Abstract—A neuro-fuzzy detector in the continuous wavelet transform (CWT) domain is developed to enhance the performance of wideband acoustic signal detection in a noise-limited environment. The aim of the detector is to determine the motion parameters (radial range and velocity) of moving targets in active wideband sonar echolocation system at very low signal-to-noise ratio (SNR). The detection is based on time-scale and time-delay of the received echo. The fuzzy detector is composed of two parts: noise reduction based on the adaptive noise cancelling (ANC) concept, and motion parameters estimation based on the correlation process. Using learning intelligent systems named adaptive neuro-fuzzy inference systems (ANFIS), noise embedded in the return signal is minimized which improves the output SNR. The resultant signal is then proceeded by a similarity measurement technique known as the wideband cross correlation process equivalent to the CWT operation for determining the motion parameters. Simulation results demonstrate that the neuro-fuzzy detector is effective in accurately predicting the motion parameters with less than 0.2% false target detection rate.

1. INTRODUCTION

In active wideband sonar system involving the estimation of location and velocity of some targets, it is well known that the implementation of detectors suggests to exploit the time-scale representation of these targets or objects [1]. Technique used to identify and localize objects is commonly known as the cross correlation processing or matched filter processing [2], [3]. As in wideband applications, this technique measures the time-delay and scale-change components of the target echoes by cross correlation operation of overlapping segments of the received echo with a replica of transmitted signal. The peak value of its output is then used in a subsequent threshold test. The time shift causing the peak is an estimate of the true delay. From the linearity of time range between the reference delay and estimated one, the target’s velocity is then measured. Thus, in general, the replica correlator output gives rise to a similarity measurement between the hypothesized signal and the received one in the time-scale plane, which is equivalent to the form of continuous wavelet transform (CWT) [4], [5]. This suggests that the processing of wideband waveform should be done in the CWT domain.

Takings advantage of CWT properties, this model then offers significant motions between sensors and objects in terms of continuous dilations or contractions (related to high velocity targets), and fine time and scale resolutions [4], [5].

For each desired set of motion parameters, the wideband correlation processing (and hence CWT processing) works well and is optimum under the noise-free condition. The processing has also been shown to be an optimal technique for signals corrupted by additive Gaussian white noise with the maximum output SNR [6]. In the presence of serve interference or in highly distorting media such as spread or multipath channels [7], the wideband processing in the CWT domain, however, degrades the underlying backscattering returns, thus inhibiting the process of extracting the target echo from its background interference. This is because sharp peaks are more sensitive to errors introduced by finite observation time, particularly in cases of low SNR.

A possible remedy for the active wideband sonar signal detection involving noise interference is commonly offered by the technique of adaptive processor named adaptive noise cancelling (ANC) [8]. In this paper, an effective neuro-fuzzy detector in the CWT domain is proposed in Fig. 1 in order to enhance the performance of underwater wideband signal detection in a noise-limited environment. The fuzzy detector consists of two parts: noise reduction, and motion parameters estimation. In the noise reduction, a hybrid learning intelligent system named adaptive neuro-fuzzy inference systems [9], is introduced as a driving force in the core of ANC to identify the nonlinear characteristics of noise part and then subtracting it from the received noisy signal. This results in an estimate of the true target return, which serve as an input data set to the operation of motion parameter estimation in the CWT domain.

The operation of ANFIS, a fuzzy inference system implemented in the framework of adaptive networks, is served as a basis for constructing a set of fuzzy if-then rules with appropriate choice of membership functions to generate the stipulated input-output pairs. In particular, the learning algorithm combines gradient descent approach and least-squares method to yield an efficient hybrid training algorithm for system identification. The stage of noise cancelling exploits the ANFIS capabilities in tracking both linearity and non-linearity in multidimensional input spaces [9]. Comparisons with conventional adaptive signal processing techniques in noise cancellation have been reported in [10], [11], [12], which suggested that the ANFIS possesses an outperform on real-time processing and computational efficiency.

The similarity measurement in terms of CWT implementation is optimized in the scale domain by the combination of golden section search and successive parabolic interpolation method [13]. The advantages of using the optimization process follow:

- Increasing the prediction accuracy of motion parameters, never being achieved by finer sampling of scale range.
- Decreasing the need of hardware memory storage for the CWT coefficients. With the help of the optimization technique, the CWT coefficients in the time-scale plane arrive at a vector form instead of a matrix one obtained by conventional finer sampling.
- Decreasing the time consumption taken by the implementation of similarity measurement.

Combining techniques of ANFIS for effective noise cancellation and CWT for optimal similarity measurement, the
proposed method can serve as a fast convergent estimating procedure for underwater target detection in a very low SNR environment.

2. WIDEBAND CORRELATION PROCESS AND CWT OPERATION

Let us consider a finite duration of an outgoing signal \( \psi(t) \in L^2(\mathbb{R}) \) propagating through the medium. In the presence of a target, this signal is returned to the source with a certain delay, due to the target’s location, and a certain distortion (Doppler effect), due to the target’s velocity. For wideband signals in a single nondirectional sonar channel, the received total signal can be mathematically modelled as

\[
g(t) = g(t) + \eta(t) \tag{2.1}
\]

where \( \eta(t) \) is an additive background interference and \( g(t) \) is a hypothetical noise-free target return at time \( t \) with \( S \) and \( D \), the true scale and round-trip time-shift of the return signal due to the target’s motion and location, respectively [3]

\[
g(t) = \sqrt{S} \psi(S(t - D)). \tag{2.2}
\]

Let \( \psi_s(t) \equiv \sqrt{S} \psi(st) \) with \( s \) being the scale factor given by \( s = \frac{c-v}{c+v} \), where \( v \) is the radial velocity of the target in linear motion, and \( c \) is the speed of propagation. In the wideband correlation processing, \( \psi_s(t) \) constituting the form of the hypothetical signal is served as a template (or basis function). Thus, for model of the form of Eq. (2.1), the wideband replica correlation function between the incoming signal and the reference one is

\[
WC_{\psi,\tilde{\psi}}(s, \tau) = \int g(t)\tilde{\psi}_s(t - \tau)dt.
\]

Defining \( \psi_{s,\tau}(t) \equiv \psi_s(t - \tau) \), the replica correlator becomes an inner product of the form:

\[
WC_{\psi,\tilde{\psi}}(s, \tau) = \int \tilde{g}(t)\psi_s(t - \tau)dt = \langle \tilde{g}, \psi_{s,\tau} \rangle. \tag{2.3}
\]

If the incoming signal receives maximum output SNR and \( \eta(t) \) is an additive white Gaussian noise, the correlation process is optimum [6]. As the correlation is calculated in time over the entire signal and consecutive high correlations are obtained, the detection process is then accomplished when the correlated signal is proportional (parallel) to the template one, i.e., they are completely alike but in a different scale. The detection problem due to the correlation process can now be described as to maximize the correlation function \( WC_{\psi,\tilde{\psi}}(s, \tau) \) over both parameters simultaneously:

\[
\max_{s,t,(s\approx \varepsilon S, \varepsilon > 0)\in \mathbb{R}} \{ ||WC_{\psi,\tilde{\psi}}(s, \tau)||^2 \} = \max_{(s^*, \tau^*)\in \mathbb{R}} ||WC_{\psi,\tilde{\psi}}(s^*, \tau^*)||^2 \tag{2.4}
\]

for which \( s^* \approx \varepsilon S, \varepsilon > 0 \) and \( \tau^* \approx D \). One of the principle drawbacks to the optimization process above is that it is computationally expensive with two decision variables involved, which is not suitable for real-time applications. This is true, especially when fine scale and good time resolution both are required in the detection process. Since the detection problem strongly links to time-scale analysis of a signal, it suggests to consider basis functions \( \psi_{s,\tau}(t) \) already appeared in Eq. (2.3) as wavelets. Provided the variable change \( s \mapsto \frac{1}{s} \), the inner product used as a similarity measurement is then a CWT of \( \tilde{g}(t) \) with respect to \( \psi(t) \) [5]. The estimator thus becomes a CWT operation with mother wavelet \( \psi(t) \):

\[
WC_{\psi,\tilde{\psi}}(s, \tau) = \langle \tilde{g}, \psi_{s,\tau} \rangle \equiv \text{CWT}_\psi\tilde{g}(s, \tau). \tag{2.5}
\]

From Eq. (2.5), we can see that the wavelet transform performs:

- a decomposition of the signal \( \tilde{g}(t) \) into a weighted set of scaled mother wavelet, i.e., \( \psi_{s,\tau}(t) \). This forms sustainable similarity measurement in terms of wavelet coefficients.
- a suitable analysis to the signal containing short high-frequency components (due to the contraction of \( \psi_{s,\tau}(t) \) at small scale) and extended low-frequency components (due to the dilation of \( \psi_{s,\tau}(t) \) at large scale), which is the case for signals we are encountered.
- robustness later in the maximization problem of Eq. (2.6) for determining the scale parameter, whereas the dilation parameter in the problem of Eq. (2.4) stays on the order of magnitude of 1 due to physical reasons. Consequently, the aim of echolocation detection problem may be solved by seeking the local maximum of CWT coefficients:

\[
\max_{s,\tau > 0, \tau \in \mathbb{R}} \{ ||\text{CWT}_\psi\tilde{g}(s, \tau)||^2 \}. \tag{2.6}
\]

In order to apply filtering concepts for solving the problem of Eq. (2.6), the CWT implementation initially operated by a correlation of input signal and scaled and weighted mother wavelet must be converted to a convolution form. Letting \( \psi(-t) = \psi(t) \) yields \( \psi_s(-t) = \psi_s(t) \) and

\[
\text{CWT}_\psi\tilde{g}(s, \tau) = \int \tilde{g}(\tau - t)\psi_s(t)dt = \sum_{\ell \in \mathbb{Z}} \int_{\ell}^{\ell+1} \tilde{g}(\tau - t)\psi_s(t)dt. \tag{2.7}
\]

If \( \tilde{g}(t) = \tilde{g}(\ell) \) for \( t \in [\ell, \ell+1] \), Eq. (2.7) is approximated as

\[
\int_{\ell}^{\ell+1} \tilde{g}(\tau - t)\psi_s(t)dt = \sqrt{s} \int_{\ell}^{\ell+1} \tilde{g}(\tau - t)\psi(t)dt = \sqrt{s} \int_{\ell}^{\ell+1} \tau \psi(t)dt = \sqrt{s} \int_{\ell}^{\ell+1} \tau \psi(t)dt = \sqrt{s} \int_{\ell}^{\ell+1} \tau \psi(t)dt \tag{2.8}
\]

where \( h(s, \ell) = \sqrt{s} \int_{\ell}^{\ell+1} \tau \psi(t)dt \). Now let us consider the problem of Eq. (2.6) with support \( t \in [0, T] \). Following from Eq. (2.8), the discrete-time version of the problem consists of breaking the time interval \([0, T]\) into \( N = m \times (n + L - 1)\) subintervals, and approximating the input signal \( \tilde{g} = [\tilde{g}_1, \ldots, \tilde{g}_m] \) with \( n \) samples in each signal segment \( \tilde{g}_i, i = 1, \ldots, m \). The CWT coefficients obtained for the input signal \( \tilde{g} \) at the scale \( s \) is then represented by a bank of FIR filter output response with filter coefficients \( h(s, \ell) \), i.e.,

\[
\text{CWT}_\psi\tilde{g}(s) = y(s) = [y_1(s), \ldots, y_m(s)] \in \mathbb{R}^N.
\]

with

\[
y_{k}(s, k) = \min_{\ell = \max(0, k - (L-1))}^{\min(k, n-1)} h(s, \ell)\tilde{g}_k(k - \ell), \tag{2.9}
\]

for \( k = 0, \ldots, n + L - 2 \) and \( n = L \). As can be viewed from Eq. (2.9) that \( y_k(s) = \Theta_k h(s) \in \mathbb{R}^{2L-1} \), where \( h(s) \equiv [h(s, 0), \ldots, h(s, L-1)] \in \mathbb{R}^L \) is filter impulse response and \( \Theta_k \in \mathbb{R}^{2L-1 \times L} \) is a Sylvester matrix defined by

\[
\Theta_k = \begin{bmatrix}
\tilde{g}_k(0) & 0 & \cdots & 0 \\
\vdots & \ddots & \ddots & \vdots \\
0 & \cdots & \tilde{g}_k(L-1) & \tilde{g}_k(L-2) \\
\tilde{g}_k(L-1) & \tilde{g}_k(L-2) & \cdots & \tilde{g}_k(0)
\end{bmatrix}.
\]
Eq. (2.6) may be approximated by the CWT implementation, the continuous time problem of noise WGN(0,1) sources

\[
\eta \text{ of the target can be obtained by the following expression}
\]

\[
0.5 \leq n \leq 1.5 \quad 2.5 \leq n \leq 3.5
\]

arrival time is obtained by \( \bar{\tau} = c\left(1 - \bar{S}\right)/(1 + \bar{S}) \) (2.11)

We denote \( \bar{\tau} = -\tau \) for source motion moving forward close to the receiver. Likewise, \( \bar{\tau} = +\tau \) is denoted with moving backward of the target away from the receiver. These signs are made in accord with the scale defined for the Doppler effect. As a result of Eq. (2.11), the radial position of the target due to linear motion is predicted in terms of an initial range \( R(t_i) \) and uniform radial velocity \( \bar{\tau} \) by

\[
R(t_f) = R(t_i) + \bar{\tau}(t_f - t_i).
\]

3. Noise Cancellation Procedure

The replica correlator discussed in the previous section imposes limitation in dealing with additive noise, especially for those with low SNR and nonlinear behaviors. In order to improve the accuracy of the scale estimate \( \bar{S} \) (and hence the delay estimate \( \bar{\tau} \)), it is desirable to prefilter the incoming signal prior to the correlation processing.

A. Noise input selection

Let the interference set \( n(t) = \{n_1(t), n_2(t), \ldots\} \) containing multichannel of background noise be the input noise source of the reference channel in Fig. 1. The set of noise is then fed into an unknown corruption function called noise path filter so that these channels of noise can be transformed into a single channel of unknown interference additive to the hypothesized noise-free target return, in order to form the primary channel. Furthermore, data generated by the noise path filter can be used to represent the worse detectable situation in highly distorting media such as spread or multipath channels. For simplicity but still representing an extreme case of the classical tests, the noise path filter is chosen to be characterized by a nonlinear function (Rosenbrock’s banana function) below:

\[
\eta(n_1, n_2) = 100(n_2 - n_1^2)^2 + (1 - n_1)^2
\]

with two reference inputs of white Gaussian noise WGN(0,1). The nonlinear function as illustrated in Fig. 2 is notorious in optimization examples because of the slow convergence which most methods exhibit when trying to solve this problem.

B. ANFIS learning algorithm

The architecture of the ANFIS operation [9] is designed to combine a hybrid learning procedure of a neural network with reasoning capacities of fuzzy logic. Its aim is at finding a model or mapping that correctly associates with the stipulated input-output pairs. Based on the Sugeno’s fuzzy if-then rule [14] for which the fuzzy reasoning mechanism depicted in Fig. 3(a) is derived for an output \( f \) from a given input training data set \( \{x, y\} \), the adaptive network represented by the ANFIS architecture in Fig. 3(b) is obtained containing the following five layers:

- **Layer-I.** Every node \( i \) in this layer is an adaptive node containing node Gaussian functions (or membership functions (MFs)) \( \mu_i(x) = \exp[-(\frac{x-a_i}{b_i})^2] \) whose parameters \( a_i, b_i \) are called premise parameters.

During the learning phase, these parameters change continuously resulting in various forms of membership functions on each fuzzy set. For \( m \) MFs distributed over the dynamic range input \( x_i, i = 1, \ldots, n \), this layer generates \( 2mn \) premise parameters associated with \( n^m \) fuzzy rules. These exhibited membership functions are then compared with input variables to obtain the membership values.

- **Layer-II.** Every node in this layer is a fixed node labelled \( \Pi \) whose output is the product of all
incoming signals. Output of the node represents the firing strength of a rule, for example, given below \( \{a_i, b_i\}, i = 1, \ldots, m \) and \( x_j, j = 1, \ldots, n \), we obtain

\[
\tilde{w}_k = \mu_{a_i}(x_j) \times \mu_{b_i}(x_j), k = 1, \ldots, m^n.
\]

Layer–III. Every node \( i \) in this layer is a fixed node labelled \( N \). The node \( i \) gains the ratio of the \( i-th \) rule’s firing strength to the sum of all rules’ firing strengths. Thus, outputs of this layer are called normalized firing strengths, i.e.,

\[
\bar{w}_i = w_i / \sum_{j=1}^{m^n} w_j, i = 1, \ldots, m^n.
\]

Layer–IV. Every node \( i \) in this layer is an adaptive node with a set of consequent parameters \( \{p_i, q_i, r_i\} \) pertaining to it to result in a weighted node function

\[
\bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i), i = 1, \ldots, m^n.
\]

In this layer, there are \( 3m^n \) consequent parameters to be generated where each set of consequent parameters is awaited to be determined.

Layer–V. The single node in this layer is a fixed node labelled \( \Sigma \), which computes the overall outputs as the summation of all incoming signals, for instance,

\[
f = \sum_{i=1}^{m^n} \bar{w}_i f_i = \sum_{i=1}^{m^n} \frac{w_i}{\sum_{j=1}^{m^n} w_j} f_i.
\]

An overview of the adaptive network suggests that ANFIS is a hybrid learning algorithm, which combines the gradient descent method to upgrade the premise parameters and least-squares method to identify the consequent parameters. More specifically, in each epoch of the hybrid learning procedure, given input data with fixed premise parameters, functional signals go forward to gain each node output until the layer-IV and the consequent parameters are identified by the sequential least squares estimator. This procedure has formed a forward pass. After parameters have being identified, the functional signals keep going forward to calculate the error measure of the training data set resulting in the error rates propagating backward from the output end towards the input end. Thus, for a given set of fixed consequent parameters, the premise parameters in Layer-I, 16 firing strengths in Layer-II, 16 normalized firing in Layer-III and 48 consequent parameters in Layer-IV. Due to the sample frequency, there are totally \( 2^{15} \) input-output data pairs involved in the ANFIS system and are used to predict the behavior of the unknown nonlinear channel. Among them 50% of the data set is taken for the training nodes, whereas 50% of the others is for checking modes to validate the identified fuzzy model. Subtracting \( \hat{\eta}(t) \) from the primary channel yields an estimated signal of \( \hat{g}(t) \). Instead of suppressing the interference from the primary channel, the ANFIS operation takes \( \hat{g}(t) \) as a contaminated version of \( \hat{\eta}(t) \) in the primary channel for training. In such case, the desired return signal is treated as “noise” in this kind of nonlinear fitting.

### A. Implementation of ANFIS

Given the training data sets composed of input-output pairs of \( n(t) \), the ANFIS de-noising operation, a core function between the ANC, adaptively identifies the nonlinear relationship between \( \eta(n(t)) \) and \( n(t) \), and, thus, produces an estimate \( \hat{\eta}(t) \) in the output. More specifically, provided four Gaussian MFs on each of the two inputs, the generalized FIS structure contains 16 fuzzy rules with the total 96 fitting parameters, which composed of 16 premise parameters in Layer-I, 16 firing strengths in Layer-II, 16 normalized firing in Layer-III and 48 consequent parameters in Layer-IV. Due to the sample frequency, there are totally \( 2^{15} \) input-output data pairs involved in the ANFIS system and are used to predict the behavior of the unknown nonlinear channel. Among them 50% of the data set is taken for the training nodes, whereas 50% of the others is for checking modes to validate the identified fuzzy model. Subtracting \( \hat{\eta}(t) \) from the primary channel yields an estimated signal of \( \hat{g}(t) \). Instead of suppressing the interference from the primary channel, the ANFIS operation takes \( \hat{g}(t) \) as a contaminated version of \( \hat{\eta}(t) \) in the primary channel for training. In such case, the desired return signal is treated as “noise” in this kind of nonlinear fitting.

### B. Implementation of CWT

In order to obtain an estimate of the target arrival time, the following steps of CWT operation are implemented:

Step-I. The mother wavelet \( \psi(t) \) is sampled at \( 128Hz \) with effective support \( t \in [-5, 5] \) for the lowest level of similarity measurement. The length to a wavelet analysis (and hence to a FIR filter taps \( L = 128 \) was considered to provide a compromise between computational convenience and sufficient data similarity measurement. The resulting signal was then split into \( m = 256 \)-filter bank.

Step-II. Resulting from the above setting, the discrete-time CWT coefficients are computed where the optimizer pair \( (s^*, \tau^*) \) in the time-scale plane is not restricted to the finer sampling based on the convolutional octave-by-octave computation. Instead, combining golden section search and successive parabolic interpolation method [13], the local maximizer \( s^* \) of the subproblem in Eq. (2.10) was sought in the range of \( (16, 36) \).

Step-III. A vector form containing the optimized scale is maximized over the entire time range so that the time shift representing the location of the target is obtained, i.e., the estimate \( \tau^* \) is simply the abscissa value at which the RC output peaks.
In all the examples in this paper, the 10ms long Morlet wavelet [16] is adopted as the mother wavelet
\[ \psi(t) = \exp(-\alpha t^2) \exp(j2\pi f_c t) \]
which consists of a window function governed by \( \alpha = 5 \times 10^4 \text{Hz} \) and a modulation function adjusted by \( f_c = 200\text{Hz} \), a central frequency of the waveform. The modulation function is normalized so that its 2-norm is equal to 1 and the wavelet is visualized in Fig. 4.

C. Experiments

Simulation I: In this experiment, the reference echo reflected from the point object is randomly chosen at time of occurrence 0.42sec (or the straight maximum delay 637.5m) away from the receiver. Provided that the hypothesized speed of the target moving constantly towards the receiver is 150knots, the round-trip time delays in the noise-free condition can be obtained at \( \tau_0 = 0.856\text{sec} \) and \( \tau = 0.7096\text{sec} \) (or time of occurrence 0.3798sec) for the reference echo and the desired target echo, respectively. These results are given for the purpose of comparison and are shown in Fig. 5(a) where the reference signal and its corresponding occurrence are marked with square character, whereas the desired signal and its corresponding occurrence are marked with circle character. Figs. 5(b)-(c) also show a single channel of noise source generated through the nonlinear corruption function \( \eta \), and the primary input \( g(t) \) which lasts 1.0sec, respectively. As can be seen in Figs. 5(c), the received signal with \( \text{SNR} = -30\text{dB} \) is completely buried in the background interference. When the ANFIS de-noising operation was performed with the first 180 epochs for training and the next 180 epochs for validation, the de-noised signal is then obtained and depicted in Fig. 6(a) where the potential location of the target echo can be viewed in the x-axis with circle character on the top. Performing the similarity measurement in terms of the CWT operation, the desired time ranges for the echo signal and it corresponding occurrence of target are found at 0.76956sec or \( \tau_c = 0.76456\text{sec} \) and 0.3798sec, respectively, in Fig. 6(b) marked with diamond character. Consequently, the target’s radial velocity is estimated at 149.939knots and its corresponding radial position is obtained at 634.485m. The estimated difference for the radial position and velocity are 2.0 \times 10^{-3}m and 0.061knot, respectively.

Simulation II: To learn more about the effective performances of the neuro-fuzzy detector in terms of prediction accuracies of motion parameters, the number of events has been expanded to 16 for SNRs in the range of \([-30\text{dB}, 0\text{dB}] \). In this experiment, all correct values of parameters are randomly chosen and the prediction accuracy for individual instance is achieved by the computation of normalized absolute error (NAE):

\[ \text{NAE} \% = 100 \times \frac{\sum_{i=1}^{n} |x_{1i} - x_i|}{\sum_{i=1}^{n} |x_{1i}|} \]

where the relative absolute error (RAE) is adopted for measure of success of each parameter:

\[ \text{RAE} \% = 100 \times \frac{\sum_{i=1}^{n} |x_{1i} - x_i|}{\sum_{i=1}^{n} |x_{1i}|} \]

where \( x_{1i} \) and \( x_i \) are estimated value and its corresponding correct value for the \( i \)-th instance, \( \bar{x} \) is the average of the actual values of all test instances, and \( n \) is the total number of instances. To efficiently implement the fuzzy detector, the range of ANFIS epoch is set based on 6 different ranges of SNR level. That is, for the ranges of SNR level \([-5, 0] \text{dB} \) and \([-5(k+1), -5k-1] \text{dB} \), \( k = 1, \ldots, 5 \), their corresponding ANFIS epochs are set at 60k, \( k = 1, \ldots, 6 \). In view of Figs. 7, which show estimate of motion parameters compared to their correct ones, estimates in all 16 test instances with SNR ranged from 0dB to \(-30\text{dB} \) have accurately matched their corresponding correct ones with prediction errors shown in Figs. 8(a)-(d). The overall error measurement of each target parameter, as can be seen in Fig. 8(e), has less than 0.2% false detection rate.

5. Conclusion

In this paper, the neuro-fuzzy detector for wideband active sonar echolocation system was proposed to resolve the time-scale and time-shift problem simultaneously corresponding to the detection of target range and velocity, respectively. The detector involving the ANFIS de-noising operation and CWT optimal similarity measurement has for the first time been applied to the wideband signal detection problem. Instead of filtering out noise for poor signals, lost signals or other signal procurement deficiencies, the ANFIS operation was used to train and thus predict behaviors of the noise, which contaminates the signal of interest. The resultant signal was then proceeded to obtaining the optima of time-scale and time-shift in CWT operation by using the golden section search combined with successive parabolic interpolation method. Results presented in this study had clearly demonstrated the efficiency and accuracy of the neuro-fuzzy detector in predicting a point target with linear motion. For a point target with nonlinear motion is the subject of ongoing research.

References

Fig. 5. (a) noise-free received signals; “- □ -” reference echo, “- ○ -”: hypothesized target echo. (b) noise source. (c) noisy signal with SNR=-30dB.

Fig. 6. Output of (a): ANFIS de-noising operation; “- □ -”: reference echo, “- ○ -”: potential target echo. (b): neuro-fuzzy detector; “- ⬤ -”: estimated target echo and its corresponding occurrence.

Fig. 7. Measurement of motion parameters. “- ○ -”: exact value; “- × -”: estimated value. (a) range(R). (b) time-delay(τ). (c) radial velocity(v). (d) scale factor(s).

Fig. 8. Error measurements in percentage: (a)-(d): NAE of motion parameters. (e): RAE of motion parameters.