Self-Organizing Map for Blind Channel Equalization

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***Abstract*— This paper is concerned with the use of a self-organizing map (SOM) to estimate the desired channel states of an unknown digital communication channel for blind equalization. The modification of SOM is accomplished by using the Bayesian likelihood fitness function and the relation between the desired channel states and channel output states. At the end of each clustering epoch, a set of estimated clusters for an unknown channel is chosen as a set of pre-defined desired channel states, and used to extract the channel output states. Next, all of the possible desired channel states are constructed by considering the combinations of extracted channel output states, and a set of the desired states characterized by the maximal value of the Bayesian fitness is subsequently selected for the next SOM clustering epoch. This modification of SOM makes it possible to search the optimal desired channel states of an unknown channel. In simulations, binary signals are generated at random with Gaussian noise, and both linear and nonlinear channels are evaluated. The performance of the proposed method is compared with those of the "conventional" SOM and an existing hybrid genetic algorithm. Relatively high accuracy and fast search speed have been achieved by using the proposed method.**

***Index Terms*— Self-Organizing Map, Bayesian Likelihood Fitness, Blind Equalization, Linear/Nonlinear Channel.**

I. INTRODUCTION

In digital communication systems, the transmitted signal is subject to inter-symbol-interference (ISI) caused by multipath effects. The ISI will increase the symbol error rate at the receiver, sometimes preventing a correct detection of the transmitted signal. The problem becomes more severe in the presence of additive white Gaussian noise (AWGN). As a result, channel equalizers are required to remove the channel distortion. Most of them take advantage of using known training sequences to adaptively extract channel information. The difficulty with this approach is that it consumes bandwidth. To mitigate this problem, blind-equalization algorithms have been proposed [1]-[3] in which only input signal and noise statistical properties are required instead of training sequences. The original transmitted message is recovered only from the received sequence that is corrupted by noise and ISI without any training sequence or a-prior knowledge of the channel.

However, because of their inherent simplicity, most research results for blind channel equalization assume linear channels that are often inadequate for modeling channels with nontrivial nonlinearities [4]-[6]. Nevertheless, blind nonlinear equalization methods can be very useful. Considering that nonlinear distortion exists in many communication systems, such as high power amplifiers as well as high-density magnetic and optical storage channels, blind nonlinear system equalization methods can have significant practical importance. Early research for blind nonlinear channel equalization focuses on channel estimation by exploiting high order statistics [7][8], however, such methods suffer from slow convergence and local minima. Blind estimation using Volterra kernels to characterize nonlinear channels was presented by Stathaki and Scohyers [9], and a maximum likelihood (ML) method using expectation-maximization was introduced by Kaleh and Vallet [10]. Although these approaches seem to be applicable for nonlinear channels, the Volterra approach suffers from enormous computational complexity to construct a corresponding "inverse" Volterra filter, and the ML approach requires prior knowledge of the nonlinear channel structure to estimate the channel parameters. Erdogmus et al. [11] investigated the use of multilayer perceptrons for nonlinear channel equalization. However, the structure and complexity of the nonlinear equalizer must be specified in advance. The support vector equalizer proposed by Santamaria et al. [12] is a possible solution for both linear and nonlinear blind channel equalization, but it has computational requirements due to an iterative reweighted quadratic programming procedure. The deterministic approach based on second order statistics (SOS) [13] can be used to successfully design blind equalizers of nonlinear channels, but it also has high computational requirements due to the need for eigenvector decomposition. Another SOS-based method developed by Raz et al. [14] has limited practical application because it requires that every nonlinear sub-channel be linearizable by an FIR Volterra system.

A unique approach to blind channel equalization was offered by Lin et al. [15]. In their method, a simplex genetic algorithm (GA) was used to estimate the optimal channel output states. The desired channel states of a channel were constructed from the estimated channel output states and placed at the center of a radial basis function equalizer.

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With their approach, the complex modeling of the nonlinear channel can be avoided and it has been shown to work well under a simple single-input single-output communication environment. Moreover, this kind of approach can be applied to a linear channel as well, because it estimates the channel output states directly rather than the channel parameters, which is not dependent on the type of channel structure. For better performance in terms of search speed and accuracy, this approach has been implemented with a hybrid genetic algorithm combined with simulated annealing (GASA) [16]. However, in general, GA-based techniques may visibly suffer from their poor convergence properties. Therefore there is a need for new methods that provide the faster convergence speed along with the reliable estimation accuracy in search of the optimal channel output states for real-time applications. For these reasons, a new search algorithm based on a simple SOM structure is proposed in this paper. SOM is a clustering algorithm that often has faster processing time than optimization methods such as GA-based algorithms. It was first introduced by Kohonen [17], and has been widely used in pattern clustering and data analysis. In addition, it was also successfully used to detect and compensate the nonlinearities of the communication channel [18][19]. During the self-organizing process in a conventional SOM, the cluster unit whose weight vector most closely matches the input pattern is selected and updated. The weight vector for a cluster unit serves as an exemplar of the input patterns associated with that cluster. In this study, the Bayesian likelihood fitness function and the relation between desired channel states and channel output states are applied to the conventional self-organizing process. The final clustered units with this modification represent the desired channel states of an unknown channel, and then utilized to compute the decision probability of the Bayesian equalizer for blind equalization.

The organization of this paper is as follows. Section II includes a brief introduction to the equalization of linear/nonlinear channels using the Bayesian equalizer. Section III shows the relationship of desired channel states and channel output states. In Section IV, the modification of SOM is introduced. The simulation results including comparisons with GASA and conventional SOM are provided in Section V. Conclusions are presented in Section VI.

II. CHANNEL EQUALIZATION USING BAYESIAN EQUALIZER

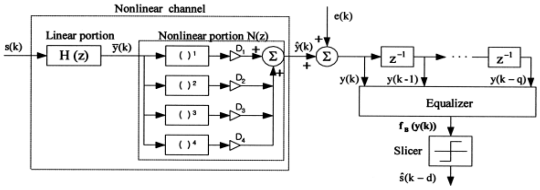


Fig.1.An overall structure of channel equalization system.

The channel equalization system is shown in Fig. 1. A digital information sequence $s(k)$ is transmitted through the channel, which is composed of a linear portion described by $H(z)$ and a nonlinear component $N(z)$, governed by the following expressions,

$$\bar{y}(k) = \sum_{i=0}^{p} h(i)s(k-i) \tag{1}$$

$$\hat{y}(k) = D_1\bar{y}(k) + D_2\bar{y}(k)^2 + D_3\bar{y}(k)^3 + D_4\bar{y}(k)^4 \tag{2}$$

where p is the channel order and D_i is the coefficient of the i^{th} nonlinear term. This nonlinearity in a channel can be due to nonlinearities associated with the transmitter and receiver. The transmitted symbol sequence $s(k)$ is assumed to constitute an equiprobable and independent binary sequence taking values from a two-valued set $\{\pm 1\}$. In addition, the channel output, $\hat{y}(k)$, is assumed to be corrupted by the AWGN, $e(k)$. Given this, the channel observation, $y(k)$, can be expressed as

$$y(k) = \hat{y}(k) + e(k) \tag{3}$$

If q denotes the equalizer order (number of tap delay elements in the equalizer), then there exist $M = 2^{p+q+1}$ different patterns of input sequences that may be received (where each component in (4) is either 1 or –1).

$$\mathbf{s}(\boldsymbol{k}) = [s(k), s(k-1), \cdots, s(k-p-q)] \tag{4}$$

For a specific channel order and equalizer order, these M input patterns influence the input vector of the equalizer, which is shown in (5) for a noise-free case.

$$\hat{\mathbf{y}}(\boldsymbol{k}) = [\hat{y}(k), \hat{y}(k-1), \cdots, \hat{y}(k-q)]. \tag{5}$$

The noise-free observation vector, $\hat{\mathbf{y}}(\boldsymbol{k})$, is referred to as the desired channel states, and can be partitioned into the two sets, $\boldsymbol{Y}_{q,d}^{+1}$ and $\boldsymbol{Y}_{q,d}^{-1}$, as shown in (6) and (7), depending on the value of $s(k\text{-}d)$, where d is the required time delay.

$$\boldsymbol{Y}_{q,d}^{+1} = \{\, \hat{\mathbf{y}}(\boldsymbol{k}) \mid s(k-d) = +1 \,\} \tag{6}$$

$$\boldsymbol{Y}_{q,d}^{-1} = \{\, \hat{\mathbf{y}}(\boldsymbol{k}) \mid s(k-d) = -1 \,\} \tag{7}$$

In the case of a linear channel (D_1=1, D_2=0, D_3=0 and D_4=0), $\hat{\mathbf{y}}(\boldsymbol{k})$ in (3), (5), (6) and (7) is just replaced with $\bar{\mathbf{y}}(\boldsymbol{k})$ in (1). The task of the equalizer is to recover the transmitted symbols, $s(k\text{-}d)$, based on the observation vector, $\mathbf{y}(\boldsymbol{k})$. Because of the presence of AWGN, the observation vector is a random process with conditional Gaussian density functions centered at each of the desired channel states, $\hat{\mathbf{y}}(\boldsymbol{k})$. The determination of the value of $s(k\text{-}d)$ becomes a decision problem. Bayes decision theory [20], which provides the optimal solution for general decision problems, is applied so that the optimal decision function for the Bayesian equalizer can be represented as follows [21][22],

$$f_B(\boldsymbol{y}(\boldsymbol{k})) = \sum_{i=1}^{n_s^{+1}} \exp\left(-\left\| \boldsymbol{y}(\boldsymbol{k}) - \boldsymbol{y}_i^{+1} \right\|^2 / 2\sigma_e^2 \right) - \sum_{i=1}^{n_s^{-1}} \exp\left(-\left\| \boldsymbol{y}(\boldsymbol{k}) - \boldsymbol{y}_i^{-1} \right\|^2 / 2\sigma_e^2 \right) \quad (8)$$

$$\hat{s}(k-d) = \text{sgn}(f_B(\boldsymbol{y}(\boldsymbol{k}))) = \begin{cases} +1, & f_B(\boldsymbol{y}(\boldsymbol{k})) \geq 0 \\ -1, & f_B(\boldsymbol{y}(\boldsymbol{k})) < 0 \end{cases} \quad (9)$$

where $\boldsymbol{y}_i^{+1}$ and $\boldsymbol{y}_i^{-1}$ are the desired channel states belonging to sets $\boldsymbol{Y}_{q,d}^{+1}$ and $\boldsymbol{Y}_{q,d}^{-1}$, respectively, and the numbers of elements in these sets are denoted by n_s^{+1} and n_s^{-1}. Furthermore, σ_e^2 is the noise variance. The optimal equalizer solution in (8) and (9) depends on the desired channel states. In other words, the blind channel equalization critically depends on how to find the desired channel states, $\boldsymbol{y}_i^{+1}$ and $\boldsymbol{y}_i^{-1}$, only from the observation vector, ***y(k)***. In this study, the modified version of a simple SOM clustering method is investigated in search of the optimal output states of an unknown channel, and its desired channel states are configured with the searched channel output states. The construction of desired channel states by using the relation with channel output states will be explained in the next section. The optimal Bayesian decision probability in (8) is used to derive the fitness function of proposed SOM algorithm, and also utilized as an equalizer, along with (9), for the reconstruction of the transmitted symbols.

III. DESIRED CHANNEL STATES BY CHANNEL OUTPUT STATES

In the previous section we observed that the knowledge of desired channel states is essential for the evaluation of the optimum decision function in the Bayesian equalizer. However, under most circumstances, it may not be available. Furthermore, the estimation of channels for nonlinear cases is very difficult in a direct manner. In the proposed algorithm, the estimation of desired channel states is accomplished by using the scalar channel states called “channel output states”. Calculation of the channel output states is simple and its computational complexity does not depend on the equalizer order. Once the desired channel states have been constructed by using the estimated channel output states, the determination of decision function for the Bayesian equalizer is straightforward.

The following example is considered to illustrate the relationship of desired channel states and channel output states. If the channel order is taken as p=1 with $H(z) = 0.5 + z^{-1}$, the equalizer order q is equal to 1, the time delay d is also set to 1, and the nonlinear portion is described by $D_1 = 1, D_2 = 0.1, D_3 = 0.05, D_4 = 0.0$ (see Fig. 1), then eight different desired channel states ($2^{p+q+1} = 8$) may be observed at the receiver in the noise-free case. The output of the equalizer is $\hat{s}(k-1)$ as shown in Table I. From this table, it can be seen that the desired channel states $[\hat{y}(k), \hat{y}(k-1)]$ are composed of four elements of the channel output states, $\{a_1, a_2, a_3, a_4\}$, where for this particular channel we have $a_1 = 1.89375, a_2 = -0.48125, a_3 = 0.53125$ and $a_4 = -1.44375$. The length of dataset, $\tilde{n}$, is determined by the channel order, p, such as $2^{p+1} = 4$, which is independent from the equalizer order. In general, if q=1 and d=1, the desired channel states for $\boldsymbol{Y}_{1,1}^{+1}$ and $\boldsymbol{Y}_{1,1}^{-1}$ are (a_1,a_1), (a_1,a_2), (a_3,a_1), (a_3,a_2), and (a_2,a_3), (a_2,a_4), (a_4,a_3), (a_4,a_4), respectively. A change in the decision delay only changes some of the positive states to negative states and an equal number of negative states to positive states. For example, if d=0, the channel states (a_1,a_1), (a_1,a_2), (a_2,a_3), and (a_2,a_4) belong to $\boldsymbol{Y}_{1,1}^{+1}$, and ($a_3$,$a_1$), ($a_3$,$a_2$), ($a_4$,$a_3$), ($a_4$,$a_4$) belong to $\boldsymbol{Y}_{1,1}^{-1}$. This relation is always valid for the channel that has a one-to-one mapping between the channel inputs and outputs [15]. Thus, the desired channel states can be derived from the channel output states if the channel order, p, is assumed to be known, and the main problem of blind equalization can be changed to focus on the determination of the optimal channel output states from the received patterns.

TABLE I
CONSTRUCTION OF DESIRED CHANNEL STATES BY CHANNEL OUTPUT STATES

Nonlinear channel with $H(z) = 0.5 + 1.0z^{-1}$, $D_1 = 1, D_2 = 0.1, D_3 = 0.05, D_4 = 0.0$, and d=1						
Transmitted symbols			Desired channel states			Equalizer output
$s(k)$	$s(k-1)$	$s(k-2)$	$\hat{y}(k)$	$\hat{y}(k-1)$	Channel output states $\{a_1, a_2, a_3, a_4\}$	$\hat{s}(k-1)$
1	1	1	1.89375	1.89375	(a_1,a_1)	1
1	1	−1	1.89375	−0.48125	(a_1,a_2)	1
−1	1	1	0.53125	1.89375	(a_3,a_1)	1
−1	1	−1	0.53125	−0.48125	(a_3,a_2)	1
1	−1	1	−0.48125	0.53125	(a_2,a_3)	−1
1	−1	−1	−0.48125	−1.44375	(a_2,a_4)	−1
−1	−1	1	−1.44375	0.53125	(a_4,a_3)	−1
−1	−1	−1	−1.44375	−1.44375	(a_4,a_4)	−1

IV. MODIFICATION OF SOM TO SEARCH OPTIMAL STATES

The SOM clustering algorithm has been widely used in pattern and data analysis since Kohonen's initial development [17][23]. During the self-organizing process of SOM, the cluster unit whose weight vector matches the input pattern most closely is chosen and updated as follows,

$$D(j) = \sum_{j} (\boldsymbol{w}_j - \boldsymbol{y}(\boldsymbol{k}))^2 \tag{10}$$

$$\boldsymbol{w}_{\boldsymbol{J}}(new) = \boldsymbol{w}_{\boldsymbol{J}}(old) + \alpha(\boldsymbol{y}(\boldsymbol{k}) - \boldsymbol{w}_{\boldsymbol{J}}(old)) \tag{11}$$

where $\boldsymbol{w}_j$ is a weight vector for the j^{th} cluster unit and $\boldsymbol{J}$ is the index of cluster unit such that $D(\boldsymbol{J})$ is a minimum. Here α is a learning rate and $\boldsymbol{y(k)}$ is a noise-corrupted observation vector at the receiver. The weight vector for a cluster serves as an example of the input patterns associated with that cluster. In general, the conventional SOM is not adequate to solve blind equalization problems because its clustering process is based on unsupervised learning. It implies, when clustering is completed, that it is not possible to classify which cluster units belong to $\boldsymbol{Y}_{1,1}^{+1}$ or $\boldsymbol{Y}_{1,1}^{-1}$. Additionally, SOM clustering is only dependent on Euclidean distance measure and ignores the statistical properties of input patterns (In this study, $\boldsymbol{y(k)}$ in (10) is a random process with conditional Gaussian density functions centered at each of the desired channel states because of the presence of AWGN). To handle these problems, the Bayesian likelihood fitness function and the fact that the desired channel states can be constructed from the channel output states are applied to the conventional SOM clustering process.

For the channel shown in Table I, the four elements ($2^{p+1} = 4$) of channel output states, $\{a_1, a_2, a_3, a_4\}$, are required to construct the optimal desired channel states. If the candidates for these elements, $\{c_1, c_2, c_3, c_4\}$, are extracted from the eight cluster units of a conventional SOM by using the relation presented in Table I (or randomly initialized at first), twelve (4!/2) different possible data sets of desired channel states can be constructed by completing matching between $\{c_1, c_2, c_3, c_4\}$ and $\{a_1, a_2, a_3, a_4\}$. To facilitate fast matching, the arrangements of $\{c_1, c_2, c_3, c_4\}$ are saved as a certain mapping set *C* such that *C(1)=1,2,3,4*, *C(2)=1,2,4,3*, …,*C(12)=3,2,1,4* before the search process starts. For example, the notation *C(2)=1,2,4,3* means that the set of desired channel states is constructed with c_1 for a_1, c_2 for a_2, c_4 for a_3, and c_3 for a_4 in Table I. The desired channel states for this set are described as $\boldsymbol{y}_{i\_C(2)}$ ($\boldsymbol{y}_{i\_C(2)}^{+1}$ and $\boldsymbol{y}_{i\_C(2)}^{-1}$ for sets $\boldsymbol{Y}_{1,1}^{+1}$ and $\boldsymbol{Y}_{1,1}^{-1}$, respectively). At this point, the Bayesian likelihood (*BL*) shown in (12) is applied. It was shown that the *BL* is maximized with respect to the desired channel states derived from the optimal channel output states [24].

$$BL = \prod_{k=0}^{L-1} max(f_B^{+1}(k), f_B^{-1}(k)) \tag{12}$$

where $f_B^{+1}(k) = \sum_{i=1}^{n_s^{+1}} \exp\left(-\left\|\boldsymbol{y}(\boldsymbol{k}) - \boldsymbol{y}_i^{+1}\right\|^2 / 2\sigma_e^2\right)$, $f_B^{-1}(k) = \sum_{i=1}^{n_s^{-1}} \exp\left(-\left\|\boldsymbol{y}(\boldsymbol{k}) - \boldsymbol{y}_i^{-1}\right\|^2 / 2\sigma_e^2\right)$ and L is the length of the received sequences. Therefore, the *BL* can be utilized as the fitness function (*FF*) of the proposed algorithm to find optimal channel output states. Being more specific, the fitness function is taken as the logarithm of *BL*, that is

$$FF = \sum_{k=0}^{L-1} log(max(f_B^{+1}(k), f_B^{-1}(k))) \tag{13}$$

The mathematical calculations needed to determine the maximum *FF* is not possible without knowledge of the channel structure [15][24]. In addition, from the relation between *FF* and channel output states shown as in Fig. 2 (where several local maxima exist), it cannot be easily solved by conventional gradient-based methods. This is one of the reasons that a clustering algorithm is considered as a way to find the maximum *FF*.

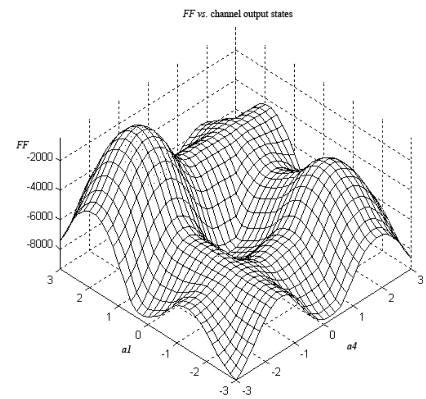


Fig. 2. *FF* vs. channel output states (a_1 and a_4) for the channel in Table I (a_2 and a_3 are set to their optimal values).

In the proposed algorithm, the fitness function for the set of desired channel states, $\boldsymbol{y}_{i\_C(2)}$, is described as *FF(2)*, and it has a maximum value if $\boldsymbol{y}_{i\_C(2)}$ is an optimal set of desired channel states. Thus at the next stage, a data set of desired channel states, which has a maximum Bayesian fitness value, is searched and selected as shown bellow

$$\begin{aligned}&[index\_j, \quad max\_FF] \\ &\quad = max(FF(1), FF(2), \cdots, FF(12))\end{aligned} \tag{14}$$

This data set ($\boldsymbol{y}_{i\_C(index\_j)}$), which is the set of desired channel states configured by the selected *C*(*index_j*), is utilized as a set of cluster units for the next clustering epoch of conventional SOM. It means that the weight matrix **w** is replaced by the data set, $y_{i\_C(index\_j)}$, at the end of each clustering epoch. These steps are repeated until the Bayesian likelihood fitness function or the weight matrix **w** is unchanged. The proposed SOM algorithm can be described using the following pseudo-code.

begin
  save arrangements of candidates, $\{c_1,c_2,c_3,c_4\}$*, to C*
  randomly initialize the candidates, $\{c_1,c_2,c_3,c_4\}$
  construct an initial set of desired channel states
    based on the structure shown in Table I and C(1)
  while (max_FF(new) – max_FF(old)) < threshold
   for k=1 to L (length of input sequences)
     conventional clustering procedure
       by (10) & (11)
   end
   extract new $\{c_1,c_2,c_3,c_4\}$ *from the eight cluster units*
    based on the structure shown in Table I and C(1)
   for j=1 to C size
     construct a set of desired channel states by C(j)
     calculate its fitness function (FF[j]) by (13)
   end
   find a data set which has a maximum FF as in (14)
   replace the weight matrix ***w***
     with the selected data set, $y_{i\_C(index\_j)}$
  end (end of while loop)
end (end of begin)

In the search process of the proposed algorithm, each of new candidates, $\{c_1,c_2,c_3,c_4\}$, for the channel output states is extracted from the cluster units by using the relations in Table I and a data set for the desired channel states which exhibits a maximum fitness value is always selected. Therefore, the set of desired channel states produced by the proposed SOM is always close to the optimal set, and its first half presents the desired channel states for $Y_{1,1}^{+1}$ and the rest presents for $Y_{1,1}^{-1}$, or reversely. In addition, for the fast searching speed, the proposed SOM does not need to check all of the possible arrangements, *C*(*1*),*C*(*2*),…,*C*(*12*), to find the data set which has a maximum *FF* after the first couple of *while*-loop. It is because the new candidates, $\{c_1,c_2,c_3,c_4\}$, are always extracted by using the arrangement *C*(*1*) and thus the set of desired channel states constructed by *C*(*1*) has the maximum *FF* after couple of clustering epochs. It will be clearly shown in the following experimental section. Therefore, in our experiments, for the fast searching of proposed algorithm, the second *for*-loop in the pseudo-code is skipped if the selected *index_j* has not been changed during the last 5 epochs. From this moment, the set of desired channel states only by *C(1)* is constructed with the new candidates and utilized for further process.

V. SIMULATION RESULTS

As mentioned in Section I, the GASA reported in [16] showed better performance than the simplex GA by Lin and Yamashita [15] in terms of search speed and accuracy. To demonstrate the effectiveness of the method, blind equalizations realized with the use of the GASA, the proposed SOM and the conventional SOM are considered in this section. The basic channel in reference [15], $H(z) = 0.5 + 1.0z^{-1}$, is used for the performance evaluations with three different communication environments. The first one (channel 1) represents a linear model with a desired time delay *d*=1. The second one (channel 2) is a nonlinear model with *d*=1. The last one (channel 3) concerns a nonlinear model with *d*=0, which produces a nonlinear decision boundary.

Channel 1(linear model with time delay *d*=1):
$H(z) = 0.5 + 1.0z^{-1}$, $D_1 = 1, D_2 = 0, D_3 = 0, D_4 = 0$, d=1
Channel 2(nonlinear model with time delay *d*=1):
$H(z) = 0.5 + 1.0z^{-1}, D_1 = 1, D_2 = 0.1, D_3 = 0.05, D_4 = 0$, d=1
Channel 3(nonlinear model with time delay *d*=0):
$H(z) = 0.5 + 1.0z^{-1}, D_1 = 1, D_2 = 0.1, D_3 = 0.05, D_4 = 0$, d=0

For channel 1 and 2, the channel order *p*, the equalizer order *q*, and the time delay *d* are 1, 1, and 1, respectively. Thus, the output of the equalizer should be $\hat{s}(k-1)$ and the eight desired channel states for $Y_{1,1}^{+1}$ and $Y_{1,1}^{-1}$, composed of the four channel output states ($2^{p+1} = 4,\ a_1,a_2,a_3,a_4$) as shown in Table I, will be observed at the receiver in a noise-free case. For channel 1 (a linear model), where the nonlinear terms of channel D_2, D_3, and D_4 are equal to zero, a_1,a_2,a_3,a_4 are 1.5, -0.5, 0.5 and -1.5, respectively, and for channel 2, they are illustrated in Table I. Channel 3 has exactly the same parameters with channel 2 except the decision time delay (*d*=0). It means that no-time delay is required between the transmitted input sequence and the equalizer output, which constitutes the nonlinear decision boundary for the equalizer. As mentioned in section III, the change of time delay only changes some of the positive states to negative states and an equal number of negative states to positive states. When *d* is equal to zero and the equalizer output is $\hat{s}(k)$, two positive states, (a_3,a_1) and (a_3,a_2), are replaced with two negative states, (a_2,a_3) and (a_2,a_4), respectively. Thus for channel 3, the channel states (a_1,a_1), (a_1,a_2), (a_2,a_3), (a_2,a_4) belong to $Y_{1,1}^{+1}$, and (a_3,a_1), (a_3,a_2), (a_4,a_3), (a_4,a_4) belong to $Y_{1,1}^{-1}$.

In the experiments, 10 independent simulations for each of three channels with five different noise levels (SNR=0,2.5,5,7.5 and 10db) are performed with 1,000 randomly generated transmitted symbols (*L*=1000). Then the results are averaged. The GASA, the proposed

SOM, and the conventional SOM have been implemented in a batch mode to facilitate comparative analysis. Unlike the GASA and our proposed SOM, the clustering procedure of conventional SOM is totally unsupervised and it is not possible to identify which cluster units belong to $\boldsymbol{Y}_{1,1}^{+1}$ or $\boldsymbol{Y}_{1,1}^{-1}$. Therefore, only for the performance measuring, the closest cluster unit to each of known desired channel states is manually selected in the experiments with conventional SOM. With this regard, the normalized root mean squared errors (NRMSE) is determined in the form

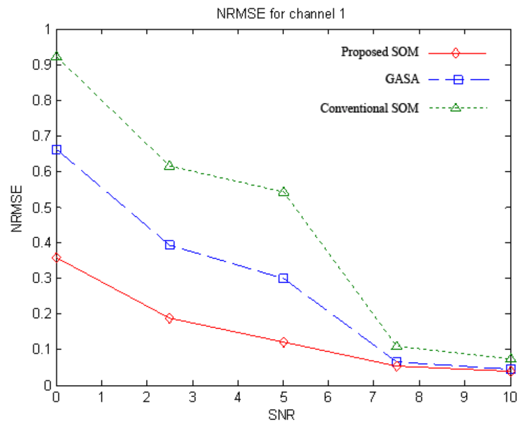
$$\text{NRMSE}=\frac{1}{\|\boldsymbol{a}\|}\sqrt{\frac{1}{N}\sum_{i=1}^{N}\|\boldsymbol{a}-\hat{\boldsymbol{a}}_i\|^2} \qquad (15)$$

where $\boldsymbol{a}$ is the dataset of optimal channel output states, $\hat{\boldsymbol{a}}_i$ is the dataset of estimated channel output states in the i^{th} simulation, and N is the total number of independent simulations (N=10). The parameters for each of three algorithms are included in Table II, and these are fixed for all experiments. The choice of the specific parameter values is not critical to the performance of GASA and proposed SOM. The fitness function described by Eq. (13) is utilized in both algorithms.

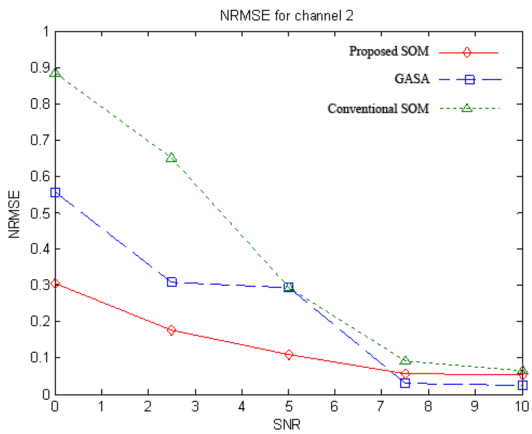
TABLE II
SIMULATION PARAMETERS FOR EXPERIMENTS.

GASA	Population size	50
	Maximum number of generation	100
	Crossover rate	0.8
	Mutation rate	0.1
	Random initial temperature	[0,1]
	Cooling rate	0.99
Proposed SOM	Initial learning rate	0.1
	Decreasing rate for learning rate	0.9/epoch
	Maximum number of epochs	100
	Number of clusters used	8
	Random initial candidates	[-0.5 0.5]
Conventional SOM	Initial learning rate	0.1
	Decreasing rate for learning rate	0.9/epoch
	Maximum number of epochs	100
	Maximum number of clusters	8
	Random initial weights	[-0.5 0.5]

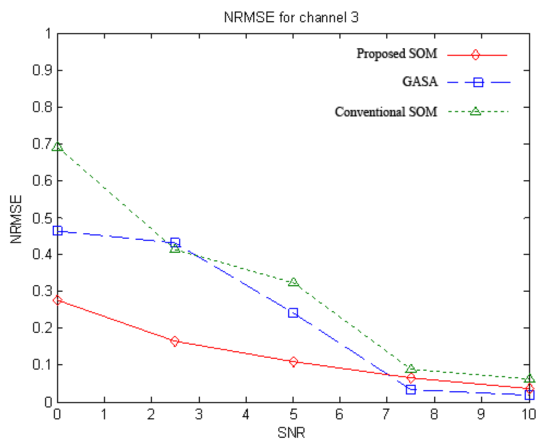
As shown in Fig. 3, the proposed SOM has the lowest NRMSE for all three channels, and the performance differences are more significant at higher noise levels. This latter result implies that the clustering procedure of the proposed SOM, which utilizes the Bayesian likelihood fitness function and the relation between desired channel states and channel output states, is a more effective technique to determine the optimal channel states when the received patterns are heavily corrupted by noise. A sample of 1,000 received symbols under 0db SNR for channel 1 and the desired channel states constructed from the estimated channel output states by each of three algorithms are shown in Fig. 4.



(a)



(b)



(c)

Fig. 3. NRMSE for channel 1(a), 2(b) and 3(c).

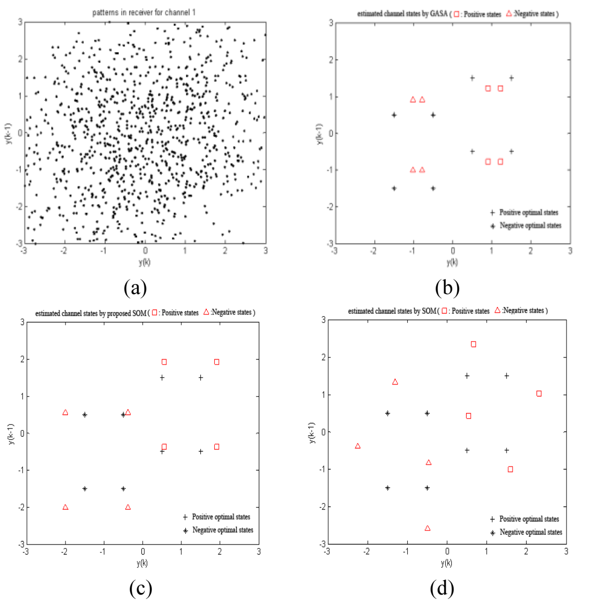


Fig. 4. A sample of received symbols under 0db SNR for channel 1(a) and its desired channel states produced by GASA(b), proposed SOM(c) and conventional SOM(d).

In addition, the search time required by the algorithms is compared. As mentioned at the end of Section IV, for the fast convergence of proposed SOM, it is not necessary to check all of the possible arrangements C in the *while*-loop during the entire procedure. As shown in the pseudo-code, the set of established cluster units after conventional clustering procedure of SOM is treated as the set of desired channel states presented in Table I, and each value for the new candidates $\{c_1,c_2,c_3,c_4\}$ is replaced with each one of the channel output states $\{a_1,a_2,a_3,a_4\}$ in the cluster units, respectively. Thus, the set of desired channel states constructed by $C(1)$ always has the maximum FF after the first couple of *while*-loop. A sample of variations of $index\_j$ and the fitness function FF during the *while*-loop iterations for channel 1 is shown in Fig. 5. To increase the search speed of the proposed SOM, the second *for*_loop (1 to C) in the pseudo-code is omitted if it has not been changed during the previous five epochs. The search times for each of three algorithms, averaged by 10 independent simulations, are included in Table III; notably, two algorithms based on SOM offer much faster search times for all three channels, which could be attributed to their relatively simple structures. In the direct comparison of two SOM based algorithms, the overall search time by the proposed SOM is slightly slower. However, their difference is not severe where the proposed SOM provides much better performance in terms of NRMSE. Additionally, as mentioned previously, the use of conventional SOM for blind equalization is not practical because it employs unsupervised learning. Only for the purpose of comparing clustering performances was it tested.

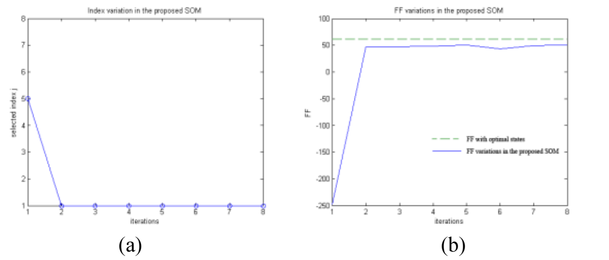


Fig. 5. Variation of the selected *index_j*(a) and the fitness function *FF*(b) during the search procedure of proposed SOM for channel 1 under 0db SNR.

TABLE III
SEARCH TIMES IN SECONDS FOR EACH
(USING MATLAB 7.0).

Channel (SNR)		GASA	Proposed SOM	Conventional SOM
Channel 1	0db	30.50	0.26	0.25
	2.5db	30.18	0.23	0.21
	5db	29.89	0.22	0.15
	7.5db	29.74	0.21	0.15
	10db	29.44	0.21	0.08
Channel 2	0db	29.60	0.47	0.30
	2.5db	29.67	0.26	0.19
	5db	29.71	0.21	0.17
	7.5db	29.77	0.21	0.11
	10db	29.36	0.20	0.09
Channel 3	0db	27.85	0.53	0.24
	2.5db	27.79	0.25	0.19
	5db	27.85	0.24	0.17
	7.5db	28.12	0.24	0.13
	10db	27.76	0.23	0.09

Finally, the bit error rates (BER) using the Bayesian equalizer is investigated as shown in Table IV. It becomes apparent that the BER with the estimated channel output states realized by the proposed SOM is almost the same as that with the optimal output states for all three channels. The decision boundaries of the Bayesian equalizer with the optimal desired channel states and the channel states estimated by each of three algorithms for channel 2 and 3 are graphed in Fig. 6 and 7, respectively.

TABLE IV
AVERAGE BER(%) (NO. OF ERRORS/ NO. OF TRANSMITTED SYMBOLS).

Channel (SNR)		With optimal states	GASA	Proposed SOM	Conventional SOM
Channel 1	0db	18.99	24.06	19.48	27.04
	2.5db	12.29	14.69	12.89	17.22
	5db	7.72	11.00	7.87	13.53
	7.5db	4.53	4.70	4.58	5.21
	10db	1.71	1.77	1.74	1.82
Channel 2	0db	17.96	23.80	18.37	24.96
	2.5db	11.58	14.33	12.15	16.57
	5db	7.25	9.67	7.34	9.71
	7.5db	3.81	3.82	3.82	4.27
	10db	1.29	1.29	1.31	1.34
Channel 3	0db	36.38	38.36	37.12	42.06
	2.5db	29.70	32.74	29.92	31.35
	5db	22.44	23.51	22.92	28.88
	7.5db	14.06	14.32	14.49	15.29
	10db	7.17	7.23	7.26	7.69

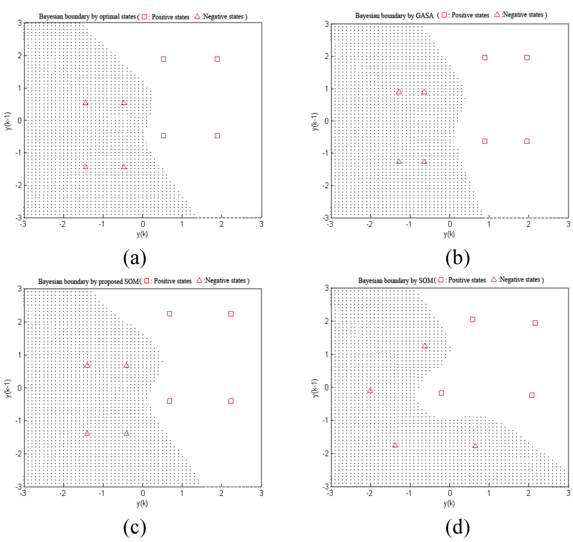


Fig. 6. A sample of decision boundaries with the optimal desired channel states(a) and the estimated channel states by GASA(b), proposed SOM(c) and conventional SOM(d) under 2.5db SNR for channel 2 (linear boundary).

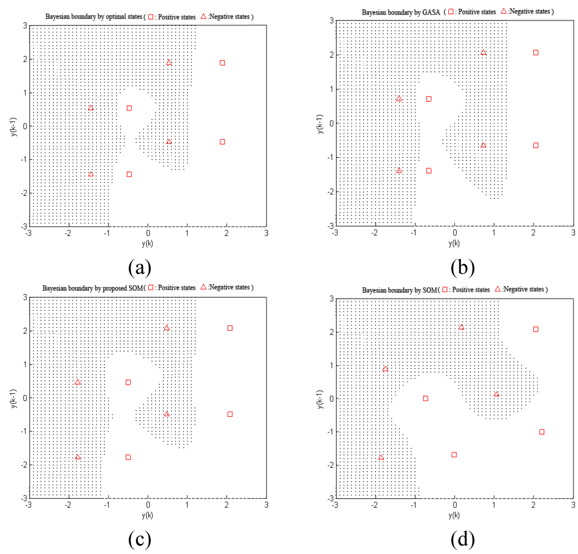


Fig. 7. A sample of decision boundaries with the optimal desired channel states(a) and the estimated channel states by GASA(b), proposed SOM(c) and conventional SOM(d) under 2.5db SNR for channel 3 (nonlinear boundary).

VI. CONCLUSIONS

A modification of SOM clustering algorithm to estimate the optimal channel states of unknown communication channel is introduced for blind equalization, and successfully evaluated with both of linear and nonlinear channels. In this approach, the demanding modeling of an unknown channel is unnecessary because the construction of the desired channel states is achieved directly using the estimated channel output states. It has been shown that the proposed SOM offers better performance compared to solutions provided by the existing GASA and conventional SOM. In particular, it has a relatively simple structure and estimates the channel output states with reliable accuracy and speed. Therefore, the proposed SOM can be a possible solution to search the optimal channel states of unknown channel for blind equalization. In the future, the proposed algorithm will be expanded and tested for more complex communication environments, such as those encountered when dealing with channels of high dimensionality and equalizers of high order. In addition, the other types of search algorithms (easier to implement and faster to compute) instead of SOM will also be investigated.

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REFERENCES

[1] Z. Ding and L. Ye, *Blind Equalization and Identification*, New York: Marcel Dekker, 2001.
[2] H. Gazzah and K. A. Meraim, "Blind ZF equalization with controlled delay robust to order over estimation," *Signal Processing*, vol. 83, pp. 1505-1518, 2003.
[3] J. Zhu, XR Cao and RW. Liu, "A blind fractionally spaced equalizer using higher order statistics," *IEEE Transactions on. Circuits and Systems. II: Analog Digital Signal Process*, vol. 46, pp. 755-764, 1999.
[4] E. Serpedin and G.B. Giannakis, "Blind channel identification and equalization with modulation-induced cyclostationarity," *IEEE Transactions on Signal Processing*, vol. 46, pp. 1930-1944, 1998.
[5] Y. Fang, W.S. Chow and K.T. Ng, "Linear neural network based blind equalization," *Signal Processing,* vol. 76, pp. 37-42, 1999.
[6] Yun Ye and Saman S. Abeysekera, "Efficient blind estimation and equalization of non-minimum phase communication channels via the use of a zero forcing equalizer," *Signal Processing*, vol. 86, pp.1019-1034, 2006.
[7] S. Mo and B. Shafai, "Blind equalization using higher order cumulants and neural networks," *IEEE Transactions on Signal Processing*, vol.42, pp.3209-3217, 1994.
[8] X. H. Dai, "CMA-based nonlinear blind equaliser modelled by a two-layer feedforward neural network," *IEE Proceedings: Communications*, vol. 148, pp. 243-248, 2001.
[9] T. Stathaki and A. Scohyers, "A constrained optimization approach to the blind estimation of Volterra kernels," *Proc. of the IEEE International Conference on ASSP*, vol. 3, pp. 2373-2376, 1997.
[10] G.K. Kaleh and R. Vallet, "Joint parameter estimation and symbol detection for linear or nonlinear unknown channels," *IEEE Trans. Commun.*, vol. 42, pp. 2406-2413, 1994.
[11] D. Erdogmus, D. Rende, J.C. Principe and T.F. Wong, "Nonlinear channel equalization using multilayer perceptrons with information theoretic criterion," *Proc. of IEEE workshop Neural Networks and Signal Processing*, pp. 443-451, MA, U.S.A., 2001.
[12] I. Santamaria, C. Pantaleon, L. Vielva and J. Ibanez, "Blind equalization of constant Modulus signals using support vector machines," *IEEE Transactions on Signal Processing*, vol. 52, pp. 1773-1782, 2004.
[13] R. Lopez-Valcarce and S. Dasgupta, "Blind equalization of nonlinear channels from second-order statistics," *IEEE Transactions on Signal Processing*, vol. 49, pp. 3084-3097, 2001.
[14] G. Raz and B. Van Veen, "Blind equalization and identification of nonlinear and IIR systems - a least squares approach," *IEEE Transactions on Signal Processing*, vol. 48, pp. 192-200, 2000.
[15] H. Lin and K. Yamashita, "Hybrid simplex genetic algorithm for blind equalization using RBF networks," *Mathematics and Computers in Simulation*, vol. 59, pp. 293-304, 2002.
[16] S. Han, W. Pedrycz and C. Han, "Nonlinear Channel Blind Equalization Using Hybrid Genetic Algorithm with Simulated Annealing," *Mathematical and Computer Modeling*, vol. 41, pp. 697-709, 2005.
[17] T. Kohonen, *Self-organization and Associative Memory (3rd ed.)*, Berlin: Springer-Verlag, 1989.
[18] T. Kohonen, K. Raivio, O. Simula, O. Venta, and J. Henriksson, "Combining linear equalization and self-organizing adaptation in dynamic discrete-signal detection," *Proc. of the International Joint Conference on Neural Networks*, vol. 1, pp. 223-228, 1990.
[19] G. A. Barreto and L. G. M. Souza, "Adaptive filtering with the self-organizing map: A performance comparison," *Neural Networks*, vol. 19, pp. 785–798, 2006.
[20] R.O. Duda and P.E. Hart, *Pattern Classification and Scene Analysis*, Wiley, New York, 1973.
[21] S. Chen, B. Mulgrew and S. McLaughlin, "Adaptive Bayesian equalizer with decision feedback," *IEEE Tranactions on Signal Processing*, vol. 41, pp. 2918-2927, 1993.
[22] S. Chen, B. Mulgrew and M. Grant, "A clustering technique for digital communication channel equalization using radial basis function network," *IEEE Transactions on. Neural Networks*, vol. 4, pp. 570-579, 1993.
[23] L. Fausett, *Fundamentals of Neural Networks*, New Jersey: Prentice-Hall, 1994.
[24] H. Lin and K. Yamashita, "Blind equalization using parallel Bayesian decision feedback equalizer," *Mathematics and Computers in Simulation*, vol. 56, pp. 247-257, 2001.

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