Overcoming Co-channel Interference in TDMA Systems Using SOM Equalizer

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***Abstract*— This paper studies the co-channel interference (CCI) problem for time-division-multiple-access (TDMA) cellular mobile communication system with burst transmission. We present a method using self-organizing-map (SOM) to overcome CCI for such a system. The SOM is realized as a classification equalizer with a decision feedback adaptive filter. An extremely small number of unique words (UWs) is utilized to initialize the SOM equalizer. Simulation results show that the bit error rate (BER) of our proposed method is much better than that of the recently proposed nearest neighbor classification equalizer.**

I. Introduction

Cellular mobile communication systems rely on an intelligent allocation schema and reuse of channels throughout a coverage region. The reuse of channels is realized by reusing the same frequency, which means that several cells in a given coverage area use the same set of frequencies. For a particular cell, all channels from the surrounding cells with the same frequency are called co-channels and the interference from these co-channels is called *co-channel interference* (CCI) [2].

For cellular mobile communication system, the radio link performance is usually limited by CCI rather than noise. Therefore, equalizer is employed at the receiver to cancel CCI. In [3], an adaptive radial basis function network was used to overcome CCI. In [4], polynomial perceptions were applied to equalize fading channel and suppress CCI. In [5], a Bayesian decision feed back equalizer (DFE) was designed to overcome CCI. Recently, Savazzi *et al.* [6] applied nearest neighbor classification (NNC) equalizer to overcome inter-symbol interference (ISI) and CCI for a GSM system. The most important advantage of NNC equalizer they claimed is a significant reduction in computational complexity compared with the maximum likelihood sequence estimation equalizer (MLSE), which is already used in GSM systems and is well known to be optimal for detecting an information sequence corrupted by ISI and additive Gaussian noise . Even though the performance of NNC equalizer is mildly worse than that of MLSE, it is still kept in the bit error rate (BER) limitation of the specification of GSM [6]. In [1], a type-2 fuzzy adaptive filter was employed to reject the CCI for a cellular mobile communication system, a lower BER was obtained compared to both the type-1 fuzzy equalizer and NNC equalizer. In this paper, a SOM based equalizer is proposed. The hardware implementation of our proposed equalizer is similar to that of NNC. SOM equalizer can perform well when the number of UWs is very limited (less than 2% of one whole burst), however NNC equalizer can not.

The rest of this paper is organized as follows. In section II, we discuss the system model. In section III, we introduce an equalizer based on a pattern classification method, NNC and its extension K-NNC. In section IV, we describe our algorithm: SOM equalizer. Simulation results are given in section V and we conclude this paper in section VI.

II. System Model

Cellular mobile channels are often modelled as Rayleigh fading channels. The channel gain can be treated as a wide-sense stationary complex Gaussian random process:

$$g(t) = g_I(t) + j \cdot g_Q(t) \tag{1}$$

where $j = \sqrt{-1}$, $g_I(t)$ and $g_Q(t)$ are statistically independent Gaussian random process with zero means and common variance δ^2. The magnitude of the received complex envelop $r(t) = \sqrt{g_I(t) + g_Q(t)}$ then has a Rayleigh distribution:

$$p(r) = \frac{r}{\delta^2} e^{(-\frac{r^2}{2\delta^2})}, 0 \leq r \leq \infty \tag{2}$$

and the phase of the channel gain is uniformly distributed between $-\pi$ to π.

The discrete-time model of a communication system that is subject to CCI, ISI and additive Gaussian noise (AWGN) is shown in Fig. 1. When sampled in time synchronization the received signal plus interference and noise r(k) can be modelled as

$$\begin{aligned} r(k) &= r'(k) + u(k) + e(k) \\ &= \sum_{i=0}^{n} a_i(k) s(k-i) + u(k) + e(k) \end{aligned} \tag{3}$$

where $s(k)$ is the symbol to be transmitted, $e(k)$ is the noise and $u(k)$ is CCI from the N co-channels. n is called channel order [1], and $a_i(k)$ are complex channel gains or tap coefficients. We assume that BPSK modulation is used in this

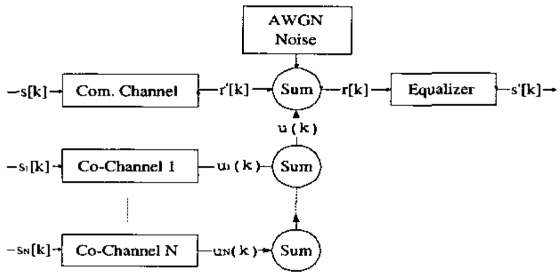

Fig. 1. Block diagram of a baseband communication system

paper so that $s(k)$ is either +1 or -1 with equal probability. Let n_j denote the jth co-channel's order, and b_{ij}, $i = 0, 1, 2...n_j$ are their corresponding channel gains, we thus can express the CCI u(k) as

$$u(k) = \sum_{j=1}^{N} u_j(k) = \sum_{j=1}^{N} \sum_{i=0}^{n_j} b_{ij}(k) s'_j(k - i) \tag{4}$$

where s'_j is the interference from jth co-channel which also takes a binary value, but it is always blind to the equalizer. Since we model channel as a Rayleigh fading channel, it is reasonable that we also model all the co-channels as Rayleigh fading channels.

III. Channel Equalization Based on NNC Rule

A. Preliminaries for Channel Equalization

In this paper we Assume n=1 in (3), i.e., there is only one adjacent ISI, the received noise-free signal can be expressed as

$$r'(k) = a_0(k)s(k) + a_1(k)s(k-1) \tag{5}$$

where $a_0(k)$ and $a_1(k)$ are statistically independent complex channel gains with Rayleigh distributions. As $s(k)$ and $s(k$-1) take value of either +1 or −1 in a BPSK system, the received noise-free signal $r'(k)$ in (5) has 4 states and can be partitioned into two classes so that the signal been transmitted can be detected:

$$\begin{aligned} R^+ &= \{r'(k)|s(k) = 1\} \\ &= \{a_0(k) + a_1(k), a_0(k) - a_1(k)\} \end{aligned} \tag{6}$$

$$\begin{aligned} R^- &= \{r'(k)|s(k) = -1\} \\ &= \{-a_0(k) + a_1(k), -a_0(k) - a_1(k)\} \end{aligned} \tag{7}$$

where R^+ is a set whose elements indicate that '1' was transmitted, while R^- is a set whose elements indicate that '-1' was transmitted. The received $r(k)$ in (3) is corrupted by CCI and AWGN noise but centered at the corresponding channel state. Therefore, based on the analysis above and the nature of the NNC classifier, it is possible to design an equalizer based on NNC rule.

B. Equalizer Based on NNC Rule

The nearest neighbor classifier is used for many pattern recognition applications where the underlying probability distribution of the data is unknown *a priori*. The classification error rate of NNC is bounded by 2 times as the optimal Bayes risk [9]. A NNC assigns an incoming sample to the class associated with the nearest labelled sample whose class label is known. The design procedure of NNC is as follows [6]: let Xs = $\{x_1,..., x_m\}$ be a set of m labelled samples and x_i $\in$Xs be a labelled sample nearest to a test point x. Then the nearest neighbor rule for classifying x is to assign x the class associated with x_i. Its extension K-NNC classifies x by assigning x the class associated with the most frequently appeared among K nearest labelled samples of x. K is odd to avoid ties, and the optimal choice of K is $K = \sqrt{N}$.

TABLE I
THE STRUCTURE OF THE GSM INFORMATION BURST

T bits	Info	Midamble	Info	T bits	Guard
3	58	26	58	3	8.25

Here we briefly introduce the NNC equalizer implemented in [6]. Tabel I shows the structure of the GSM information burst. Note the 26 central bits, named midamble according to the GSM terminology, which is training sequence used for channel estimation and adaptation for equalizer parameters. We call these midamble as unique words (UW) in this paper. Savazzi, et. al, used the channel states (corrupted by noise and ISI) generated by those midamble as the labelled samples, and detected the information symbols using K-NNC rule so that a NNC equalizer has been implemented.

The key idea of our proposed method is that since each symbol received by equalizer carries channel information. After one symbol has been detected, if the K nearest labelled channel states of the detected symbol be moved towards the detected symbol, the equalizer can be adaptively adjusted to the channel characteristics, and if the labelled channel states adaptively track the channel thus it can give a good result when it detect the next symbol. In order to move such labelled channel states in a convergent way, in this paper SOM network is utilized to govern the number of labelled channel states that will be moved as well as the distance of such movements. Traditionally, SOM is widely utilized as a vector quantizer to generate codebooks for data compression but rarely used in wireless communications. In our method, the labelled channel states correspond to the synaptic weights in SOM, which move adaptively towards the currently detected symbol (the input vector). Thus, the labelled channel states are adaptively adjusted to the channel and a decision feedback equalizer is implemented. We introduce SOM in the following section.

IV. Self-Organizing-Map Network

The main goal of the SOM is to transform an input signal pattern of arbitrary dimension into a topologically ordered map

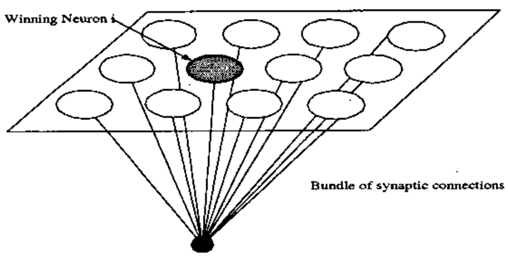

Fig. 2. Kohonen's SOM model

usually of one or two dimensions [8]. Three essential processes involved in the SOM are discussed in the subsection.

A. Competition Process

Fig. 2 shows Kohonen's two-dimensional SOM model, in which $\mathbf{X} = [x_1 x_2 \ldots x_m]^T$ denotes the input vector and $\mathbf{W}_j = [w_{j1}, w_{j2} \ldots w_{jm}]^T$, j = 1,2...l. denotes the synaptic weight vector connected from input vector to the neuron in the output layer, where m is the number of inputs and l is the number of neurons in the output layer. After computing the inner products $\mathbf{W}_j^T\mathbf{X}$, we pick the largest one and we declare it the winner of the competition. Thus, we determine the location where the topological neighborhood of the wining neuron is to be centered. Note that maximizing the inner product $\mathbf{W}_j^T\mathbf{X}$ is mathematically equivalent to minimizing the Euclidean distance between $\mathbf{X}$ and $\mathbf{W}_j$:

$$i(x) = arg \min_j \|\mathbf{X} - \mathbf{W}_j\|, j = 1, 2, \ldots, l \qquad (8)$$

where $\|\mathbf{X}\|$ is the norm of $\mathbf{X}$. We say the neuron i is the winning neuron for input $\mathbf{X}$. Based on the application, the response of the network could be either the index or synaptic weight vector of the winning neuron.

B. Cooperative Process

For human brain there is neurobiological evidence of lateral interaction among a set of excited neurons. SOM is similar to those that occur in the brain. To emulate human brain, we let some neighbors of the winning neuron be excited by the following rule: Let d_{ji} denote the lateral distance between the winning neuron i and the excited neuron j in the output layer, and let h_{ji} denote the topological neighborhood function of neuron i, here hji satisfies two requirements:

1) *it is symmetric about the winning neuron i.*
2) *it decreases monotonically with increasing d_{ji}, i.e.,*

$$\lim_{d_{ji}\to\infty} h_{ji} = 0.$$

A typical choice of h_{ji} is

$$h_{ji} = exp\{\frac{-d_{ji}^2}{2\sigma^2(n)}\} \qquad (9)$$

the effective width $\sigma(n)$ shrinks with time as

$$\sigma(n) = \sigma_0 exp\{\frac{-n}{\tau_1}\} \qquad (10)$$

where τ_1 is a time constant and σ_0 is a initial value. (9) and (10) determine which neighbor(s) will be excited. It is worth to note that the number of excited neighbors decreases with time, at the beginning, there are more than one neurons are involved in the learning process, as time going on, eventually there is only one neuron, the winning neuron, will be updated in the learning process. By using these functions, the SOM algorithm converges more quickly than a pure rectangular topological neighborhood function.

C. Adaptive Process

After locating the winning neuron and its excited topological neighbors, we then move their synaptic weight vectors $\mathbf{W}_j$ (s) towards input vector $\mathbf{X}$ by performing

$$\mathbf{W}_j(n+1) = \mathbf{W}_j(n) + \eta(n)h_{ji(x)}(n)(\mathbf{X} - \mathbf{W}_j(n)) \qquad (11)$$

where $\eta(n)$ is the learning rate, which starts at a small initial value η_0 and decrease with time n:

$$\eta = \eta_0 \cdot exp\{\frac{-n}{\tau_2}\} \qquad (12)$$

In our proposed method, the labelled channel states move towards currently detected symbol's channel states under the rule of SOM so that a better and stable receiver for CCI cancellation can be implemented.

V. Simulation and Results

Fig. 3 shows the system model we used for simulation in this paper, which consists of a random bit generator, a burst builder, a BPSK modulator, an up-sampler by 16, a pulse shaping filter

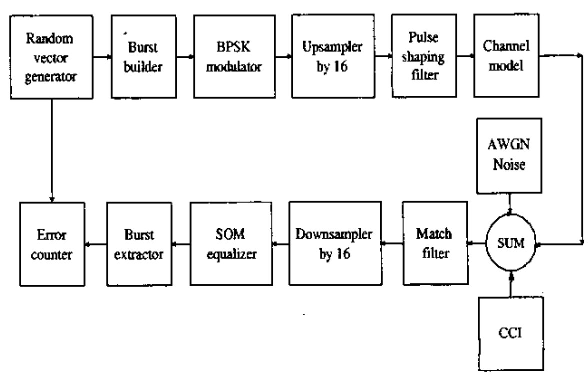

Fig. 3. System model used for simulation

TABLE II
THE BURST STRUCTURE USED IN THE SIMULATION

Guard bits	Unique Words	Info bits	Guard bits
10	13	1000	10

(a square root raised cosine filter with roll off factor 0.35), a Rayleigh fading channel model, a AWGN noise adder, a CCI interference generator, a match filter which is same as the pulse shaping filter, a down-sampler by 16, a SOM equalizer, a burst extractor, and a bit error counter.

The burst structure used in the simulation is show in Table II. It is 1033 BPSK symbols long, in which 1000 symbols are information symbols (payload). There are 10 guard bits at each end of the burst, and the 13 symbols unique words located just before the payload. The random bit generator generates a binary data stream with equally likely zeros and ones as the payload. The burst builder inserts unique word and guard bits, then makes a complete burst with 1033 bits which will be modulated to 1013 BPSK symbols.

UWs are designed as

$$UWs = \{1 -1 -1 \quad 1 \quad 1 -1 -1 \quad 1 \quad 1 -1 -1 \quad 1 \quad 1\}$$

from which 12 channel states can be generated using (5) with each state repeats 3 times. In the simulation, we assume that the channel order is 1 for all the channels and, all of which are subject to Rayleigh fading. The Rayleigh fading generator is based on Jakes' model [7] in which an ensemble of sinusoidal wave forms are added together to simulate the coherent sum of scattered rays with Doppler spread f_d arriving from different directions to the receiver, the number of oscillators to simulate Rayleigh fading is 62. Two cases are considered in our simulation. In the first case, Doppler spread f_d is chosen to be 10 Hz, signal-to-noise ratio (SNR) is fixed to be 20dB and the signal-to-interference ratio (SIR) varies from 15dB to 24dB. For the second case, Doppler spreading is changed to 20 Hz while SIR varies form 15dB to 24dB also. We compare our method with the NNC equalizer and plot the average bit error rate verse SIR in Fig. 4 and Fig. 5. A large improvement of the performance is achieved compared to that of NNC.

Note that in GSM system, UWs occupy 16.7% of the whole burst, while our system uses only 1.3% of the whole burst as UWs, and SOM equalizer performs acceptably with these 1.3% UWs. Therefore, it is possible to save bandwidth for the GSM system if our method were used in such a system. We can either increase the length of the burst while keep the same number of UWs or reduce the number of UWs and keep the length of burst the same, both ways decrease the portion of the UWs in a whole burst so that we saved bandwidth since UWs do not convey any user information.

VI. Conclusion

A SOM based adaptive equalizer is proposed to overcome ISI and CCI in TDMA cellular mobile communication system. Our method can adaptively track the fading channels. A considerable reduction in the required SIR for a certain BER is achieved by using our method compared to the NNC equalizer, while the computation complexity is kept similar and less number of unique words (less that 2% of one whole burst) is used to save bandwidths.

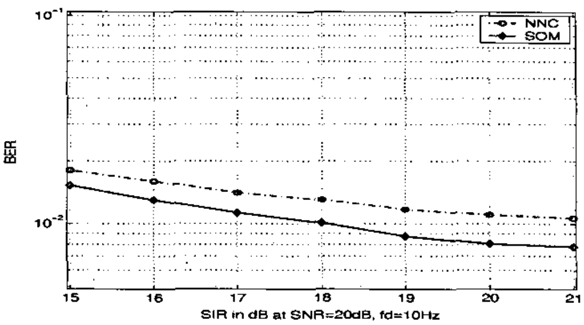

Fig. 4. Simulation result for fd=10Hz

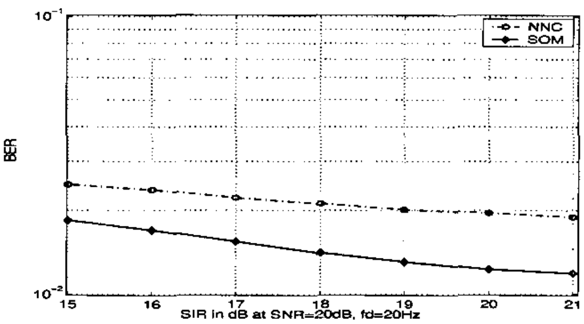

Fig. 5. Simulation result for fd = 20Hz

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