

A NEURAL DEMODULATOR FOR AMPLITUDE SHIFT KEYING SIGNAL

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I INTRODUCTION

Neural networks are effectively applied to signal processing and pattern recognition [1]-[3]. Features of the neural networks include self-organization, learning, nonlinear functions, and parallel implementation. How to utilize these features in each application is an important point.

Demodulation problems are dealt with. In the demodulation process, unnecessary signals and noises are removed using filters. The extracted signal is transferred to its original or another desired waveform. Noise rejection filters usually cause waveform distortion. If the original waveform is very sharp, like pulse waveform, this distortion causes fatal error.

In this paper, a neural demodulator is proposed. A multilayer neural network and backpropagation are employed. The purpose of this model is to achieve both noise rejection and a very sharp waveform response, which are difficult to be done by linear filters. Demodulation of amplitude shift keying (ASK) signals is the subject. Trained network structure, internal representation and an optimum activation function are discussed. Simulation results are shown.

II STRUCTURE OF NEURAL DEMODULATOR

Figure 1 shows the proposed neural demodulator. The received signal is expressed by $x(n)$, including the ASK signal $x_A(n)$ and noise $e(n)$.

$$x(n) = x_A(n) + e(n) \quad (1)$$

The input layer is composed of a delay line. T is a sampling period. The output of the i th delay element is denoted $x(n-i)$. N samples, that is $x(n-i)$, $i=0 \sim N-1$, are transmitted through connections in

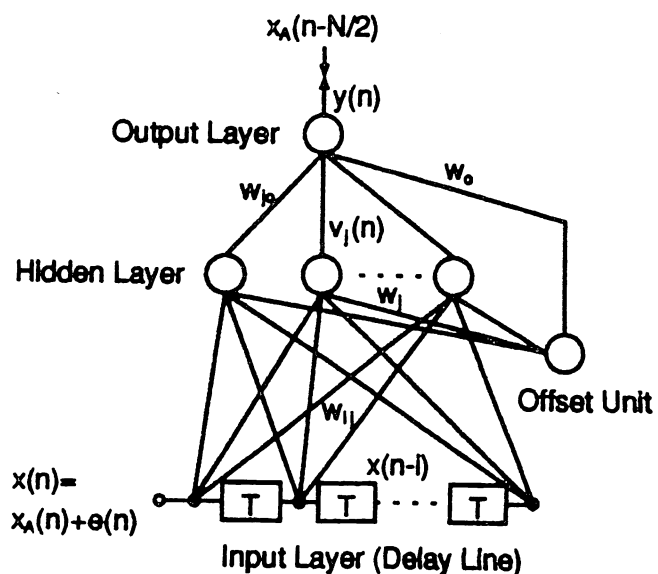


Fig.1 Proposed neural demodulator.

parallel. An offset unit is used, which always outputs 1 to the hidden and output units. Let connection weights from $x(n-i)$ to the j th hidden unit be w_{ij} , and from the j th hidden unit to the output unit be w_{j0} . Network equations are expressed as follows:

$$u_j(n) = \sum_{i=0}^{N-1} w_{ij}x(n-i) + w_j \quad (2)$$

$$v_j(n) = f_H(u_j(n)) \quad (3)$$

$$\text{net}(n) = \sum_{j=0}^{N-1} w_{j0}v_j(n) + w_0 \quad (4)$$

$$y(n) = f_O(\text{net}(n)) \quad (5)$$

w_j and w_0 are weights from the offset to the j th hidden unit and the output unit. $f_H(\cdot)$ and $f_O(\cdot)$ are activation functions.

Pure ASK signal $x_A(n)$ is used as target. $x_A(n)$ has correlation among its adjoining samples, that is $x_A(n-i)$, $-N/2 \leq i \leq -1$ and $1 \leq i \leq N/2$. The output $y(n)$ is calculated using $x(n-i)$, $0 \leq i \leq N-1$. Therefore, $x_A(n-N/2)$ is used as the target for $y(n)$. The output error is evaluated by

$$\delta(n) = x_A(n-N/2) - y(n) \quad (6)$$

It should be pointed out that the proposed model does not separate functions, rather all functions are included in the same network.

III LEARNING ALGORITHM AND ACTIVATION FUNCTIONS

3.1 Learning Algorithm

Backpropagation algorithm is very powerful for multilayer neural networks [4]. It is employed in our model. An important point of the learning is to automatically design necessary functions, including noise rejection and regeneration of pulse waveform. Because these abilities cannot be held in linear signal processing. This point will be investigated in Sec. IV.

3.2 Activation Functions

Another important point of neural network design is to optimize activation functions for each application. However, this issue still remain as an open question. In this study, we apply a sigmoid function $f_{\text{sig}}(\cdot)$ and a valley function $f_{\text{val}}(\cdot)$ given by

$$f_{\text{sig}}(x) = \frac{1 - e^{-x}}{1 + e^{-x}} \quad (7)$$

$$f_{\text{val}}(x) = \frac{x^2}{1 + x^2} \quad (8)$$

IV SIMULATION AND DISCUSSIONS

4.1 Conditions of Simulation

The minimum pulse width is 50 msec, the carrier frequency is $f_c=880\text{Hz}$, and the sampling frequency is $f_s=4\text{kHz}$. Thus, the

minimum pulse width includes 200 samples. Examples of the ASK signal and random noise are shown in Figs.2(a) and 2(b). The number of samples, applied to the network in parallel, is chosen to 200, which can cover the minimum pulse width. The input signal having 100 sec length is used for training. It includes 200 minimum pulses and 4×10^5 sampling points. After 100 sec, the received signal is used for evaluating performance of the trained neural demodulator.

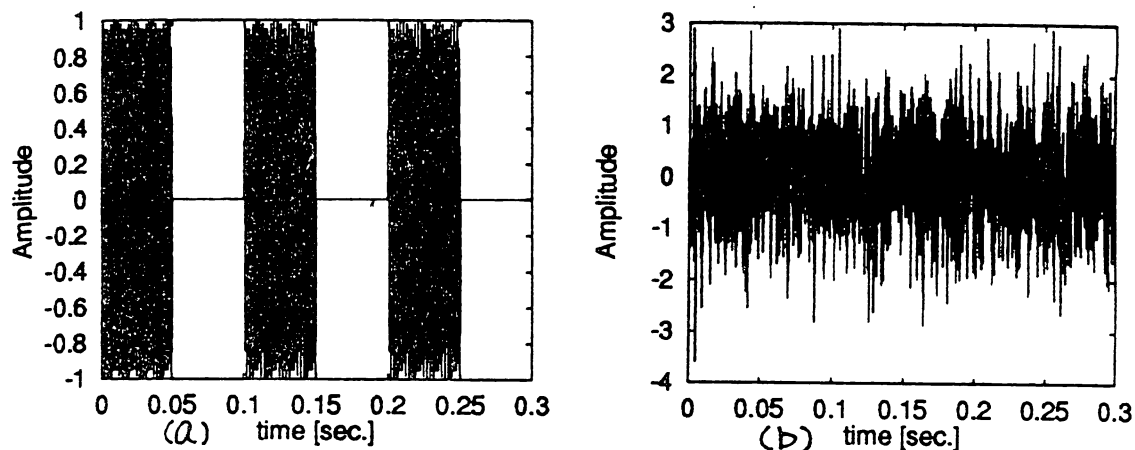


Fig.2 Examples of (a) ASK signal, and (b) random noise.

4.2 Convergence Property

Figure 3 shows learning curves. A indicates one hidden unit with $f_{\text{sig}}()$. Group B includes two hidden units with $f_{\text{sig}}()$ and one hidden unit with $f_{\text{val}}()$. Group C includes three hidden units with $f_{\text{sig}}()$ and 2 and 3 hidden units with $f_{\text{val}}()$. In the first period from 0 to 100 sec., the neural network is trained, and the rest 100 sec., the trained network is examined using new coming signal. After 100 sec., the error is not increased. This guarantee generalization for untraining data. The valley function is more useful than the sigmoid one. Three hidden units are sufficient in this problem.

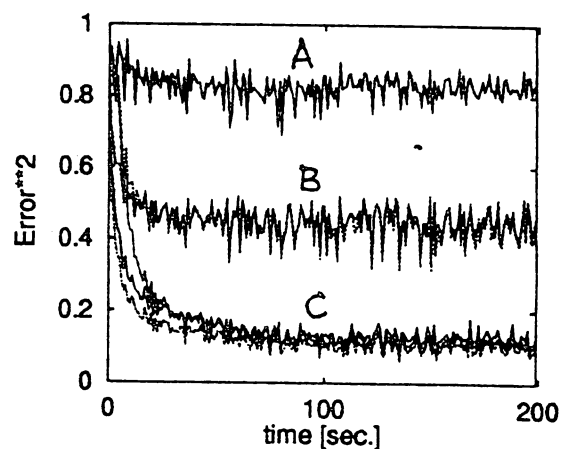


Fig.3 Learning curves.

4.3 Characteristics of Neural Network

Figure 4 shows the output $y(n)$ with a solid line and the error $\delta(n)$ squared with a dotted line. The target is also expressed with dashed line. From this figure, the neural network can outputs very sharp waveform. A single linear filter, designed to reject noise, cannot produce this sharp response. A high-Q filter usually causes distortion in time a response.

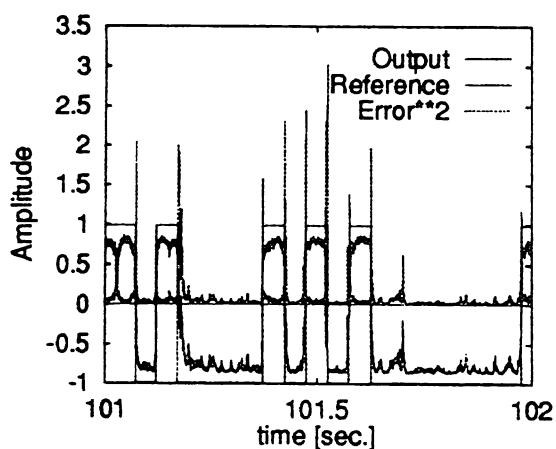


Fig.4 Examples of output waveform, target and error

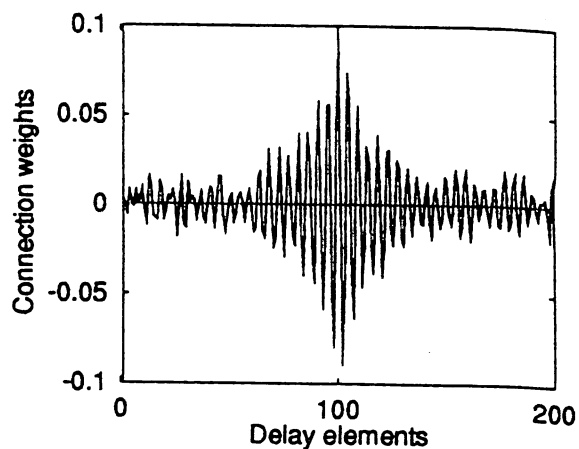


Fig.5 Connection weights from input layer to hidden unit.

4.4 Activation Functions

In the trained network, the valley function can work as rectifier. Thus, rectifier function is self-organized.

4.5 Connection weights

Figure 5 shows the connection weights from the input layer to one of three hidden units. The other weights are similar to this distribution. Fourier transform of the weights has peak amplitude at signal frequency $f_0=880\text{Hz}$. This frequency response can be easily expected. However, Three sets of connection weights cooperate with each other in order to produce very sharp time response. For this purpose, it is necessary to carefully adjust their phase response. The neural network can do this optimization. However, it is very difficult to design linear filters for this purpose.

V CONCLUSION

The neural demodulator for ASK signal is proposed. Capability of noise rejection and sharp waveform response can be achieved. Furthermore, rectifier function is internally realized. Computer simulation demonstrates very low error rates. The neural network is superior to the conventional from the point of automatic optimization.

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