Adaptive Interference Signal Processing with Intelligent Neuro-Fuzzy Approach

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Abstract: An intelligent learning-based approach using neural network and fuzzy logic to the problem of interference canceling is proposed in the paper. The famous signal-processing structure of adaptive noise canceling is used for the research of interference signal canceling, in which a neuro-fuzzy system is used as the adaptive notch filter. Four T-S fuzzy rules are in the neuro-fuzzy filter. The filter integrates the adaptation capability of neural network and the inference ability of fuzzy logic, so that the signal-processing policy and the meaning of learning are transparent. To explore the excellent nonlinear mapping ability of the neuro-fuzzy adaptive, an appropriate machine-learning algorithm has to be used for the learning purpose, so that the optimal or near-optimal parameter set of the neuro-fuzzy filter can be obtained. The well-known Random Optimization (RO) algorithm and the famous Least Square Estimate (LSE) algorithm are used in hybrid way for the filter. To demonstrate the proposed approach, an exemplar experiment is implemented. The proposed neuro-fuzzy adaptive filter shows great filtering performance. A good discussion for the approach is given.

Key-Words: interference canceling, intelligent signal processing, neuro-fuzzy, adaptive notch filtering, machine learning.

1. Introduction
The study of adaptive signal filtering has been receiving much attention in research community. For its adaptive ability in self-adjustment to changing environment, an adaptive system as a filter is an excellent potential processor for signal processing. In real-world applications, signal nature and complexity are usually nonlinear and time-varying. Adaptation in filtering is viewed as an outstanding property for interference canceling or noise canceling. In adaptive system, learning algorithm is an important role for learning convergence, and the structure of system is also important for nonlinear input-output mapping ability of the system, which can in turn affect the system performance. In the paper, a neuro-fuzzy system is used as an adaptive filter. This proposed filtering approach is to make the neuro-fuzzy filter functioning as a notch filter for the problem of interference canceling [1-2].

The research of interference canceling can be traced back to 1960s [3-5], or even earlier. Interference signals can be viewed as some signals not desired, which can be stochastic, deterministic or both, mixed with the desired signal to become a composite signal. Interference signals can also be viewed as noises that mess about the desired signal. The research motive of interference canceling is to identify the complexity for interference signal itself and for its signal environmental structure, so that further signal processing can be implemented to improve the signal-to-noise ratio. For ideality, one may desire to remove the interference completely from the desired, but this expectation can be done only in hypothetical way along with some assumptions [2]. In reality, interference signal can be complex of signal structure, in terms of time-varying and highly nonlinear statistic properties. Thus, removal of interference signal from the composite signal is not possible in real implementation, but the interference signal can be suppressed or diminished so that the desired signal can be extracted or recovered from the composite in statistical sense. Recently, intelligent approach such as neural networks and fuzzy logic [6-7], [13-16] and machine learning methods such as back-propagation (BP), least mean square (LMS), genetic algorithm (GA), and the well-known random optimization (RO) learning algorithm [8], have been applied on a variety of research areas and practical applications, including signal processing, controls, image processing, adaptive system identification, function
approximation, communications, software/hardware engineering, consumer electronics, and more. In the
study, the neural and fuzzy theories are integrated and used in the research to become a neuro-fuzzy system
which is served as an adaptive filter for the problem of interference canceling. The proposed neuro-fuzzy
filter is trained using the well-known RO algorithm and the least square estimate (LSE) algorithm.
In section 2, the methodology of adaptive interference canceling is specified. In section 3, learning algorithm is specified. In section 4, an examplar experiment is implemented to demonstrate the
proposed approach. In section 5, a good discussion is given. Finally, the paper is concluded.

2. Methodology of Adaptive Interference Canceling

The elementary concept of adaptive interference canceling is to use a so-called adaptive filter to model
the interference signal in the composite corrupted signal, and then to subtract it from the composite
signal so that the original or desired signal can be recovered as possible as can be. In other words, the
basic idea of the adaptive interference canceling is to estimate the desired signal from its corrupted version.
It is supposed that the interference signal source can always be obtained and that the signal complex and
its environment are statistic or changed slowly. The basic structure of adaptive interference canceling [2]
is given in Fig. 1. The interference canceling approach is based on the assumptions that the signals
s, y and the interference signals n₀, n₁ are zero-mean process, that the signal s is uncorrelated with n₀ and
n₁, that the interference signals n₀, n₁ and the filter output y are correlated, and that the adaptive filter can
catch adaptively the statistic properties of the interference signal process. The signals n₀ and n₁ are
related with some unknown transfer channel function.
The recovered signal e, which is the error signal in the signal-processing process in Fig.1, is given as follows.

$$ e = s + n₀ - y $$

(1)

By squaring of equation (1), we have

$$ e^2 = s^2 + (n₀ - y)^2 + 2s(n₀ - y) $$

(2)

Taking the expectation of equation (2), we have

$$ E[e^2] = E[s^2] + E[(n₀ - y)^2] + 2E[s(n₀ - y)] $$

(3)

where $E[\cdot]$ represents the expectation operator. Based on the assumptions stated, the third item of equation
(3) can be ignored because of signal-uncorrelation, and the equation becomes as follows.

$$ E[e^2] = E[s^2] + E[(n₀ - y)^2] $$

(4)

In the nature of application, the power of the desired signal s remains unaffected while the adaptive filter
proceeds to minimize the power of the recovered signal. In other words, the power difference is minimized between the corrupted signal and the filter output in the adaptation process, given as follows.

$$ E_{\min}[e^2] = E[s^2] + E_{\min}[(n₀ - y)^2] $$

(5)

From equation (5), the conclusion is deducted that the power minimization of the signal e is equivalent to
minimizing the power of interference signal (or noise).

In the paper, for the excellent nonlinear mapping capability [9], a neuro-fuzzy system is used as an
adaptive filter that is expected to remove or diminish interference signal in the adaptive process. The
neuro-fuzzy filter (NF filter) is to act as a notch filter adaptively [10]. A notch filter in its functionality is to
remove the signal with some specific frequency. The neuro-fuzzy filter is to be trained performing the task.
The structure of frequency adaptive notch filtering is shown in Fig. 2, in which the NF filter receives the
input signals from interference signal source to modeling the channel transfer function. Two key signals are basically used in the adaptive signal processing structure of interference canceling, and
they are known as the primary signal and the reference signal [1-2]. With the proposed filtering approach, the adaptive neuro-fuzzy notch filter is used to eliminate the interference of specific frequency, and the desired signal can be obtained in statistic sense, if the stated assumptions are satisfied.
Assume that the clean signal is an arbitrary signal s, and it is corrupted by an interference signal with some specific frequency and amplitude. The corrupted composite signal is denoted as
d(t), d(t) = s + n₀, served as the primary input signal to the signal processing system. The signal n₁ in Fig.1 is interpreted as the interference signal in Fig.2 with a specific frequency $\omega₀$. The reference input is assumed to be a sinusoidal signal, given as $A\cos(\Omega₀t + \phi)$, where A is the amplitude.
Through the phase delay of 90° and synchronous sampling implementation, the two inputs to the NF filter, denoted as $x_{1k} = A\cos(\omega_0 k)$ and $x_{2k} = A\sin(\omega_0 k)$, can be obtained from the reference signal. Through learning process for the adaptive NF filter, the proposed adaptive canceller is assuming to eliminate the noise $n_0$, and the desired signal can be recovered.

The NF filter used in the paper appears with six-layered neuro-fuzzy structure, shown in Fig. 3, which is composed of the layers of inputs, fuzzy sets, fuzzy rules, normalization, and output [7], [9]. The Takagi-Sugeno (T-S) fuzzy model [9] is used in this paper. Each fuzzy rule can be represented in the form given as follows.

If $x$ is A and $y$ is B, then $F = f(x_{1k}, x_{2k})$ \hspace{1cm} (6)

There are four rules in the rule base for the NF filter used in the paper, given as follows.

If $x$ is A1 and $y$ is B1, then $f = p_1 x + q_1 x + r_1$

If $x$ is A1 and $y$ is B2, then $f = p_2 x + q_2 x + r_2$

If $x$ is A2 and $y$ is B1, then $f = p_3 x + q_3 x + r_3$

If $x$ is A2 and $y$ is B2, then $f = p_4 x + q_4 x + r_4$

where \{$(p_i, q_i, r_i)$, $i=1,2,3,4$\} are the set of the consequent parameters of the fuzzy rules, $x$ and $y$ the input variables, and $f$ the output variable. For the NF filter, the inputs $x$ and $y$ denoted as $x_{1k}$ and $x_{2k}$ are from the sampled data of the reference signal. The output of the NF filter is used to mimic the unknown channel output $n_0$ hindering the desired signal $s$. The corrupted composite signal is subtracted with the filter output signal to recover the desired signal as possible as can be. The specifications for the layers of the NF filter are given briefly. Layer 1 - Input layer: The nodes accept the input signals and transmit them to Layer 2. Layer 2 - Membership layer: Each node performs a membership function and acts as a processing element for membership degree calculation, where the Gaussian function is adopted as membership function. Note that $O(.)$ used in the following represents the signal of a node output and that $\mu(.)$ indicates membership degree of fuzzy set.

$O_{1,i} = \mu_{A_i}(x)$ for $i = 1,2$ \hspace{1cm} (8)

$O_{2,i} = \mu_{B_i-2}(x)$ for $i = 3,4$ \hspace{1cm} (9)

where

$\mu_{A_i}(x) = \exp\left(-\frac{(x-m_i)^2}{2\sigma_i^2}\right)$ \hspace{1cm} (10)

$\mu_{B_i}(x) = \exp\left(-\frac{(x-m_i)^2}{2\sigma_i^2}\right)$ \hspace{1cm} (11)

Layer 4 - Normalization layer: The nodes in the layer are to perform the process of normalization for the rule firing strengths so that the contribution degree of each rule can be identified. The contribution information of the rule is then used to reach the decision. Layer 5 - Consequent-part layer: The nodes in this layer are to calculate for the contributed consequents by using the signals from Layer 4 and the inputs to the NF filter. Layer 6: The node in the layer is to summarize the filter output by summing all signals from Layer 5. Now the filter output is obtained.

To be a proper adaptive filter, the proposed NF filter has to be trained so that the free parameters in the filter can be evolved to optimal or near-optimal solution. The learning method for the proposed filter is given in the following section.
The well-known random optimization (RO) is used together with the least square estimation (LSE) for fast convergence of learning process for the proposed NF filter. The LSE algorithm [7] is famous for quick convergence to optimal solution of linear algebra. The LSE procedure is performed at the learning of Then-parts, while the RO algorithm is used for the If-parts of the NF filter. The detail of the well-known RO algorithm can be found in literature [8-9]. The RO algorithm is shown in Fig.4 in flow chart form. Without the need for the derivative information of the objective function which is established using the error signal in Fig.2, the RO algorithm features derivative-free and intuitive exploration in the input space for If-parts of the proposed NF filter. This property is important that the propagation process of derivative information (used by other gradient-based algorithm such as back-propagation) to update the free parameters inside the inner layers for the If-parts can be avoided. Moreover, the RO method excels not only at its simplicity and convenience, but also ensures to converge to global minimum with probability one in a compact set [8]. Along with the distinctive advantages of alleviating the design complexity in system learning, the RO can provide an alternative method for computational intelligence. The RO and the LSE are used in hybrid and simultaneous way for the learning of the filter, and the learning process is expected to converge in fast way. With the integration of RO and LSE, each candidate point generated by RO is viewed as a potential premise parameter solution, and the corresponding solution for the consequent parameters to the potential premise parameter can be obtained using the LSE. The detail of the filter RO-LSE learning is given in literature [11].

4. Experiment using the Proposed Approach
To verify the proposed approach, an example of computer experiment is given for application of the proposed adaptive notch filtering. In the computer experiment, the original signal is given and shown in Fig.5. The reference signal is a sinusoidal signal $\sin(\omega t)$ with $\omega = 2\pi$. The corrupted signal is given in Fig. 6 with 2000 sample data. For the If-parts of the neuro-fuzzy filter, the initial settings are given in Table 1. For the Then-parts, all consequent parameters are set to zero initially. For the learning process of the proposed filter, the first 1000 sample data from the corrupted signal are collected as the

<table>
<thead>
<tr>
<th>A1</th>
<th>A2</th>
<th>B1</th>
<th>B2</th>
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<tr>
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<td>-1</td>
<td>1</td>
</tr>
<tr>
<td>Deviation</td>
<td>1</td>
<td>1</td>
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<td>0.7036</td>
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<tr>
<td>Deviation</td>
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<td>3.2884</td>
<td>3.1780</td>
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</table>
training data. After 491 learning epochs (iterations) for the NF filter, the results for If-part parameters are shown in Table 2, and for Then-parts in Table 3. The filtering performances in terms of Mean Square Error (MSE) between the original and the recovered signals for before and after learning are 0.125 and 0.0015, respectively. For the first 1000 data the recovered signal is shown in Fig. 7. To further validate the performance by the trained filter, the remaining 1000 sample data of the corrupted signal are used for testing purpose. The results of filtering are shown in Fig.8, with the MSE performance of 0.0289. The learning curve for the learning process is shown in Fig. 9.

### Table 3. Then-part parameters after learning.

<table>
<thead>
<tr>
<th>Rule #</th>
<th>p</th>
<th>q</th>
<th>r</th>
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<tr>
<td>1</td>
<td>-4.9016e-02</td>
<td>8.9928e-01</td>
<td>-2.9895e-01</td>
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<tr>
<td>2</td>
<td>0.068623</td>
<td>-0.24927</td>
<td>0.45436</td>
</tr>
<tr>
<td>3</td>
<td>9.6307e-02</td>
<td>1.7383e-02</td>
<td>-1.0342e-02</td>
</tr>
<tr>
<td>4</td>
<td>-0.26175</td>
<td>-0.45485</td>
<td>0.71869</td>
</tr>
</tbody>
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### 5. Discussions

The proposed approach using neuro-fuzzy model as an adaptive filter for the problem of interference canceling has been specified, and the approach has been demonstrated to being successful. The integration of neural network and fuzzy logic, known as the famous neuro-fuzzy computational model, has been shown great power in signal processing. This great computational power is based on the nonlinear mapping capability for the input-output functional relationship. A neuro-fuzzy system possesses the combined merits of neural network and fuzzy inference, and this computational model has the great flexibility for adaptation (from neural network) and the excellent ability for decision-making (from fuzzy logic). Either a neural network or a fuzzy inference system has been proved as a universal approximator, which can model any function (continuous or discrete) to any modeling accuracy, if it has enough internal information encoding structure. The neuro-fuzzy filter integrates both of the universal approximation property to become a powerful computational model for the adaptive signal processing so that the computational policy (if-then rules) is transparent to human being and the learning for adaptation (neural structure) can be understood. To explore the excellent nonlinear mapping capability of the neuro-fuzzy filter, an appropriate learning method for the filter is a must. The methods for machine learning can be divided into two categories, and they are the gradient-based methods.
such as BP and LMS and the gradient-free methods such as GA and RO. In the proposed approach, the well-known RO and the famous LSE are used in hybrid way to train the adaptive neuro-fuzzy filter. Both of the methods are gradient-free, by which no derivative information is needed. This learning nature is an excellent property that the learning process is not entrapped in midway, while a gradient-based method such as BP has the potential problem of being entrapped due to its nature for updating. In the proposed approach, the If-parts and the Then-parts are updated by the RO and the LSE simultaneously and respectively. The filtering performance by the proposed neuro-fuzzy adaptive filter is excellent, as shown in Figs. 7 and 8, although four fuzzy rules were used for the filter only. The filtering performance by the filter is measured in terms of MSE. For the case of the example given in the previous section, the MSE is 0.0015 for the training stage and 0.0289 for the test stage. Using the RO-LSE hybrid-learning algorithm, the filter has been trained near to the optimal solution.

6. Conclusions

The proposed intelligent neuro-fuzzy approach to the problem of adaptive interference canceling has been presented, in which the neuro-fuzzy system acts as an adaptive notch filter. The hybrid-learning algorithm using both the well-known Random Optimization (RO) method and the Lease Square Estimate (LSE) method is utilized for the learning of the proposed neuro-fuzzy filter. The RO algorithm for the update of IF-parts and the LSE algorithm for the Then-parts of the proposed filter are implemented hybridly and simultaneously. An example of interference canceling using the proposed approach has been demonstrated successfully. The filtering performance is great as shown in Figs. 7 and 8.

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References: