ADAPTIVE RECEPTION OF WIRELESS CDMA SIGNALS USING EMPIRICAL DETECTION

Lin Yue and Don H. Johnson

Computer & Information Technology Institute
Department of Electrical & Computer Engineering
Rice University
Houston, Texas 77005-1892

ABSTRACT

Channel characteristics of practical code division multiple access (CDMA) systems are usually unknown and difficult to model accurately. Type-based receivers, without assuming any *a priori* model, extract signals successfully from background noise. In this paper, we develop type-based receivers that address two major issues in CDMA signal reception: multiple access interference and multipath fading. We first present the type-based receiver with interference suppression capability, assuming the knowledge of the code and timing of the intended user only. We then show that equal-gain combining (EGC) of type-based statistics is the asymptotically optimal technique for diversity empirical detection. Compared with maximal ratio combining of matched filter outputs, the diversity receiver with EGC of type-based statistics assumes less channel knowledge and yields competitive detection performance in Gaussian noise and better performance in Laplacian noise.

1. INTRODUCTION

In the wireless communication environment, where channel modeling can be a real challenge, blind receivers and receivers based on training data provide attractive alternatives to "clairvoyant" receivers. Specifically, for the downlink (from base station to mobile) of CDMA communications, the receiver has to extract its intended user's signal and in doing so it must effectively suppress the unknown interference from other users and the unknown noise. The matched filter receiver has the simplest structure, but its performance suffers from the well-known near-far problem. One of the blind receivers that have attracted much attention recently– the blind adaptive multiuser detector (BAMD) [4] – implements the multiuser linear minimum mean squared error detector [7] through multi-dimensional blind adaptation. Unfortunately, the adaptation is slow and the signal-to-interference ratio exhibits large variance even after adaptation.

We investigate the universal classification theory [3] and its induced asymptotically optimal detectors based on empirically observed sequences. The basic idea of universal classification is to infer the underlying probabilistic model of the source through training sequences, without assuming any *a priori* models, and to classify the test sequence based on the non-parametric model inferences obtained. For digital communication systems using direct sequence spread spectrum (DS/SS), the baseline type-based receiver yields competitive error performance with reasonable amount of training data in additive white noise [5, 12]. In a CDMA system with multiple access interference (MAI), however, such a receiver requires extremely large signal-to-noise ratio (SNR) for signal detection [6]. We propose a quantizer design criterion for type-based receivers and improve the baseline receiver through quantizer optimization during training to achieve good MAI suppression performance. The improved empirical receiver outperforms the matched filter receiver and blind receivers in the reasonable SNR region.

Another major issue in wireless communication is the multipath fading effect. Diversity reception is one of the most powerful techniques that combat fading effectively. Among linear combining schemes, maximal ratio combining (MRC) of received signals from each diversity branch achieves the maximal SNR and thus sets the performance limit. For type-based detection, we observed previously through simulations the performance gain by MRC of multiple type-based statistics [12]. We reexamine the empirical data based diversity detection problem analytically in this paper and show that the generalized likelihood ratio test (GLRT) leads to equal-gain combining (EGC) of type-based statistics as the asymptotically optimal scheme. We compare the EGC diversity type-based receiver with the MRC diversity matched filters in both Gaussian and Laplacian noise, and demonstrate the effectiveness of type-based receivers in diversity reception.

By suppressing the MAI at each diversity branch individually and combating the fading through multiple-branch EGC, the type-based receiver we propose provides a promising receiver structure for signal reception in situations such as the wireless CDMA downlink.

2. BASELINE TYPE-BASED RECEIVER

Based on empirically observed sequences, a *type* is the information theory term for the histogram estimate of the underlying discrete probability function [1]. Denote by $\widehat{P}_{\mathbf{x}}$ the type of sequence $\mathbf{x}$ (length-n) generated according to P; then $\widehat{P}_{\mathbf{x}}(x) = \frac{1}{n}\sum_{j=1}^{n} \mathrm{I}(x = \mathbf{x}_j)$, $x \in \mathcal{A}$, a finite alphabet. $\mathrm{I}(\cdot)$ is the indicator function.

We briefly explain the universal classification theory for discrete stationary Markov source [3] by a two i.i.d. sources example. Given training sequences $\mathbf{t}_i$ (length N) from sources i, $i = 0, 1$ respectively, and a test sequence $\mathbf{x}$ (length n) to be classified, the type-based detector considers

$$S_i = \frac{N+n}{n} H(\widehat{P}_{\{\mathbf{t}_i,\mathbf{x}\}}) - \frac{N}{n} H(\widehat{P}_{\mathbf{t}_i}), \quad i = 0, 1,$$

where $\widehat{P}_{\{\mathbf{t}_i,\mathbf{x}\}} = \dfrac{N\widehat{P}_{\mathbf{t}_i} + n\widehat{P}_{\mathbf{x}}}{N+n}$, and $H(\cdot)$ is the entropy estimate. The decision is made by choosing the minimum of the sufficient statistics S_0 and S_1. Type-based detection is asymptotically optimal for detection based on empirically observed sequences [3].

The application of type-based detection to DS/SS signal reception was first studied in a very simple scenario, BPSK signal reception in additive white noise [5]. The type-based receiver solves the binary hypothesis testing problem (bit 0 or bit 1). The receiver uses training sequences from each hypothesis during preamble reception to estimate the underlying probability distributions, and bit detection is done based on these estimates upon the reception of n (the processing gain) test chips. Figure 1 illustrates the receiver structure.

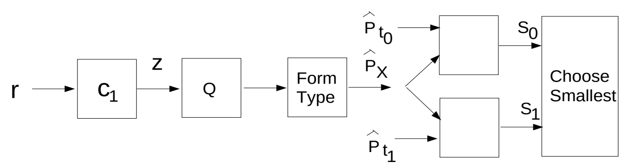

Figure 1. Type-based receiver. We consider the BPSK signaling and BPSK spreading scheme. The conventional chip matched filter output of the received signal is sampled at chip rate to obtain a length-n vector $\mathbf{r}$, the input to the type-based receiver. The sequence $\mathbf{r}$ is first de-spread with the intended user's code (say, $\mathbf{c}_1$) to get $\mathbf{z} = \mathbf{r}.{*}\mathbf{c}_1 = [\mathbf{r}(\mathbf{1}){*}\mathbf{c}_1(1), \ldots, \mathbf{r}(\mathbf{n}){*}\mathbf{c}_1(n)]$, which is then quantized into a finite-sized alphabet to form a type. The sufficient statistic S_i obtained based on training types and test types determines the bit decision.

3. IMPROVED TYPE-BASED RECEIVER

3.1. Optimization for Interference Suppression

In applying the type-based detection theory to communications, the discrete source constraint requires a front-end quantizer in the receiver because the components of the received vector $\mathbf{r}$ have continuous values and must be quantized before forming types. Although we found that a simple pre-determined quantizer works well in the noise-only environment [5, 12], extremely large SNR per bit (about 40dB) is required in MAI for the type-based receiver to outperform matched filter [6]. Since Markov representation for the intended user is impossible due to the unknown interference, the key step in type-based receivers is to reject MAI via quantization. More sophisticated quantization optimization is necessary for the type-based receiver to suppress MAI, especially when the number of quantization intervals is small.

Let $p_i, i = 0, 1$ be the true probability distribution of the received signal under bit 0 and bit 1 respectively, and $\widehat{P}_{\mathbf{t}_i}, i = 0, 1$ be the corresponding type obtained from the quantized training sequences. From the classic binary hypothesis testing theory, Stein's lemma states that the Neyman-Pearson criterion leads to detectors such that if the error probability under hypothesis 1 is fixed then the error probability under hypothesis 0 decays exponentially with the test sequence length at the rate of $D(p_1||p_0)$, the Kullback-Leibler (KL) distance between p_1 and p_0. For type-based detection, the asymptotic error rate is closely related to KL distances [3]. Based on these results, and considering the fact that bit 0 and bit 1 have equal importance in communication systems, we set the criterion that the optimal quantizer for type-based detection is the one that achieves the best error rate under *both* hypotheses. Mathematically, the optimal quantizer Q is given by

$$\arg\max_{Q} \min(D(Q(p_0)||Q(p_1)), D(Q(p_1)||Q(p_0))).$$

Although a quantizer that maximizes an Ali-Silvey distance measure (KL distance, for example) of the quantized distributions can always be chosen to be a so-called likelihood ratio quantizer [11], the design of such a quantizer requires *a priori* knowledge of the distributions. To be precise, our problem is

$$\arg\max_{Q} \min(D(\widehat{P}_{\mathbf{t}_0}||\widehat{P}_{\mathbf{t}_1}), D(\widehat{P}_{\mathbf{t}_1}||\widehat{P}_{\mathbf{t}_0})),$$

where the quantization is performed on training sequences rather than true distributions. Consider the numerical optimization of the quantizer during the training period. If we fix the number of quantization intervals q, the quantizer optimization process is at most $q-1$ dimensional, since it is sufficient for the output levels of the quantizer to be distinct *letters* as opposed to *values* for types and thus only the input levels need to be optimized. While q depends on power levels of all users, we found that a small number is usually sufficient for the optimized quantizer to set its input levels to mimic the the underlying distributions, and thus to suppress MAI successfully.

We compare the performance of the above improved type-based receiver with that of the matched filter and the BAMD[1] in MAI plus additive noise. The spreading codes are length-31 Gold codes with random shift

[1] The BAMD [4], which can be viewed as a blind adaptive implementation of the multiuser LMMSE detector [7], aims at the minimization of the mean squared error through an n (usually bigger than q) dimensional optimization process. This detector has many desirable properties and is expected to be among the most likely candidates for practical application of multiuser detection [9]. For performance analysis of BAMD, see also [8].

uniformly on $[0, n-1]$, and remain the same from bit to bit. It should be pointed out that type-based receivers can cope with time-varying codes, such as the long pseudo-noise (PN) sequence codes proposed in IS-95, without any difficulty. All the $K-1$ interferers have the same power, and a 1-D quantization optimization is done with a $2K$ interval quantizer for the type-based receiver (since the uniform quantizer with the best step size is optimal in this case because of the interference structure). The bit-error rate (BER) is obtained by Monte-Carlo simulations after the adaptation or the training period of 128 bits.

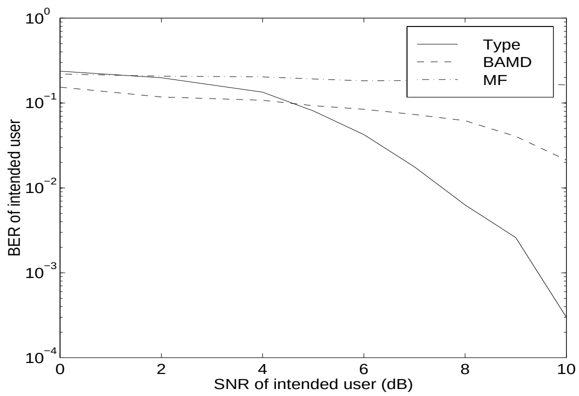

Figure 2. A 3-user system is simulated in Gaussian noise. Each interference power is 15 times as strong as the intended user. BER of the intended user is plotted as a function of its SNR.

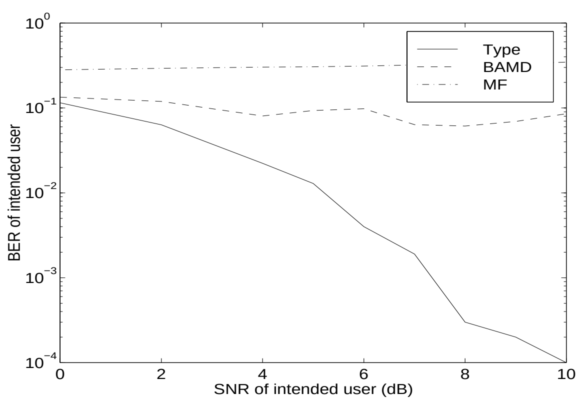

Figure 3. Same interference scenario as in figure 2, but in Laplacian noise. Generally speaking, the type-based receiver outperforms $\boldsymbol{L}^2$ receivers in non-Gaussian noise.

Consistent with our previous findings [5, 12] that the type-based receiver performs better in non-Gaussian noise, we found that it tracks the BAMD in Gaussian noise and outperforms it in non-Gaussian noise (figure not included). The MAI rejection performance of our receiver is superior both in the large SNR region (figure 2) and in non-Gaussian noise (figure 3). Additional results (figure not included) show that the BER of the type-based receiver is relatively insensitive to the number of interfering users and in near-far situations.

3.2. Diversity

In situations where multiple simultaneous receptions of an intended user's signal are available, rake-like receivers that combine different versions of the signal can greatly improve performance [10]. For example, space (or path) diversity techniques can be employed to overcome the severe consequences of fading. Assume the relative delays of each path (branch) have been acquired, then the task is simply to seek the optimal combining technique for synchronized multiple versions of the signal for detection.

We posed the diversity problem in a soft handoff setting, i.e., the simultaneous signal reception at multiple base stations in [12] and simulated the MRC of type-based statistics. While the MRC of received signals directly achieves the maximal combined SNR for any linear combining schemes (e.g. see [2]), and consequently, so does the MRC of the soft decisions of *linear* detectors, such operation on soft decisions of *non-linear* detectors (type-based statistics, for example) is solely based on intuition. In this section, we obtain the combining scheme that guarantees good performance by deriving the asymptotically optimal detector based on empirical data, when the multiple receptions are statistically independent.

Denote the *unknown* underlying probability distributions of the i^{th} branch reception $P_0^{(i)}$ when bit 0 is sent, and $P_1^{(i)}$ when bit 1 is sent, where $P_0^{(i)}, P_1^{(i)} \in \mathcal{P}$, discrete stationary Markov sources of known order. Again, the bit detection is a binary-hypothesis testing problem. Given training sequences $\mathbf{t}_0^{(i)}$, $\mathbf{t}_1^{(i)}$ (length N) under the two hypotheses respectively, and test sequence $\mathbf{x}^{(i)}$ (length n) from branch i, $i = 1, \ldots, B$, where B is the number of multiple receptions, the generalized likelihood ratio test (GLRT) considers

$$P_0 = \max_{P_0^{(i)}, P_1^{(i)}} \left(\prod_i P_0^{(i)}(\mathbf{r}^{(i)}) \prod_i P_0^{(i)}(\mathbf{t}_0^{(i)}) \prod_i P_1^{(i)}(\mathbf{t}_1^{(i)}) \right),$$

$$P_1 = \max_{P_0^{(i)}, P_1^{(i)}} \left(\prod_i P_1^{(i)}(\mathbf{r}^{(i)}) \prod_i P_0^{(i)}(\mathbf{t}_0^{(i)}) \prod_i P_1^{(i)}(\mathbf{t}_1^{(i)}) \right),$$

where $i = 1, \ldots, B$. Solving the GLRT by assuming equal-probable hypotheses, we obtain the following functions of training and test types

$$S_0 = \sum_{i=1}^{B} \left(\frac{N+n}{n} H(\widehat{P}_{\{\mathbf{t}_0^{(i)}, \mathbf{x}^{(i)}\}}) - \frac{N}{n} H(\widehat{P}_{\mathbf{t}_0^{(i)}}) \right),$$

$$S_1 = \sum_{i=1}^{B} \left(\frac{N+n}{n} H(\widehat{P}_{\{\mathbf{t}_1^{(i)}, \mathbf{x}^{(i)}\}}) - \frac{N}{n} H(\widehat{P}_{\mathbf{t}_1^{(i)}}) \right),$$

and the decision rule is to choose the smallest. Here, the type $\widehat{P}_{\{\mathbf{t}_1^{(i)}, \mathbf{x}^{(i)}\}}$ is a linear combination of $\widehat{P}_{\mathbf{t}_j^{(i)}}$ and $\widehat{P}_{\mathbf{x}^{(i)}}$ as in the single-branch case in section 2. Compared with the single-branch decision rule, the multiple-branch type-based receiver performs equal-gain combining of type-based statistics obtained from each single-branch type-based receiver.

The performance comparison of diversity reception is shown below by a two-branch example in additive white noise. In Gaussian noise, the MRC of matched filter outputs is optimal, and it sets the performance limit in figure 4. The EGC of type-based statistics is only asymptotically optimal. It tracks the optimal performance without assuming any channel model. The performance of EGC of *matched filter* outputs is much worse, however, due to the different characteristics of the two branches. Thus, the type-based receiver is at advantage where EGC is preferred to MRC[2]. In Laplacian noise (figure 5), as always, the type-based receiver greatly outperforms matched filter. At the BER of 10^{-3}, type-based diversity receiver gains about 2dB and 3dB over MRC and EGC of matched filter outputs respectively.

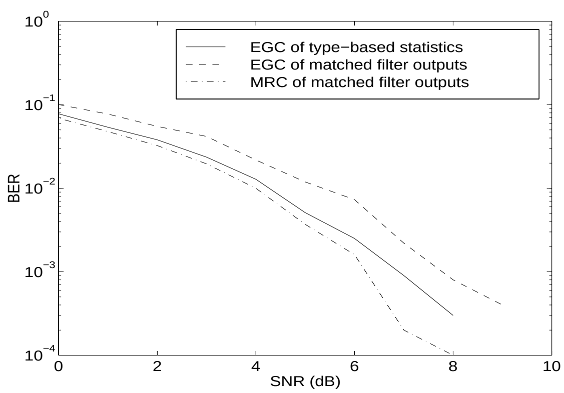

Figure 4. A 2-branch system is simulated in Gaussian noise. The BER is plotted against the SNR of one branch, and the other branch's SNR is 12dB worse. The results are based on 10^4 Monte-Carlo simulations.

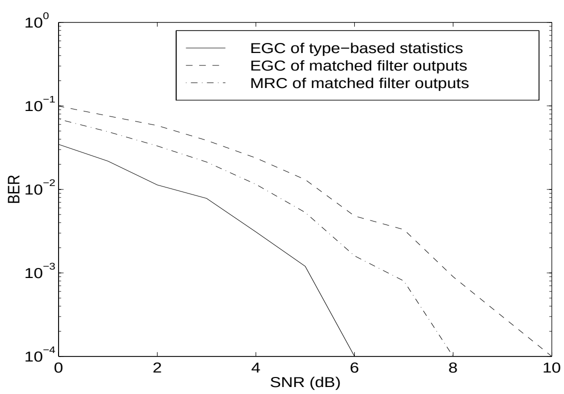

Figure 5. Same scenario as in figure 4, but in Laplacian noise. EGC of type-based statistics outperforms linear schemes.

[2] MRC weighs the reception at branch i by $A^{(i)}/(\sigma^{(i)})^2$, where $A^{(i)}$ is the received signal amplitude, and $(\sigma^{(i)})^2$ is the noise power [2]. EGC does not require these channel knowledge.

4. CONCLUSION

Type-based receivers do not require any *a priori* model, and yield impressive detection performance. We improved the baseline type-based receiver through quantizer optimization so that MAI is effectively suppressed. EGC of type-based statistics yields the asymptotically optimal diversity scheme for empirical data based detection. Such multiple-branch reception is expected to combat fading effectively. Note that the quantizer design is specific to each branch since each branch provides the type-based statistic through single-branch detection independently. Thus, when MAI is present, the quantization optimization process we presented applies directly to multiple-branch reception. These two results together, by addressing the two major issues of CDMA single-user signal reception, suggest a practical receiver structure.

REFERENCES

[1] T. M. Cover and J. A. Thomas. *Elements of Information Theory.* John Wiley & Sons, Inc., 1991.

[2] V.K. Garg and J.E. Wilkes. *Wireless and Personal Communication Systems.* Prentice Hall, 1996.

[3] M. Gutman. Asymptotically optimal classification for multiple tests with empirically observed statistics. *IEEE Trans. Info. Th.*, 35:401–408, 1989.

[4] M. Honig, U. Madhow, and S. Verdu. Blind adaptive multiuser detection. *IEEE Trans. Info. Th.*, IT-41:944–960, 1995.

[5] D.H. Johnson, Y.K. Lee, O.E. Kelly, and J.L. Pistole. Type-based detection for unknown channels. *ICASSP'96*, pages 2475–2478, 1996.

[6] Y.K. Lee, D.H. Johnson, and O.E. Kelly. Type-based detection for spread spectrum. *ICC'97*, 1997.

[7] U. Madhow and M. I. Honig. MMSE detection of CDMA signals. In *International Symposium on Information Theory*, page 49, 1993.

[8] D.A. Pados and S.N. Batalama. Low-complexity blind detection of DS/CDMA signals: Auxiliary-vector receivers. *IEEE Trans. Comm.*, submitted, 1997.

[9] H.V. Poor and S. Verdu. Probability of error in MMSE multiuser detection. *IEEE Trans. Info. Th.*, 43:858–871, 1997.

[10] J.G. Proakis. *Digital communications.* McGraw Hill, 1995.

[11] John N. Tsitsiklis. Extremal properties of likelihood-ratio quantizers. *IEEE Trans. Comm.*, 41(4):550–558, April 1993.

[12] L. Yue and D.H. Johnson. Type-based detection in macro-diversity reception for mobile radio signals. *ICASSP'97*, pages 4013–4016, 1997.