of 20 m, while the receiver, the horizontal line array having 11 sensor elements, was installed on the sea bottom. Data sampling rate in analog-to-digital conversion is 24.4 kHz. The digitized data are transformed into the frequency domain using the fast Fourier transform(FFT), the size being 2^{11}(or 2048).

Spectrograms are obtained by applying the Order Truncate Average(OTA)[8,9] normalizer. The process of whitening the noise spectrum is called normalization and is mathematically defined by $N_k = X_k/\mu_k$, where X_k is the magnitude in bin k and μ_k is the noise mean estimate in bin k. The OTA normalizer was developed in 1978 by Wolcin.[10] The following steps describe the OTA scheme briefly: (1) The K bin values in the particular set Ω_k are ordered to form a new sequence $(Y_1, Y_2, \cdots, Y_K)$, where Y_1 is the smallest, and Y_K is the largest. (2) The sample median Y_M is identified, and all bins having values greater than $r\,Y_M$ are excluded (a value r is given by 1.4 in this study). Assume L bins remain after the exclusion process. (3) The noise mean estimate μ_k is then obtained using the L remaining bins:

$$\mu_k = \sum_{i=1}^{L} \frac{Y_i}{L}. \tag{3}$$

The details of the OTA scheme are given in the previous study.[7]

The normalized signals are applied to the ANN in order to filter random noise in the frequency domain. For the comparison, the moving average (11 frequency bins of size) is also employed. The spectrograms of the filtered signals are compared with those of without filtering and of the moving averaged.

Ⅲ. Application of an ANN

The unique characteristics of an ANN approach is that the output of the weighted sum (linear combination of the inputs) is transformed using a nonlinear function such as a sigmoid or sine function. These nonlinearities make the creation of multilevel systems possible and are responsible for several resultant characteristics.[11]

The ANN employed in this study is the semilinear feedforward network having 3 layers of input, hidden, and output. Figure 1 shows the architecture of the network. The number of PEs in the input and output layers is chosen as 19 for the synthesized signals, while it is 11 for the measured signals. The number of PEs in the hidden layer varies from 3 to 11 both for the synthesized and measured signals.

The network is known to have a greater capability to get arbitrary complex nonlinear mappings and to generalize from given data than the linear perceptron.[12] The outputs of PEs in one layer are transmitted to PEs in another layer through links that amplify or inhibit the outputs by multiplying weighting factors. The net input to kth PE, y_k, is the sum of the weighted outputs of the PEs in the prior layer:

$$y_k = \sum_j w_{kj} o_j , \tag{4}$$

where w_{kj} is the weighting factor for the jth PE in the previous layer transmitting to the kth PE and o_j is the output from the jth PE in the previous layer. The activity of each PE is determined by its input and its activation function together with an associated bias term. Thus the output of jth PE is,

$$o_j = f(y_j) \tag{5}$$

where f is the activation function. In this study, a sigmoidal activation function is employed as following:

$$o_j = \frac{1}{1+\exp[-(y_j+\theta_j)/\theta_o]} \tag{6}$$

where θ_j is the bias term.

The learning process is as follows: The network starts off with a random set of weight values. One of the training set patterns p is chosen. Using this pattern as input, the outputs are calculated in a feedforward manner. In general, the outputs o_{pk} will not be the same as the target values t_{pk}. For each pattern, the mean square error(MSE) E is defined by

$$E = \frac{1}{2p} \sum_p \sum_k (t_{pk} - o_{pk})^2 . \tag{7}$$

The corrections to the weights are made by taking small changes (Δw_{ji}) proportional to $-\partial E/\partial w_{ji}$ as follows: Using the back-propagation scheme,[13] the network calculates $\Delta_p w_{ji}$ for all the w_{ji} for that particular p, where $\Delta_p w_{ji} = \eta \delta_j o_i$, $\delta_j = -\partial E/\partial y_j$, and η = constant. This procedure is repeated for all the patterns in the training set to yield the resulting Δw_{ji} for all the weights for that one iteration; that is,

$$\Delta w_{ji} = \sum_p \Delta_p w_{ji} . \tag{8}$$

In a successful learning exercise, the MSE will decrease with the number of iterations, and the procedure will converge to a stable set of weights.

The way we train the network is to randomly select a block of 19 (or 11) sequencial samples from the noisy signal sequence, and to use this as both the input and desired output of the network. This is subjected to repeat 100000 times for each of the networks, which takes about 1 minute on the Convex C3420 system. In fact, however, the ANN converges very rapidly during the process of training. Figure 2 shows the mean square error(MSE) for the ANN having 19 PEs in the input and output layers, and 5 PEs in the hidden layer. It can be shown that the MSE approaches almost 0 within the iteration number 1000. Each time a block of inputs is applied to the net-

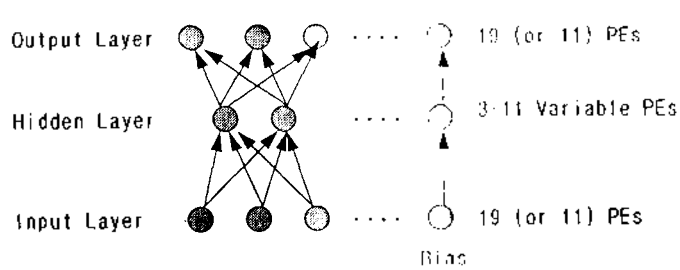


Figure 1. ANN architecture having 3 layers of input, hidden and output.

work, the weights are slightly adjusted to make the actual network output closer to the desired output.

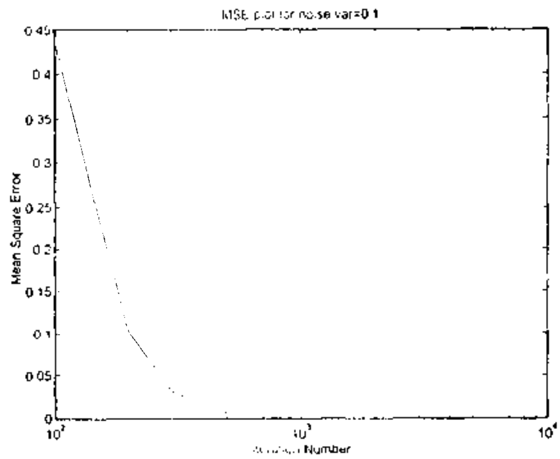


Figure 2. Mean square error with iteration number in the process of the ANN training.

During the recall process, the noisy signal set is shifted through a 19-element long shift register and the output is computed with that of inputs. The signal is shifted one position and the process is repeated like the way in the moving average (Fig. 3). Only the middle output element is used as the filtered output.

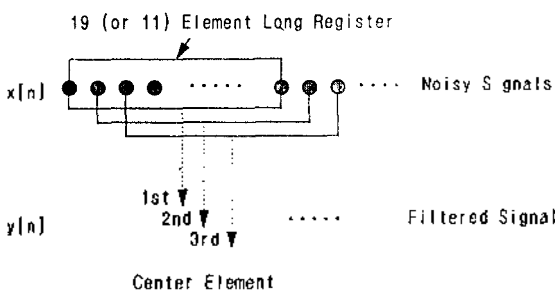


Figure 3. Filtering process using the ANN. Recalling data is repeated by shifting one position through a 19-element long register.

Ⅳ. Results and Discussions

The filtered results by applying the ANN are obtained for four cases: two cases for the synthesized signals with constant amplitude, one case for the synthesized signals with variable amplitude and the other for the measured signals. Table 1 summarizes all cases. All types of signals are scaled in order to confine their amplitudes in between 0 and 1. This is necessary because we use a sigmoidal activation function in our all applications.

4.1 Constant amplitudes and noise variance 0.1(Case Ⅰ)

Figure 4 shows the sequences of the noisy and filtered signals with 5 tones and constant amplitudes. The noisy signal is generated by eq.(1) of which noise is mean 0 and variance 0.1. The signal filtered by the ANN with 3 PEs in the hidden layer (Fig. 4b) gives the patterns similar to the noise-free signals but gives somewhat unreasonable ones particularly on the lower peaks. The signal with 11 PEs (Fig. 4c) gives better results and reconstructs almost all signatures of the noise-free signals. That is, they also give major signal patterns but no longer unreasonable results as seen in those with 3 PEs in the hidden layer.

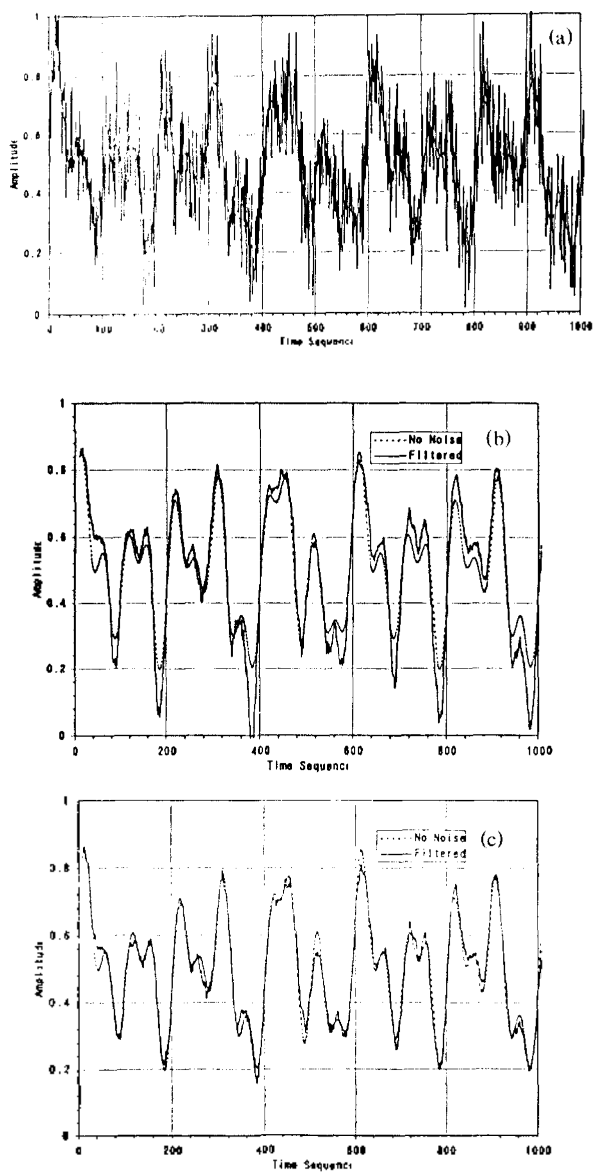


Figure 4. Sequences of the noisy and filtered signals by the ANN. (a) Noisy signals with noise variance 0.1. Filtered signals with (b) 3 PEs (c) 11 PEs in the hidden layer.

In filtering process, only the middle output element (i. e., the 10th element among 19 output elements) is used as the filtered output. This is reasonable because when we are to have only one output element that is trained to produce the value of the middle input, the output is affected almost exclusively by the center input, all other inputs being ignored.[5]

4.2 Constant amplitudes and noise variance 0.5(Case II)

Case II is same with Case I except the noise variance is increased from 0.1 to 0.5. This case is aimed to examine the applicability of the ANN-based filter against the noisy signals with increased noise level.

Figure 5 presents the sequences of the filtered signals with 3 and 11 PEs in the hidden layer. At a glance, the two results show that most of the underlying signals are retained while noise is greatly filtered out.

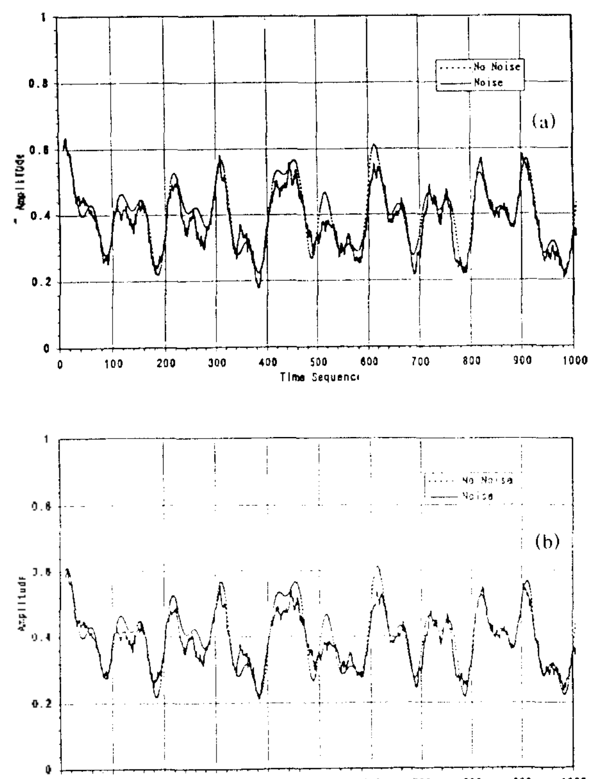


Figure 5. Signal sequences filtered by the ANN for the noisy signals generated by eq. (1) having noise variance 0.5: with (a) 3 PEs and (b) 11 PEs in the hidden layer.

To examine the characteristics of the ANN-based filter, the amplitude spectra are determined for the noisy and filtered signals (Fig. 6). Figure 6a shows the amplitude spectra (linear and not normalized) with frequency bins for the noisy signals. In the figure, it is evident that there exist 5 tones as expected in eq.(1). The filtered results with 6 PEs (Fig. 6b) show that most of the noise is filtered in the higher frequency region measured from bin number 150 but still remained in the lower region. When the number of PE in the hidden layer is decreased to 3

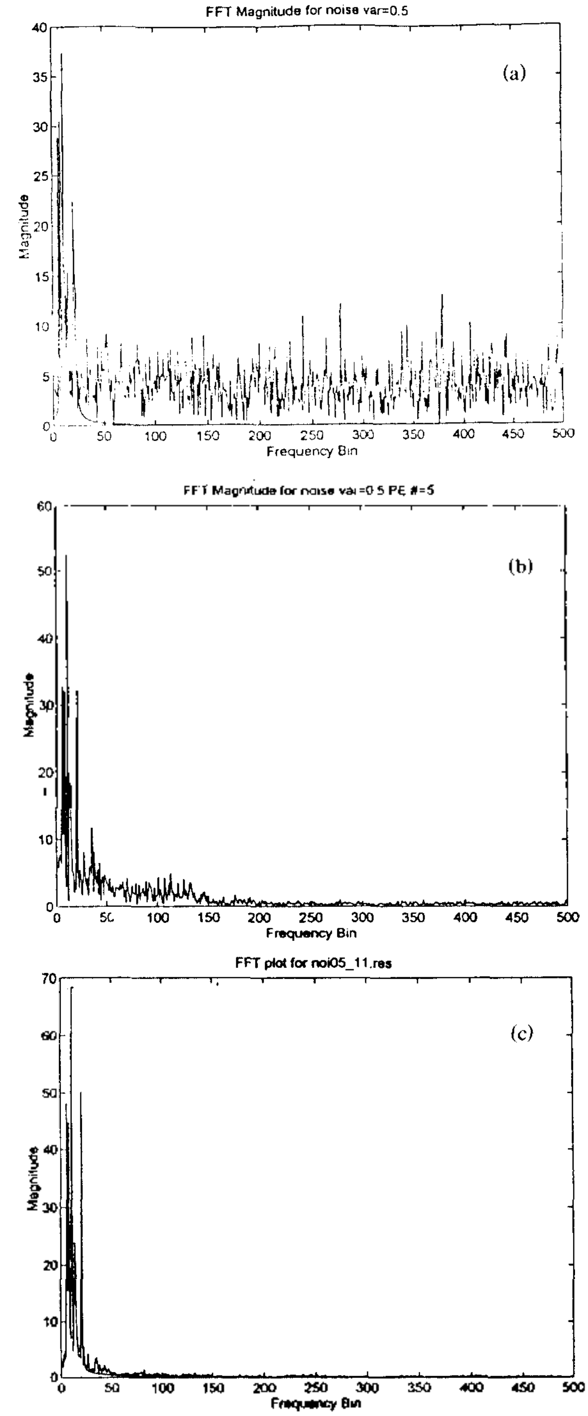


Figure 6. Amplitude spectra (linear and not normalized) of the noisy and filtered signals. (a) Noisy signals with noise variance 0.5 (eq.(1)) and the filtered signals by the ANN with (b) 6 PEs and (c) 3 PEs in the hidden layer.

(Fig. 6c), most of the noise is filtered in the whole frequency range. This fact implies that the fewer PEs in the hidden layer, the more information is lost in tranforming inputs to outputs as in data compression. On the contrary, the more PEs, the more detail (including noise) is preserved.

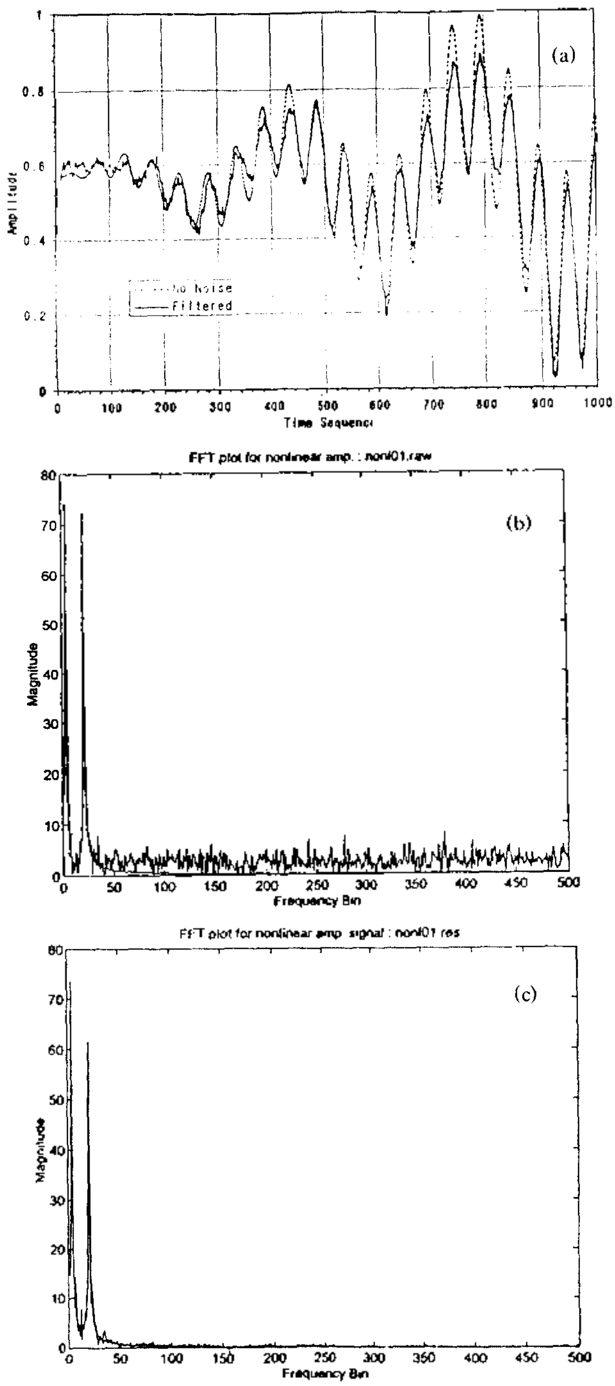


Figure 7. Sequences of the noisy (variance = 0.1) and filtered signals with two variable amplitudes (eq.(2)), and their spectra (linear and not normalized). (a) Sequences of the noise-free and filtered signals by the ANN with 10 PEs in the hidden layer, (b) their amplitude spectra of the noise-free and noisy signals and (c) those of the filtered signals with 3 PEs in the hidden layer.

4.3 Variable amplitudes and noise variance 0.1(Case Ⅲ)

To examine the adaptability of the ANN-based filter against the noisy signals having variable amplitudes, the ANN is tested with the signals generated by eq.(2). As seen in Table 1, the signals have two tones of variable amplitudes and noise of variance 0.1. In this case, the number of PEs in the input and output layers is fixed for 19 while that in the hidden layer varies from 3 to 10.

Figure 7 shows the sequences of the noisy and filtered signals, and their amplitude spectra (linear and not normalized). Compared with the noise-free signals, the signals filtered with 10 PEs keep major signal signatures (Fig. 7a). Figure 7b presents the amplitude spectra of the noise-free and noisy signals with noise variance 0.1. As can be seen in the figure, two peaks exist in both types of the signals at the frequencies specified in eq.(2), and fluctuations due to noise last in the whole frequency range. However, the spectra of the signals filtered with 3 PEs in the hidden layer show almost no such fluctuation implying that the noise is filtered out.

The fact that the ANN can filter noise from the signals having variable amplitudes guarantees its applicability to a "real signals" which, in general, contaminated by noise and subject to change in their amplitudes.

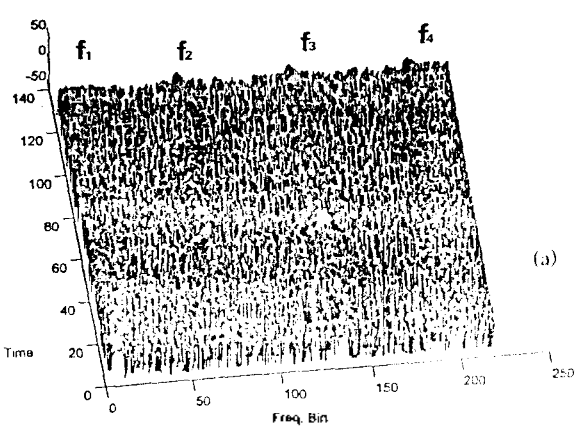
4.4 Measured signals with variable amplitudes(Case Ⅳ)

The "real signals" are measured using the horizontal line array having 11 acoustic sensor elements. The sound source transmits the signals of 4 tones ranging from 200 to 250 Hz for about 30 minutes.

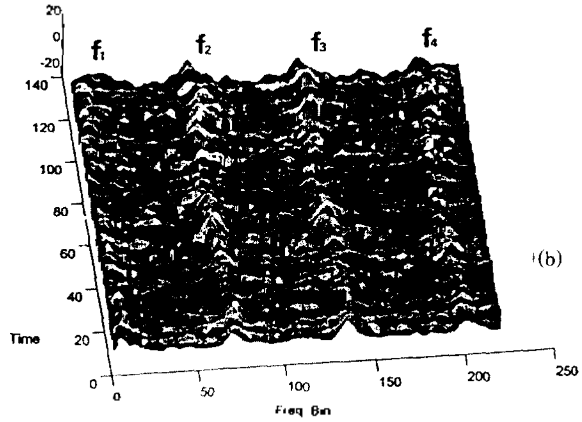
Although the transmitting signals are operated to keep steady constant power, the receiving signals have no longer steady constant power in the ocean. In general, the signals are embedded by noise and fluctuate (relative to a steady signals) over a period of time. Moreover, they may be changed depending on receiver locations at a given time. Coherence is defined as a measure of the phase and amplitude relationship between sets of acoustic waves. In the ocean, coherence is characterized by both temporal and spatial variations. The effect of medium on small-amplitude wave propagation can be described in terms of coherence time, coherence bandwidth, spatial coherence and angular coherence.[14] Signal fluctuations can be caused by a number of physical processes including source/receiver motion, oceanic fine-scale features, internal waves and tides. Through the previous study,[7] the measured signals are shown to have temporal fluctuations mainly caused by source motion and multipaths of the propagating waves.

The measured raw data are transformed by FFT and pink noise is normalized by the OTA scheme. Pink noise, being different from random noise, is defined as that has constant slope within a limited range of frequency. Even after pink noise is normalized, there still remains highly fluctuating random noise in the frequency domain. The ANN, having 11 PEs in the input and output layers, and 5 PEs in the hidden layer, is applied to filter the random noise. For the training of the ANN, a block size of 11 samples are selected randomly from the normalized data. After the training is completed, the ANN is applied to filter random noise from the normalized data by the same way in the previous cases.

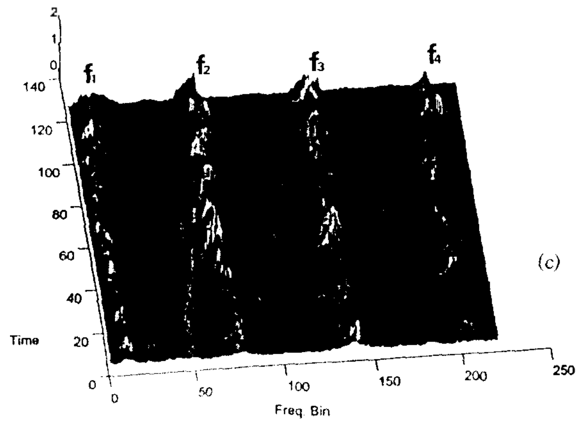
Figure 8 presents three spectrograms for the signals measured on the 6th sensor of the horizontal line array: without filtering, filtered by the moving average, and filtered by the ANN. The window of the moving average is 11 frequency bins. The 1st picture (Fig. 8a) comes from the data normalized by the OTA scheme. If examined carefully, the definite 4 signals can be seen but they are severely contaminated by noise. The spectrogram of the moving averaged data (Fig. 8b) shows better picture to identify underlying 4 signals but noise level is still high. Moreover, the four signals undergo frequency shifting and spreading which are caused by the source movement and multipaths of acoustic waves.[7] The last one (Fig. 8c) is the spectrogram of the signals filtered by the ANN with 5 PEs in the hidden layer. It gives much better picture to identify deterministic 4 signals. In the figure, it is clear that the random noise is almost suppressed. The levels on the vertical axis are normalized between 0 and 1 because they suffer scaling by the ANN which employs a sigmoidal activation function.



(a)



(b)



(c)

Figure 8. Spectrograms of the signals measured on the 6th sensor in the shallow sea. (a) Without filtering, (b) moving averaged with the size of 11 frequency bins and (c) filtered by the ANN with 5 PEs in the hidden layer.

Table 1. Cases to examine the applicability of the ANN for filtering noise.

case no.	signal type	no. of tones/ amplitude type	noise variance	remarks
I	synthesized	5/constant	0.1	eq.(1)
II	synthesized	5/constant	0.5	eq.(1)
III	synthesized	2/variable	0.1	eq.(2)
IV	measured	4/variable	variable	

Figure 9 shows another three spectrograms for the signals measured on the 7th sensor. As in Fig. 8, most of the random noise is filtered in the spectrogram to which the ANN is applied (Fig. 9c), while still remains in others (Fig. 9a, b).

As a general technique, an ANN offers an interesting and potentially powerful approach for noise filtering. One of the particularly interesting characteristics of an ANN is the capability to develop an adaptive filtering technique that can be tuned to preserve varying degrees of detail.[14] However, significant experimentation remains to develop these technique to the point where it is well characterized and understood.

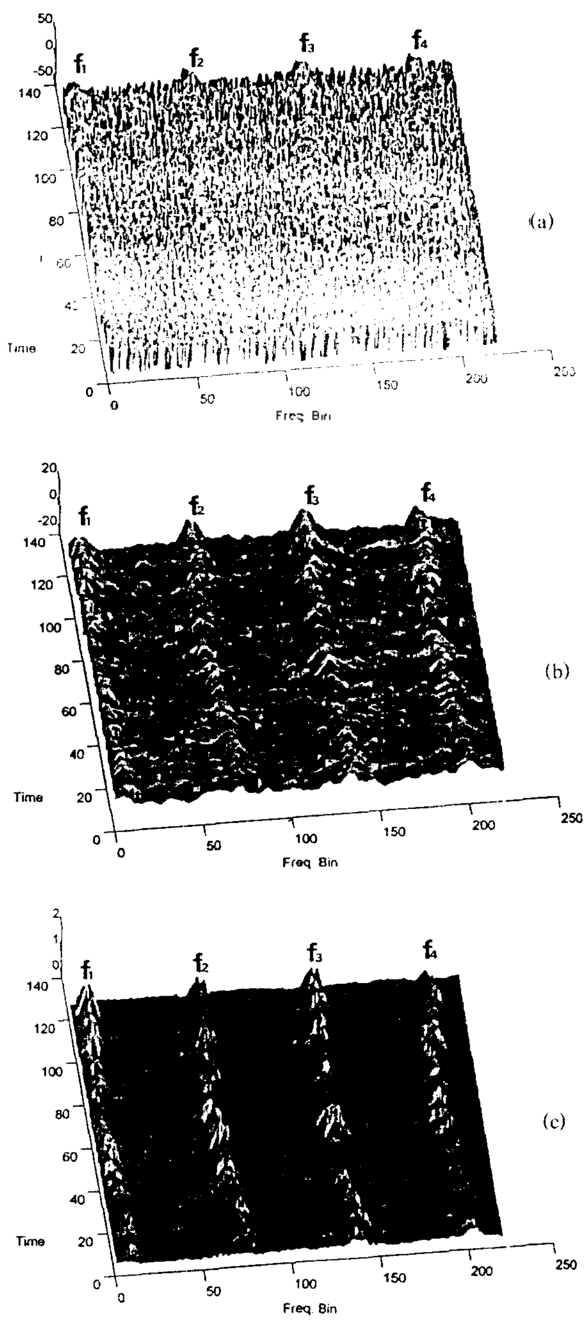


Fig 9. Spectrograms of the signals measured on the 7th sensor in the shallow sea (a) Without filtering, (b) moving averaged with the size of 11 frequency bins and (c) filtered by the ANN with 5 PEs in the hidden layer.

V. Conclusion

In this study, we examine the applicability of an ANN to filter random noise from noisy signals. Two kinds of signal, synthesized and measured, are considered.

To conclude, the ANN is shown to filter random noise and to extract the underlying signals from the synthesized or measured noisy signals. This filtering process is achieved without using any multiband or specially designed filter. The training data set is chosen to be independent of the signal so that, unlike conventional filters, the ANN-based filter requires no parameter estimation or priori knowledge of noise characteristics. Moreover, the ANN converges very rapidly to the desired output during the process of learning, approaching almost 0 within 1000 iterations.

In this article, it is just examined the applicability of an ANN for filtering underwater random noise. Efforts are directing to the statistical characterization of the ANN such as its optimal structure and tuning to preserve varying degrees of detail. Much more experimentation needs to be conducted to develop this technique to the level of complete understanding.

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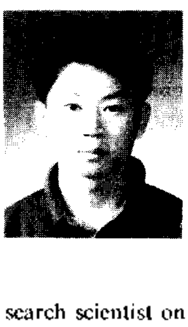

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