DEMODULATION FOR WIRELESS ATM NETWORK USING MODIFIED SOM NETWORK

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ABSTRACT

We study the demodulation problem in time division multiple access (TDMA) wireless asynchronous transfer mode (ATM) networks, where Rician flat fading channels are considered. A linear interpolation with decision feedback combined with a modified version of the self-organizing-map (LIDF-SOM) demodulator is proposed for such a system. We obtain the training sequence by exploiting medium access control (MAC) and data link control (DLC) protocols such that a semi-blind adaptive demodulator is implemented. Simulation results show that LIDF-SOM obtains $0.4-1.0$dB gain over Rician fading channels as compared to LIDF alone.

1. INTRODUCTION

Wireless Asynchronous Transfer Mode is the core of the future broadband integrated services digital network (B-ISDN). Many researchers have investigated wireless ATM physical layer design. The most important technical challenge facing ATM designers is how to compensate for time-varying impairments of radio channels [1]. Bao and Lang [2] proposed a blind channel estimation with decision feedback equalizer aided with MAC and DLC ATM protocols, and achieved better performance than the conventional blind equalizer. Liang [3] investigated a Type II fuzzy logic demodulator for time-varying channels. Unfortunately, both of these algorithms require a training epoch, which is not computationally efficient. A very popular scheme named LIDF, which was proposed by Viterbi [4], uses a maximum-likelihood method to estimate the phase gain of the channel. The training sequence (also called unique words (UWs)) is utilized to remove the phase ambiguity caused by the estimation procedure's inverse-tangent function. This method has been widely used in mobile communications with burst transmission. However, LIDF does not perform well for fading channels if the number of UWs are not enough since LIDF lacks adaptation property. SOM can generate a set of code book using a self organizing process, and it has been widely used for data compression but rarely used for communication systems. In this paper we propose a hybrid-structured LIDF-SOM demodulator, aided by the MAC and DLC protocols, for ATM networks. SOM is altered so that it is suitable to be used as a demodulator over fading channels. In Section 2, we discuss the channel model. In Section 3, the LIDF algorithm is reviewed. In Section 4 we describe a data mining technique. SOM and its modified version are introduced in Section 5. Simulation results are presented in Section 6, and we conclude this paper in Section 7.

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2. CHANNEL MODEL

Rician fading occurs when there is a strong specular (line of sight) signal in addition to the scatter (multipath) components. The received waveform in complex form is $r(t) = c(t) \cdot s(t) + n(t)$, where $n(t)$ is additive white gaussian noise with power spectral density $N_0/2$ (Watts/Hz) and $s(t)$ is the transmitted signal. The complex channel gain, $c(t) = c_I(t) + jc_Q(t)$, can be treated as a wide-sense stationary complex gaussian random process, where $c_I(t)$ and $c_Q(t)$ are Gaussian random processes with identical variance δ and non-zero means $m_I(t)$ and $m_Q(t)$, respectively. The phase of the channel gain is uniformly distributed between $-\pi$ and π, and the magnitude of the channel gain has a Rician distribution,

$$f_r(x) = \frac{x}{\delta^2} e^{(-\frac{x^2+s^2}{2\delta^2})} I_0(\frac{xs}{\delta^2}) \qquad x \geq 0 \tag{1}$$

where $s^2 = m_I^2(t) + m_Q^2(t)$, $I_0(\cdot)$ is the modified Bessel function of zeroth order, and x is a dummy variable. A Rician channel is characterized by the Rician factor K, which is the ratio of the direct path power to that of the multipath, i.e., $K = s^2/2\delta$, and the Doppler spread (or single-sided fading bandwidth) f_D. Also, the direct path is shifted in frequency by a factor of $0.7f_D$. The auto-correlation function associated with this channel is [3]

$$R_c(\tau) = \frac{K}{K+1} e^{j2\pi 0.7 f_D \tau} + \frac{1}{K+1} J_0(2\pi f_D \tau) \tag{2}$$

where $J_0(\cdot)$ is the Bessel function of zeroth order. The output of the matched filter sampled in time synchronism can be modelled as $r[k] = s_k \cdot c[k] + n[k]$, where s_k is the information symbol and $c[k]$ is the sampled complex-valued channel gain. QPSK modulation is assumed in this paper. In QPSK every 2 bits are mapped to 1 symbol as: $00 \to 1, 01 \to j, 11 \to -1$ and $10 \to -j$ so that s_k can be $1, j, -1$ or $-j$, where $j = \sqrt{-1}$. The noise at the output of the matched filter, $n[k]$, is an additive white gaussian noise (AWGN). We simulate the Rician fading channel using a direct path added to a Rayleigh fading generator. The Rayleigh fading generator is based on Jakes' model [5], in which an ensemble of sinusoidal waveforms are added together to simulate the coherent sum of scattered rays with Doppler spread f_D arriving from different directions to the receiver. The amplitude of the Rayleigh fading generator is controlled by the Rician factor K, and the number of oscillators for simulating the Rayleigh fading is 62.

3. REVIEW OF LIDF AND THE OPTIMAL RECEIVER

Fig.1 illustrates the general structure of the phase estimator used in LIDF [4]. Let the estimation period be T_E and let it encompass $2N+1$ m-ary symbols, where $T_E = (2N+1)T$ and T has a time duration of one symbol. Suppose we wish to estimate the phase at the midpoint of the estimation interval so that there are N samples before and after the sample whose phase is to be estimated. Obviously, for the $m > 1$ case, the phase takes on one of m different values during each successive symbol. In Fig. 1, the first box therefore performs $r'_{In} + ir'_{Qn} = F(\rho_n)e^{im\Phi_n}$, where $\rho_n = \sqrt{r_{In}^2 + r_{Qn}^2}$ and $\Phi_n = tan^{-1}(r_{In}/r_{Qn})$. Multiplying the phase by m and then dividing the arctangent function by m gives rise to an m-fold ambiguity in the phase estimate. This ambiguity can be removed by referring to the UWs. After estimating the phase of the received symbol, detecting the symbol is a hypothesis test procedure based on UWs which determine the decision boundary.

When QPSK modulation is used, it is well known that the probability of error for the optimal receiver over a white gaussian channel is $P_e = Q(\sqrt{E_s/N_0})$, where E_s is the symbol energy. If the channel is subject to Rician fading, however, we must average P_e over all possible received symbol energy $E_R = E_s|c|^2$, where $|c|$ is the magnitude of channel gain which is random. During the hypothesis test, an optimal receiver will use a varying decision boundary depending upon the received symbol, and will have to be adaptive. Assuming that we know the channel gain exactly, the performance of the optimal receiver in fading media can be analyzed by determining the probability of error for a given received symbol energy and then averaging over the known probability density function of E_R. Since $|c|$ follows a Rician distribution (1), $v = E_R/E_s = |c|^2$ then has a non-

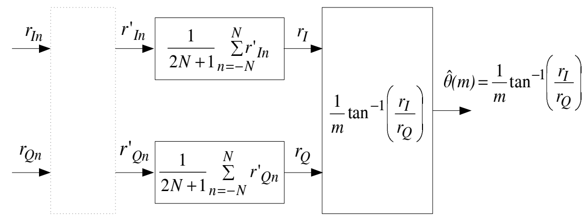

Fig. 1. Structure of phase estimator for m-PSK system

central chi-square distribution with 2 degrees of freedom,

$$f_V(x) = \frac{1}{2\delta}e^{-(s^2+x)/2\delta^2} I_0(\sqrt{x}\frac{s}{\delta^2}) \qquad (3)$$

where s, δ and $I_0(\cdot)$ have the same meaning as in (1). Now the probability of error expression becomes

$$P_{e,fading} = \int_0^\infty Q(\sqrt{\frac{E_s x}{N_0}}) f_V(x)dx. \qquad (4)$$

Note that LIDF lacks the adaptive process which is needed for an optimal receiver. For the slow flat fading considered in this paper, the envelope, though random from bit to bit, assumes a constant value over each bit interval. Furthermore, from the channel auto-correlation function (2), the channel gains among several bits are dependent with their extent determined by K and f_D. So it is possible to track the channel gain, and an adaptive decision boundary, even though it is not optimal, will be available for the hypothesis test. The optimal receiver, however, only exists theoretically since we don't know the channel gain exactly in real communications. It is known that in a SOM network the cluster centers (code book) are adaptively adjusted towards the input vectors. If we let the cluster center vectors and the input vector in a SOM network represent UWs and a received symbol in a demodulator respectively, it is possible to make UWs adapt to a fading channel. In the following sections, we introduce a method for obtaining UWs from protocols, give a brief review of SOM and describe how to tailor the SOM for demodulation.

4. OBTAINING UWS BY DATA MINING

In a real communication system, some training sequences (UWs), which are known to both transmitter and receiver, are intentionally sent from transmitter to receiver. The channel response can be estimated based upon the UWs by many methods such as Kalman filtering [6]. For the uplink in the ATM network, however, some known headers can be obtained from the MAC and DLC protocols based on Bao and Lang's idea [2], which is derived from NEC's WATMnet prototype [7]. These headers are known both to transmitter and receiver, so they can be used as UWs. However, since the known cell's header is mined from protocols, we cannot guarantee it contains all the QPSK symbol patterns: 1, j, -1 and $-j$. It is possible that we only have the 1 and -1 patterns. We developed the following method to overcome this limitation.

If we multiply the received symbol $r[k]$ by j^m, where $j = \sqrt{-1}$ and $m \in \{1, 2, 3\}$, we can get

$$j^m r[k] = j^m s_k c[k] + j^m n[k]. \quad (5)$$

Since $n[k]$ is AWGN, it's easy to prove that for a fixed value of m, $j^m n[k]$ is also AWGN with the same mean and variance. Observe that on the right hand side of (5), $c[k]$ is a channel gain, $j^m n[k]$ is AWGN and $j^m s_k$ is another QPSK symbol. Then $j^m r[k]$ is a new constructed QPSK symbol pattern for the case that $j^m s_k$ is transmitted through current channel. It is evident that if one pattern is available, it is possible to construct the other 3 patterns so that we can get all 4 QPSK symbol patterns. We then find the average of each of the 4 patterns and use them as the initial 4 symbol patterns of the UWs. The UWs determine the decision boundary which can be used in the hypothesis test. Note that the channel estimation procedure is not needed here.

5. SELF-ORGANIZING-MAP NETWORK

In this section, we first introduce the traditional SOM network, then we give a modified version of SOM which is suitable for adaptive demodulation. In the traditional SOM model [8], $\mathbf{x} = [x_1 x_2 \ldots x_m]^T$ denotes the m-dimensional input vector, $\mathbf{w}_j = [\mathrm{w}_{j1}, \mathrm{w}_{j2} \ldots \mathrm{w}_{jm}]^T$, $j = 1,2 \ldots l$. denotes the jth cluster center vector which is initialized randomly. For each input vector $\mathbf{x}$, we compute the inner product between $\mathbf{x}$ and $\mathbf{w}_j$ as $\mathbf{w}_j^T \mathbf{x}$. The ith center is declared to be the winning center if $\mathbf{w}_i$ has the largest inner product with $\mathbf{x}$. In addition, there are some neighbors of the winning center declared to be excited centers under the control of a topological neighborhood function h_{ji}. Letting $d_{ji} = |j - i|$ denote the lateral distance between the winning center i and the candidate center j to be excited, a typical choice of h_{ji} is $h_{ji} = exp\{-d_{ji}^2/2\sigma^2(n)\}$, where $\sigma(n)$ is the effective width of the topological neighborhood which shrinks with time n as $\sigma(n) = \sigma_0 exp\{-n/\tau_1\}$, here τ_1 is a time constant, and σ_0 is an initial value. After locating the winning center and its excited neighbors to $\mathbf{x}$, we move them towards the input vector by performing

$$\mathbf{w}_j(n+1) = \mathbf{w}_j(n) + \eta(n) h_{ji(x)}(n)(\mathbf{x} - \mathbf{w}_j(n)). \quad (6)$$

Here $\eta(n)$ is the learning rate, which starts at a small initial value η_0 and decreases with time n as $\eta = \eta_0 \cdot exp\{-n/\tau_2\}$, where τ_2 is a time constant. $\mathbf{w}_j(n)$ represents the winning or an excited center's vector.

SOM is a clustering method, in which the winning and excited cluster center vectors move towards the incoming data samples. The cluster centers finally converge to the locations that represent the probability distribution of the data [9]. Recall that in section 3 the optimal receiver for fading channels must be adaptive, can we adapt UWs to the received symbol by the SOM rule above?

We can adopt SOM directly to the demodulation problem. In a 4 cluster centers SOM network, for example, we can use the 4 center vectors and the input vector to represent UWs and the received symbol in a demodulator. We then move the winning and excited UWs towards the received symbol by performing (6) to adjust the decision boundary. However, from section 4 we know that we can construct the other received QPSK symbols using the currently demodulated one. Based on this idea we modified (6) as

$$\mathbf{w}_j(n+1) = \mathbf{w}_j(n) + \eta(n) h_{ji(x)}(n)(\mathbf{x} - \mathbf{w}_i(n)). \quad (7)$$

The difference between them is that $\mathbf{x} - \mathbf{w}_j(n)$ in (6) is changed to $\mathbf{x} - \mathbf{w}_i(n)$ in (7), where $\mathbf{w}_i(n)$ denotes the winning UW, and $\mathbf{x}$ denotes the received symbol in the demodulation problem. By doing this, we rotate the winning and excited UWs in the same direction but with a different magnitude in the QPSK signal constellation (note that the rotation direction is controlled by $\mathbf{x} - \mathbf{w}_i(n)$ which is fixed, while the rotation magnitude is computed by $h_{ji(x)}$ that is different for each UW). The motivation behind this modification is that there are four groups of QPSK symbols at the receiver side, and each group of symbols is detected based on their corresponding UW by a minimum distance criteria in the hypothesis test. The modified SOM is equivalent to that we construct a QPSK symbol based on the received one for each excited UW, then make each excited UW move towards its corresponding constructed symbol. Therefore, the winning and excited UWs move towards and finally converge to their corresponding group centers. However, if we use the original SOM, the excited UWs may move towards another group's center so that it is not as suitable as the modified version of SOM for demodulation. The other rules in traditional SOM are unchanged and they warrant the convergence of our algorithm.

6. SIMULATION STUDIES

Here we study the uplink demodulation problem for an ATM network, where QPSK modulation is considered. The standard ATM data cell is 53 bytes long [7]. In our paper we assume that the known header is 2 bytes, which is equivalent to 8 UWs and 216 information symbols. We then concatenate 5 such cells into a burst. At the beginning of each cell inside a burst, we re-initialize the UWs using the known cell header such that the propagation error is blocked through the cell. The LIDF-SOM algorithm is described as follows,

1. Calculate the initial UWs from the known cell header using the data mining technique.
2. Use LIDF ($N = 32$) to detect the received symbol.

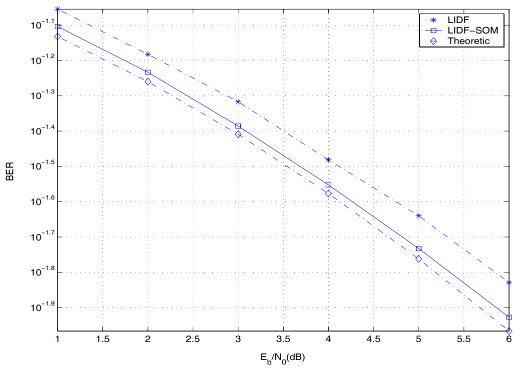

Fig. 2. Simulation results for $K = 9$dB, $f_D = 20$Hz

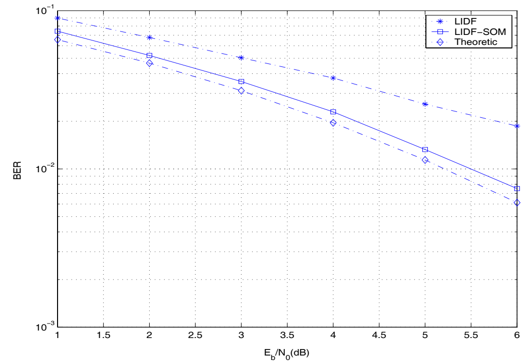

Fig. 3. Simulation results for $K = 12$dB, $f_D = 100$Hz

3. Adapt the UWs to the received symbol using the modified version of SOM.
4. If we have reached the end of a cell, go to 1. If we have reached the end of the burst, stop. Otherwise go to 2.

We compared our algorithm to LIDF and the theoretical bit error rate (BER) calculated from (4). Two Rician channels were studied: one with Rician factor $K = 9$dB and doppler shift $f_D = 20$Hz; and the other one with Rician factor $K = 12$dB and doppler shift $f_D = 100$Hz. For each channel we ran our simulation for different values of E_b/N_0(dB), where $E_b = E_s/2$ is the bit energy. The performances of LIDF and LIDF-SOM for both channels are plotted in Fig. 2 and 3 respectively. It is clear that our algorithm outperforms LIDF and approaches the theoretical BER. For the first case, the SNR in LIDF-SOM only has roughly 0.15dB loss from the theoretical value at BER = 4%, where LIDF has about 0.55dB loss. For the second case, LIDF cannot perform well because the transmitted signal is severely distorted by the channel, and the information of the channel provided by such a limited number of UWs is not enough to obtain a good estimate for the channel. As described in section 3, the optimal receiver for a fading channel requires adaptive decision boundary. Therefore if we adapt UWs as in the LIDF-SOM algorithm, the BER can still approach the theoretical value and we achieve about 1dB gain over LIDF. Note that though the SOM has a training process with several iterations involved, our method does not go through the training process but instead utilize the SOM as an adaptation process. Therefore, the training phase was competed at the same time as the detection procedure.

7. CONCLUSIONS

Using a modified SOM based demodulator, an adaptive and near-optimal receiver is implemented for an ATM system. Our algorithm avoids training or channel estimation, which is required by many other receivers. UWs are not required at the transmitter. Instead, we obtain them by a data mining technique. Even though the computational load of our method is slightly more than that of LIDF, it is worthwhile to pay that cost for the performance gains we have obtained.

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