A Fuzzy-ARTMAP Equalizer for Compensating the Nonlinearity of Satellite Communication Channel

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ABSTRACT

In this paper, fuzzy-ARTMAP neural network is applied for compensating the nonlinearity of satellite communication channel. The fuzzy-ARTMAP is made of using fuzzy logic and ART neural network. By a match tracking process with vigilance parameter, fuzzy ARTMAP neural network achieves a minimax learning rule that minimizes predictive error and maximizes generalization. Thus, the system automatically learns a minimal number of recognition categories, or hidden units, to meet accuracy criteria. Simulation studies are performed over satellite nonlinear channels. The performance of proposed fuzzy-ARTMAP equalizer is compared with MLP-basis equalizers.

I. 서 론

For the purpose of efficiency, power amplifiers used in communication systems are very often operated near the saturation region such that the signals are distorted due to that nonlinearity[1-4]. The traveling wave tube (TWT), used in microwave signal power amplification, introduces nonlinear distortions, in both amplitude (AM-to-AM conversion) and phase (AM-to-PM conversion). When combined with a transmitter or a receiver filter, the system constitutes a nonlinear system with memory.

To deal with the nonlinearity, many researchers have been concerned with applying neural networks, such as multilayer perceptrons (MLP) and radial basis functions (RBF), to equalizer[5,6]. The basic idea of applying neural network to equalization comes from the fact that channel equalizer problems can be regarded as patterns classification (detection). However, each of these networks internally has significant shortcomings. MLP equalizers typically require long training and are sensitive to the initial choice of network parameters (especially initial weights). Also, they need to decide by trail and error how many hidden units are needed. RBF equalizer is simpler and fast to train, but usually require a large number of centers, which increases the complexity of computation. In addition, it is not easy to determine both the number and the location of centers required for training. Recently, Lee et al. introduced a fuzzy -ARTMAP to equalize the linear channels[7]. The paper presents the superiority of fuzzy -ARTMAP equalizer to other neural network-basis equalizers.

In this paper, a fuzzy-ARTMAP neural network is, also, proposed to compensate the nonlinearity on satellite communication channel. The main purpose of an proposed fuzzy-ARTMAP equalizer is to overcome the obstacles, such as complexity and long training, in implementing the previously developed neural basis equalizers. The fuzzy-ARTMAP is made of using fuzzy logic and adaptive resonance theory (ART) neural network. By a match tracking process, the fuzzy-ARTMAP neural network achieves an new minimax learning rule that minimizes predictive error and maximizes the predictive generalization. Also, it automatically learns a minimal number of recognition categories,

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논문번호 : K01074-0216, 접수일자 : 2001년 2월 16일
※ 본 논문은 정보통신연구진흥원 대학기초연구 지원으로 수행됨

or hidden units. In simulation studies for satellite channels, QPSK signals with Gaussian noise are generated at random from Volterra model.

Section II presents background of fuzzy-ARTMAP neural network. Section III presents nonlinear modeling for digital satellite channel. Section IV gives the structure and learning procedure for the fuzzy-ARTMAP equalizer. Experimental results are provided in Section V, and Section VI gives the conclusion.

II. Fuzzy ARTMAP Neural Network

1. Background

ART networks are biologically motivated and were developed as possible models of cognitive phenomena in humans and animals. Also, ART nets are designed to allow the user to control the degree of similarity of patterns placed on the same cluster, and provides the desirable characteristics of fast training and user control of network complexity.

Since the advent of ART as a cognitive and neural theory[8], a number of ART neural network architectures have been progressively developed. These models include ART1, ART2, ARTMAP[9-12]. ART1 networks require that the input vectors be binary. ART2 networks are suitable for processing analog patterns. On the other hand, ARTMAP is a class of neural network that perform incremental supervised learning of recognition categories. The first ARTMAP system was used to classify inputs by the set of features they possesses, that is, by an ordered o n-tuple of binary values representing the presence or absence of each possible feature.

For several decades, the fields of artificial intelligence (AI), neural networks, and fuzzy logic were developed by separate intellectual communities. Recently, a growing number of models computationally synthesize properties of neural networks, and fuzzy logic.

2. Function of Fuzzy-ARTMAP

Fuzzy-ARTMAP, a generalization of ARTMAP,

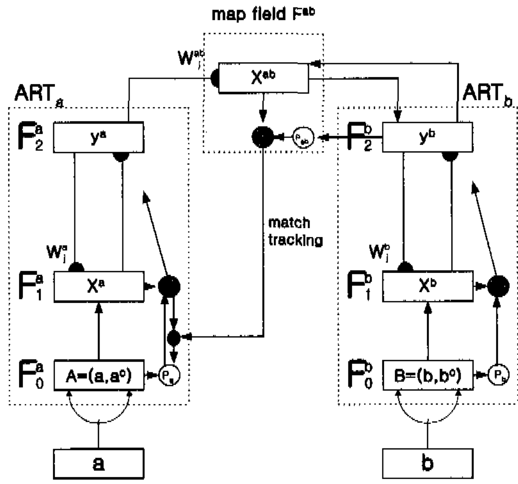


Fig. 1. Sructure of Fuzzy ARTMAP

is a neural network architecture that performs incremental supervised learning recognition categories and multi-dimensional maps in response to arbitrary sequences of analogue or binary input vectors, and learns to classify inputs by a fuzzy set of features, or a pattern of fuzzy memberships values between 0 and 1 indicating the extent to which each feature is present. As shown in Fig. 1, fuzzy-ARTMAP system includes a pair of fuzzy ART modules (ART_a and ART_b) that create stable recognition categories in response to arbitrary sequences of input patterns. During supervised learning,

ART_a and ART_b receive a stream of input patterns. These modules are linked by an associative learning network and an internal controller that ensures autonomous system operation in real time. Fuzzy-ARTMAP realizes a minimax learning rule that conjointly minimizes predictive error and maximizes generalization. As a result, the system automatically creates the minimal number of recognition categories needed to meet accuracy criteria.

In fuzzy ARTMAP, the input and stored prototype are said to resonate when they are sufficiently similar. When an input pattern is not sufficiently similar to any existing prototype, a new node is then created to represent a new category with the input patterns as the prototype. The meaning of similarity depends on a vigilance parameter ρ, with $0<\rho\leq 1$. If ρ is small, the similarity condition is easier to meet, resulting in a coarse categorization. On the other hand, if ρ is chosen to be close to 1, many finely divided categories are formed. A fuzzy-ARTMAP increases the network architecture (number of clusters) to the minimum level necessary for perfect performance on the training data. By selecting the desired level for the vigilance parameter, the user has control over the performance of the network.

The learning algorithm of fuzzy-ARTMAP is explained in Section IV. The reader is referred to [14], for a complete description of fuzzy-ARTMAP.

Ⅲ. Nonlinear Channel Modeling for Digital Satellite Links

Fig. 2 shows the block diagram of the bandpass-equivalent nonlinear satellite channel. For an M-arry PSK, $x(n)$ is denoted as

$$x(n)=e^{j\phi_n}\ ,\quad -\infty<n<\infty \tag{1}$$

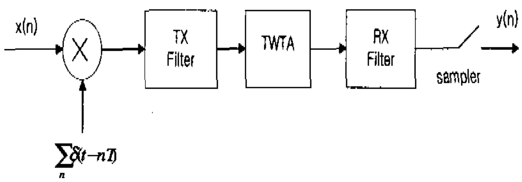


Fig. 2. Block diagram of nonlinear satellite channel

where ϕ_n is the transmitted phase belonging to $\left\{\frac{2\pi(m+1/2)}{M}\right\}$, $m=0,1,\ \dots,\ M-1$. As a convenient model of a nonlinear telecommunication channel with memory, a Volterra model, the kernels of which were obtained by Benedetto et al., is used. By referring to [1], the symbol-rate sampling of receiving output can be represented as

$$y(n)=\sum_{k=0}^{\infty}\sum_{n_1}\cdots\sum_{n_{2k-1}} x(n-n_1)\cdots x(n-n_k)x^*(n-n_{k+1})\cdots x^*(n-n_{2k-1})\, H^{(2k-1)}_{n_1,\dots,n_{2k-1}}+g(n) \tag{2}$$

where $g(n)$ is a complex Gaussian down-link noise, and $2k-1(k=1,..)$ denotes the non-linearity degree of a channel.The reduced Volterra coefficients, after reduction and deletion of the smallest, are shown in Table 1.

Table 1. Reduced Volterra Coefficients

Linear Part
$H_0^{(1)}=1.22+j\,0.646$
$H_1^{(1)}=0.063-j\,0.001$
$H_2^{(1)}=-0.024-j\,0.014$
$H_3^{(1)}=0.036+j\,0.031$
3rd Order Nonlinearity
$H_{002}^{(3)}=0.039-j\,0.022$
$H_{330}^{(3)}=0.018-j\,0.018$
$H_{001}^{(3)}=0.035-j\,0.035$
$H_{003}^{(3)}=-0.040-j\,0.009$
$H_{110}^{(3)}=-0.01+j\,0.017$
5th Order Nonlinearity
$H_{00011}^{(5)}=0.039-j\,0.022$

Ⅳ. Implementation of a Fuzzy ARTMAP Equalizer

1. Training Patterns for Fuzzy ARTMAP Equalizer

In this study, the network is trained to reconstruct the original QPSK signal based on the signal received after transmission over a nonlinear satellite channel. Therefore, input training patterns for fuzzy-ARTMAP network consist of received signals, and the corresponding target patterns are the originally transmitted signals. Fig. 3 shows the block diagram of the fuzzy ARTMAP equalizer. As shown in (2), the satellite channel exhibits the

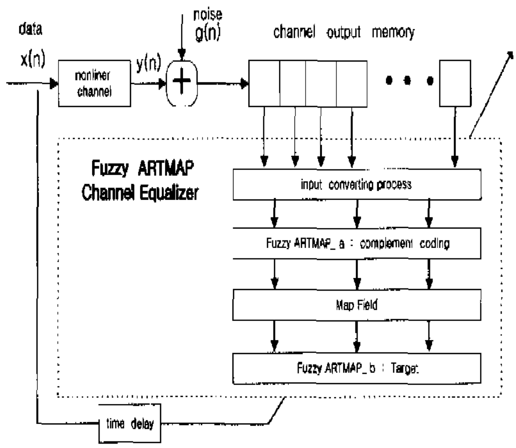


Fig. 3. Block diagram of a Fuzzy ARTMAP Equalizer

temporal behavior where the output has a finite temporal dependence on the input. Thus, the first form of input patterns for a fuzzy-ARTMAP equalizer is represented as

$$y(n)=(y(n),y(n-1),\cdots,y(n-N+1))^T \tag{3}$$

where N is the number of tap delay element in a fuzzy ARTMAP equalizer. Equation (3) can be rearranged as

$$y(n)=(\ y(n)_r, y(n)_i, y(n-1)_r, y(n-1)_i, \\ \cdots, y(n-N+1)_r, y(n-N+1)_i\ )^T \tag{4}$$

Where, $y(n)_r$, $y(n)_i$ are the real and imaginary prat of $y(n)$, respectively. However, this training vector, as shown in (4), is not the proper type of input values for operating with fuzzy-ARTMAP network, since $y(n)$ is not the correct range of fuzzy-ARTMAP. To deal with this problem, the binary sigmoid function below is used to convert the given any range to [0, 1],

$$\frac{1}{1+e^{-\alpha x}} \tag{5}$$

Here α is the steepness of sigmoid function, the x is the general function parameter, not related with $x(n)$ from (2). Arbitrary range of x can be reduced to [0, 1] by (5). In this research, a variety of converting functions were chosen, and used with training. As a result, sigmoid function produced the best result for reconstructing the originally transmitted symbols. The proper range of α value is [0.7, 1.0]. In addition, the property of using complement-coding in fuzzy-ARTMAP leads to the final form of input training vectors, $Y(n)$,

$$Y(n)=(\ y(n)_t\ ,\ y(n)_t^c\ )^T \tag{6}$$

where, $y(n)_t$ is the $y(n)$ vector after transformation by (5), and $y(n)_t^c$ denotes the complement part of $y(n)_t$

$$y(n)_t=(\ y_{0r}, y_{0i}, \cdots, y_{kr}, y_{ki}, \cdots, y_{N-1r}, y_{N-1i}\ ),$$

$$y(n)_t^c=(\ 1-y_{0r}, 1-y_{0i}, \cdots, 1-y_{kr}, 1-y_{ki}, \\ \cdots, 1-y_{N-1r}, 1-y_{N-1i}) \tag{7}$$

$$y_{kr}=\frac{1}{1+e^{-\alpha y(n-k)_r}}\ ,\quad y_{ki}=\frac{1}{1+e^{-\alpha y(n-k)_i}}, \\ k=0,1,\cdots,N-1 \tag{8}$$

As described in [14], complement coding, called preprocessing, used on-cell, and off-cell responses to prevent category proliferation. Complement coding normalizes input vectors while preserving the amplitudes of individual feature activations. Without complement coding, an ART category memory encodes the degree to which critical features are consistently present in the training exemplars of that category.

Next thing for making the training patterns for fuzzy-ARTMAP equalizer is find the target patterns. For example, QPSK symbols are transmitted, the possible target vectors, $T(n)$, are $(1,0,0,0)^T$, $(0,1,0,0)^T$, $(0,0,1,0)^T$, and $(0,0,0,1)^T$. A corresponding target for a symbol could be arbitrarily determined.

2. Training Rules

If pure training patterns were available, they could be used directly, but if neural networks, including fuzzy-ARTMAP, are trained with noisy signals, preprocessing is necessary to prevent the network from learning the noise. In this study, the action of noisy transmission path is simulated by adding Gaussian noise to the received signal after each possible transmission sequence is passed through the Volterra channel model. Then, the $y(n)$ with free noise is estimated by applying the supervised K-means clustering algorithms. Details of the K-means are given in [7].

Training algorithms:

(1) Determine the input pattern for ART_a, $Y(n)$ and output (or target) pattern for ART_b, $T(n)$

(2) Create the categories

When training starts, no category is created. For this reason, in the beginning, a category can be made without any competition by fuzzy rule. However, when more than one category have already been created and a new input comes to fuzzy-ARTMAP equalizer, the category will be created by the following rule,

$$C_j(Y(n)) = \frac{|Y(n) \wedge w_j|}{a + |w_j|} \qquad (9)$$
$$C_J = \max\{T_j : j = 1 \cdots N_{cat}\}$$

where the C_j is choice function, and N_{cat} denotes the total number of categories created.

(3) Check if resonance occurs

When $|Y(n) \wedge w_J| \, |Y(n)|^{-1}$ is greater than or equal to ρ, a match happens. Otherwise, a mismatch occurs. Despite that a match happens, the corresponding target for the introduced input pattern may not be matched with the selected category. In this case, the vigilance parameter is increased until it is slightly larger than $|Y(n) \wedge w_J| \, |Y(n)|^{-1}$. Then, the search for another category starts, except the previously selected categories. The search process continues until the chosen category satisfies the above conditions. If all the trial fail, a new category is created.

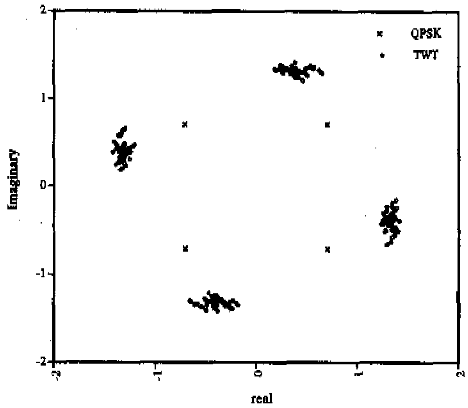


Fig. 4. Constellation of QPSK due to TWT

(4) Update weights

Once search ends, the weight vector is updated according to the equation

$$w_J^{(new)} = \beta(Y(n) \wedge w_J^{(old)}) + (1-\beta) w_J^{(old)} \qquad (10)$$

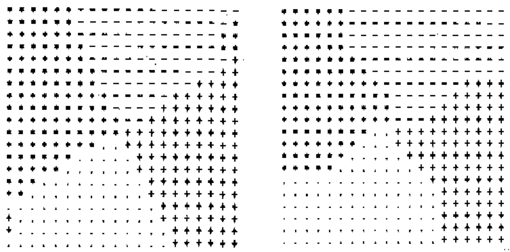
where, J denotes the selected category index. When β is set to 1, that leads to the fast learning.

(5) stopping condition

If any new category is created for all patterns throughout the steps(1-4) above, retraining for all patterns begins until no category is created.

V. Simulation Results

For convenience, QPSK signal is generated using Volterra series. Fig. 4 shows the constellation of QPSK signal with nonlinearity effect. The reduced Volterra coefficients are used to generate those signals. In this study, the capability of fuzzy ARTMAP equalizer for determining the decision boundary (or reconstructing original symbol) is compared with that of contentional MLP equalizer. As shown in Fig. 5(a), MLP equalizer requires a large number of input patterns and training epochs. Fig. 5(b) illustrates the different boundaries for fuzzy ARTMAP equalizer due to the number of training input patterns. In contrast to MLP equalizer, the decision boundaries for fuzzy ARTMAP equalizer are properly determined with just a few number of random input patterns and training epochs. Despite of MLP equalizer's many training inputs and epochs to make decision boundaries, it's performance is not as good as in fuzzy ARTMAP equalizer. In the Fig. 5, -, *, ., and + represent the possible areas of corresponding QPSK symbols, $e^{j\frac{\pi}{4}}$, $e^{j\frac{3\pi}{4}}$, $e^{j\frac{5\pi}{4}}$, and $e^{j\frac{7\pi}{4}}$, respectively, and ranges of x axis and y axis are both (-3, 3).



(a) (b)

Fig. 5. Decision boundary of QPSK (a)MLP (1000 inputs, 2000 epochs) (b)Fuzzy-ARTMAP (15 inputs, 3 epochs)

Training efforts in the fuzzy ARTMAP equalizer are compared with the MLP equalizer. MLP equalizer required four, eight, and two number of units in the input, hidden, and output layers, respectively. In fuzzy ARTMAP equalizer, the number for input, category, and output units were eight, four, and one respectively. It is seen that the number of input units for fuzzy ARTMAP equalizer is double times as big as in MLP equalizer. This comes from the fact that fuzzy ARTMAP uses complement coding in input process.

The values of sigmoid steepness parameter were used in the range (0.7, 1.0). The value of the vigilance influences the number of categories (or clusters) formed, but fuzzy ARTMAP networks increase the vigilance, if required, to ensure that the training data are learned perfectly. The value for proper vigilance parameter used in simulation was higher than 0.75, resulting in four number of categories.

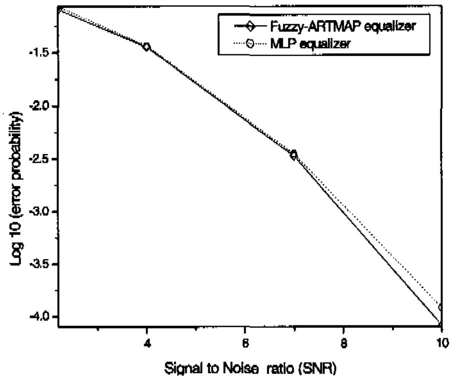


Fig. 6. Comparison of Eaqualizer Performance

Fig. 6 shows the comparison of error rate performance between fuzzy ARTMAP and MLP equalizer. Simulation results above show that the training of fuzzy-ARTMAP equalizer is much easier and faster than that of MLP equalizer, while maintaining better error rate performance than MLP equalizer.

Ⅵ. Conclusions

In this paper, a new fuzzy-ARTMAP equalizer system is developed for mainly for solving the problems of long time of train and complexity, which are often encountered in previously developed neural-basis equalizers such as MLP and RBF equalizers. The fuzzy ARTMAP equalizer is fast and easy to train and includes capabilities not found in other neural network approaches; a small number of parameters, no requirements for the choice of initial weights, and capability of adding new data without retraining previously trained data. By a match tracking process with vigilance parameter, fuzzy ARTMAP equalizer discovers on its own the categorical hidden units. Also, learning is stable because all adaptive weights can only decrease in time. Throughout the simulation studies, it was found that an fuzzy ARTMAP equalizer performed favorably better than MLP equalizer, while requiring just a few number of training inputs and training epochs. The main advantage of the fuzzy ARTMAP equalizer is fast training due to the structural simplicity of fuzzy ARTMAP. Training speed of fuzzy ARTMAP equalizer was approximately one seventh times that of MLP equalizer. These features of an fuzzy ARTMAP equaliter makes its implementation more feasible.

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