The Interference Cancellation of Radio Fuze
Based on Hopfield Neural Network

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Abstract—Radio fuze needs to detect exactly target signal from the echo signal being polluted by noise in real time. Traditional interference cancellation system cannot meet the needs. The Hopfield neural network not only has the ability of nonlinear mapping but also has the ability of self-learning. So it can be used to possess a desired result against the effect of uncertainties and incomplete information in signal processing. In this paper, the authors unify the performance function of adaptive noise cancellation and the energy function of Hopfield neural network by the precise deduction. The model of radio fuze interference cancellation system based on Hopfield neural network was designed. And the concerned simulation indicates Hopfield neural networks will improve radio fuze capability of obtaining useful information from interfered noise.

Index Terms—Adaptive Noise Cancellation; Hopfield neural networks; Radio Fuze

I. INTRODUCTION

It is important for radio fuze to detect target signal from the echo signal being polluted by noise. The generally way is pick-up useful signal through certain filter such as adaptive noise cancellation filter. It restrains the noise though using the signal correlated with noise to adjust the parameter of filter. There are some algorithms to realize the filter such as LMS, RMS, Method of Newton, but those algorithms can not meet the need of radio fuze because they are so slowly. A Hopfield Neural network not only has the ability of nonlinear mapping but also has the ability of self-learning. So it can be used to possess a desired robust filter to realize the real time signal process against the effect of uncertainties and incomplete information. In this paper, an interference cancellation system of radio fuze based on Hopfield neural network was designed. And the simulated result in Matlab R2007a shows that it can meet the need of radio fuze.

II. THE BASIC THEORY OF ADAPTIVE NOISE CANCELLATION

In adaptive noise cancellation, adaptive filters make you remove noise from a signal in real time. Figure 1 shows the theory of adaptive noise cancellation. Here, the desired signal, the one to clean up, combines noise and desired information. To remove the noise, feed a signal \( n'(k) \) to the adaptive filter that represents noise that is correlated to the noise to remove from the desired signal. So long as the input noise to the filter remains correlated to the unwanted noise accompanying the desired signal, the adaptive filter adjusts its coefficients to reduce the value of the difference between \( y(k) \) and \( d(k) \), removing the noise and resulting in a clean signal in \( e(k) \).

\[
\begin{align*}
  s(k) + n(k) &\rightarrow d(k) \rightarrow SUM \rightarrow e(k) \\
n'(k) &\rightarrow Adaptive Filter \\
x(k) &\rightarrow y(k) \\
  e(k) &= d(k) - y(k) \\
  E\{e(k)^2\} &= E\{(d(k) - y(k))^2\} = E\{(s(k) + n(k) - y(k))^2\} = E\{s(k)^2\} + E\{(n(k) - y(k))^2\} + 2E\{s(k)(n(k) - y(k))\} \\
  &\text{In here } s(k), n(k) \text{ and } y(k) \text{ are uncorrelated, so } E\{s(k)(n(k) - y(k))\} = 0, \text{ and the formula (2) turns into:} \\
  E\{e(k)^2\} &= E\{s(k)^2\} + E\{(n(k) - y(k))^2\} \\
\end{align*}
\]

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Signal $s(k)$ doesn’t be included in the channels of the filter, so the algorithm estimates the filter weights vector to minimize the error $e(k)$ at between the output signal $y(n)$ and the desired signal $d(n)$. From the formula (2) we can obtain the expression (4):

$$\min E\{e(k)^2\} = E\{s(k)^2\} + \min \left\{ (n(k) - y(k))^2 \right\}$$

(4)

The weight update function for the LMS adaptive filter algorithm is defined as

$$\omega(k+1) = \omega(k) + 2\mu e(k)x(k)$$

(5)

In the formula (5), $k$ is the current time index, $\omega(k)$ is the vector of filter weight estimates of step $k$, $x(k)$ is the vector of buffered input samples of step $k$, $e(k)$ is the estimation error of step $k$, $\mu$ is the adaptation step size.

The process to seek the best weights vector is too complex and slowly to meet the need of radio fuze. So it cannot apply to radio fuze directly.

III. ADAPTIVE NOISE CANCELLATION BASED ON HOPFIELD NEURAL NETWORK

Though the analysis of part II, we can conclude that the key point of the adaptive noise cancellation is to seek the best weights vector. But the traditional algorithms constringe so slowly when they used to seek the best weights vector. Because they cannot avoid calculating the inverse of the matrix, they cannot be directly applied to radio fuze.

Neural networks not only have the ability of nonlinear mapping but also have the ability of self-learning. Another advantage of neural network is that it can be realized by hardware to reduce the calculation of system CPU. So it can be used to design a robust signal processing system replacing the traditional algorithms against the effect of uncertainties and incomplete information. In this paper, we design interference cancellation of radio fuze based on Hopfield neural network.

The goal of Hopfield neural network is to gain a network that stores a specific set of equilibrium points such that, when an initial condition is provided, the network eventually comes to rest at such a design point. The network is recursive in that the output is fed back as the input, once the network is in operation. Hopefully, the network output will settle on one of the original design points. The design method is based on a system of first-order linear ordinary differential formulas that are defined on a closed hypercube of the state space. The solutions exist on the boundary of the hypercube. These systems have the basic structure of the Hopfield model, but are easier to understand and design than the Hopfield model.

The Hopfield neural network’s state formula is defined as the following expression:

$$X(t) = WV(t) + \tau I$$

(6)

In the formula (6),

$$X(t) = [x_1(t), x_2(t), ..., x_N(t)]^T$$

$$W = [W_{ij}]_{N \times N}, \quad i, j = 1, 2, ..., N$$

$$V(t) = [v_1, v_2, ..., v_N]^T, \quad I = [i_1, i_2, ..., i_N]^T$$

The energy function of Hopfield neural network is defined as the following expression:

$$E(V) = -\frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} W_{ij} V_i V_j - \sum_{j=1}^{N} V_i I_i + \sum_{j=1}^{N} \int_{0}^{1} g^{-1}(v)dv$$

(7)

The energy of Hopfield neural network is always going towards the direct of minus grade when $W_{ij} = W_{ji}$. The extra-minimum is the minimum of overall situation when the network evolves to a stable state. It’s also the last station to solve the problem.

In the formula (7), the item of integral can be neglect when $R_i$ big enough and $I_i = 0 (i = 0, 1, ..., M)$ in the network, and then the energy function of Hopfield neural network turns into:

$$E(V) = -\frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} W_{ij} V_i V_j$$

(8)

The corresponding network developing function turns into:

$$\frac{du_i}{dt} = \sum_{j=1}^{N} W_{ij} V_j$$

(9)

We can gain the performance function of adaptive noise cancellation from the formula (10) as followed:

$$e(k) = d(k) - y(k) = d(k) - W^T(k)X(k)$$

(10)

In order to realize the adaptive filter, we can choose the energy function of Hopfield neural network as:
\[
E(V) = -\frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} W_{ij} V_i V_j = -\frac{1}{2} (d(k) - W^T(k)x(k))^2
\]

In the formula (11):
\[
\frac{1}{2} \sum_{i=1}^{N} \sum_{j=0}^{N} W_{ij} V_i V_j = \frac{1}{2} (d^2(k) + \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} w_i(k)w_j(k)x(k-i)x(k-j) - 2 \sum_{i=0}^{N-1} d(k)w_i(k)x(k))
\]

In it, when we let
\[
W_i = x(k-i+1)x(k-j+1),
\]
\[
W_{N,i}=W_{i,N}=d(k)x(k-i+1),(i,j=1,2,L , N),
\]
\[
W_{i+1,k}=W_{i+1,N}=d(k)x(k-i+1),v_i = w_i(k),v_{i+1} = 0,so the output vector of Hopfield neural network is the best weights vector of adaptive noise cancellation:
\[
V = [W_0(k),W_1(k),L ,W_{N-1}(k)]
\]

By the deduction of above, we can unify the performance function of adaptive noise cancellation and the energy function of Hopfield neural network. When the network evolves to a stable state, the output vector of Hopfield neural network is the best weights vector of adaptive noise cancellation. The evolved time of Hopfield neural network electro circuit is usually in the range of 200–300ns according to experience, and the period of radio fuze’s signal process is 100ms usually. In conclusion, interference cancellation system of radio fuze based on Hopfield neural network can meet the practical need.

IV. SIMULATION IN MATLAB

To validate the theory above, the author designed a model and simulated in Matlab R2007a. In this part, the results of simulation are given.

A. Simulation of radio fuze’s echo signal

The echo signal of radio fuze has relation with the scatter characteristic of target. We can divide the target into several geometric parts (such as column, trapezoid slab); the echo signal is the vector summation of the scatter point of these parts.

\[
s(t) = \sum A_n \cos [2\pi(f_0 + f_n)t + \Phi]
\]

B. Simulation of noise

According to the figure 1, the input signal combines noise \( n(k) \) and desired signal \( s(k) \). The noise \( n(k) \) cannot be measured directly. But we can measure signal \( n'(k) \) that correlated to noise \( n(k) \). To remove the noise we consider that noise \( n(k) \) is the result that signal \( n'(k) \) going through a nonlinear process. The thing left is to model the nonlinear process and feed a signal \( n'(k) \) to the adaptive filter. In this way, we can remove noise from the input signal.

In Matlab R2007a, we use the following code to simulate signal \( n'(k) \),

\[
n1 = \text{randn} \left( \text{size} \left( \text{time} \right) \right)
\]

Noise \( n(k) \) is the result that signal \( n'(k) \) going though a nonlinear process, we suppose that nonlinear process as follow:

\[
n(k) = 4*\sin(n1(k))*n1(k-1)/(1+n1(k-1)^2)
\]

C. Result of Simulation

According to the model given above, the authors simulate the system in Matlab. In order to observe conveniently we take the 500 sample point by the interval is 2ns. The result of simulating as figure 2 and figure 3 showing:
Figure 2 is the desired signal; figure 3 is the input signal of the adaptive filter; Figure 4 is the output signal of simulation. From the figure 4 we can see that the effect of first 60 sample points is not so evident; and the other sample points are close to the desired signal. The reason is that the neural network need a period time to self-learning in management of the adaptive filter working.

Figure 5 is the output signal error of nlms and neural network algorithms. From the figure we can see the error of neural network are smaller than the nlms’s, and the speed of convergence are faster than the nlms’s.

In order to gain the quantitative analysis of the algorithms, here we define the improvement of SNR as the standard of the filter’s performance.

$$\Delta \text{SNR} = \text{SNR}_{\text{out}} - \text{SNR}_{\text{in}}$$

We have made our experiments by the data. From Table 1, we can compare the Hopfield neural network algorithm to three common adaptive algorithms.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>$\Delta \text{SNR}$</th>
<th>Convergence Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>nnet</td>
<td>22.53 dB</td>
<td>50ms</td>
</tr>
<tr>
<td>lms</td>
<td>16.67 dB</td>
<td>146ms</td>
</tr>
<tr>
<td>nlms</td>
<td>18.27 dB</td>
<td>127ms</td>
</tr>
<tr>
<td>rls</td>
<td>19.35 dB</td>
<td>108ms</td>
</tr>
</tbody>
</table>

V. SUMMARY

A Hopfield Neural network not only has the ability of nonlinear mapping but also has the ability of self-learning and realizes simple whatever in hardware or in software. So interference cancellation system based on Hopfield neural network let the .system simpler, and it can track the characteristic of input signal real-time changing to gain the perfect effect in the lower Signal-to-Noise.

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