WIRELESS COMMUNICATIONS AND MOBILE COMPUTING
Wirel. Commun. Mob. Comput. 2002; **2**:751–761 (DOI: 10.1002/wcm.80)

Channel estimation and interference suppression for space–time coded systems in frequency-selective fading channels

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Summary

It is of great interest to provide high data rate services in wireless communication systems. In order to support such services, it is desirable to extend space-time (ST) coding, originally proposed for known, frequency-nonselective fading channels, to unknown, multipath channels. In this paper, we consider the problem of interference suppression for wireless TDMA (time division multiple access) systems equipped with multiple transmit antennas and receive antennas in frequency-selective fading channels. A novel scheme with space-time block coding based transmit diversity (STTD) is presented to estimate the multipath channel, coherently demodulate information symbols, and meanwhile suppress radio interference. The proposed scheme is simple to implement and able to mitigate interference of various origins, including intersymbol interference (ISI), cochannel interference (CCI), and others. Numerical examples are presented to illustrate the performance of the proposed estimator and detector in multipath Rayleigh-fading channels. Copyright © 2002 John Wiley & Sons, Ltd.

KEY WORDS

interference suppression
equalization
space–time coding
transmit diversity

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Contract/grant sponsor: New Jersey Center for Wireless Telecommunications (NJCWT).

1. Introduction

The rapid growth of digital wireless communications gives rise to an increasing demand for wideband high data rate communication services, which creates new challenges in the development of telecommunication systems, as shown in Reference [1].

Wireless cellular systems are known to suffer from various sources of interference, such as cochannel interference (CCI) due to frequency-reuse and intersymbol interference (ISI) caused by multipath propagation, which may degrade the system performance significantly. Therefore, simple and effective interference suppression techniques are required to mitigate the interferences for a high-quality signal reception.

The effectiveness of interference suppression and signal separation relies on the capability of separating the desired user from CCI while canceling ISI. Several interference reduction and equalization schemes have been proposed in the past. For example, joint detection of all cochannel signals (e.g. References [2,3] and references therein) was found to yield an excellent performance at the cost of computational complexity. In addition, the performance of the algorithm detailed in Reference [3] suffers when the cochannel signal levels are comparable. In particular, the complexity of optimum joint demodulation increases exponentially as the number of users increases [4]. Another approach is through channel coding, which exploits time diversity provided by channel codes and trades bandwidth for interference cancellation [5,6].

When multiple antennas are affordable, spatial receive diversity can be used to effectively suppress interference without bandwidth expansion [7–9]. This diversity technique has been shown to be beneficial in improving the tolerance of a receiver to CCI by exploiting the decorrelation of fading on both the desired user and the undesired interferers at different antennas. Winters [7] developed a diversity combining technique in the presence of interference using minimum mean-squared error (MMSE) criterion considering spatial domain covariance. In Reference [9], a method was introduced, which allows CCI suppression and equalization to be treated separately by designing an analogical spatial-temporal matched filter. It was shown in Reference [8] that when optimum combining is applied, N_r receive antennas can be used to null out $N_r - 1$ interferers in flat Rayleigh-fading channels.

While the algorithms using receive diversity are well documented, transmit diversity is a relatively new and attractive topic. Recent research in information theory has shown that large gains in capacity and reliability of communications over wireless channels could be achieved by exploiting the spatial diversity made possible by multiple antennas at both the transmit and receive sides [10]. Two approaches have emerged to implement transmit diversity. One approach, known as BLAST (Bell Labs Layered Space-Time) [11,12], features a layered architecture, which can achieve massive parallel transmission and very high data rates by using a large number of antennas at the transmitter and at the receiver. The BLAST approach has reasonable complexity; however, its performance is not optimized for diversity and coding gain. It also suffers from error propagation. As an effective transmit diversity technique, space-time block coding (STBC) [13,14] has been gaining more and more attention recently due to the attractive characteristics offered by exploiting the spatial and temporal diversity, in addition to channel coding, to provide diversity ability over an uncoded system without sacrificing the bandwidth and to increase the effective transmission rate as well as the potential system capacity.

Space-time codes were originally designed to provide a certain diversity order assuming frequency nonselective fading channels that are perfectly known to the receiver [13,15,16], but the assumption of flat-fading is not always justified, especially for wideband high data rate transmissions. More generally, in an environment with several cochannel users, there exist cochannel interfering signals at the receive side. Therefore, channel equalization and CCI suppression are required to improve the signal reception performance. It is also noted that interference in space-time coded systems is more severe than that in single-antenna systems resulting from the interference between antennas. For a system with $N_i + 1$ users in which each is equipped with N_t transmit antennas, multiuser interference (MUI) is composed of $N_i N_t$ interfering signals, rather than N_i interfering signals in a single antenna system [17,18]. By taking advantage of the spatial and temporal structure of STBC, the number of receive antennas that are required to suppress the interference can be decreased dramatically compared with the classical interference cancellation methods [8] while maintaining the same diversity order.

Though some zero-forcing (ZF) and minimum mean-square error (MMSE) methods have been proposed to mitigate interference and detect signals [19,20], they suffer complexity resulting from the requirement of channel knowledge of both the desired user and the interfering signals in addition to covariance information.

Moreover, the channel state information (CSI), which is utilized to decode the received signals and restore the initial transmitted values, is unknown in practice and has to be estimated.

Many research efforts over the past years focus on the areas in which *a priori* knowledge is not available to the receivers [21] and the desired information is estimated and detected blindly. Among these blind estimation techniques, subspace-based algorithms, such as MUSIC [22] and ESPRIT [23], were developed without considering any knowledge of the input signals except for some general statistical properties such as the second-order ergodicity. However, these two algorithms have restricted applicability in wireless systems due to the requirement that the signal waveforms including multipath reflections be less than the number of antennas. Several conditional or unconditional estimators are also devised for such blind applications. The unconditional estimators, such as the unconditional maximum likelihood (ML) estimations, model the unknown signals as random processes [24]. The conditional estimators, such as the conditional ML estimators, model the unknown signals as unknown deterministic parameters [24–27]. In References [25,26], ML estimation in a receive diversity system was solved blindly with no prior estimate of CSI using two iterative block algorithms: iterative least-squares with projection (ILSP) and iterative least-squares with enumeration (ILSE). Both of them have a lower computational complexity. But to guarantee unique signal estimates, the number of signals was assumed not to exceed the number of antennas, and the channel was assumed constant over a sufficiently large number of signal snapshots. In Reference [27], the problem of a nondispersive flat-fading channel estimation was considered, which was based on the same idea of References [25,26] and was able to obtain similar bit error rate (BER) performance, but with a significantly lower computational load compared to ILSP by treating one signal at a time and solving a weighted least-squares problem.

But in some applications especially in a mobile communication system, *a priori* knowledge is known to the receivers, although the actual transmitted symbol stream is unknown. In such a system, a known preamble is added to the message for training purposes. Such extra information may be exploited to enhance the accuracy of the estimates and may be used to simplify the computational complexity of the estimation algorithms. Therefore, besides the blind estimation methods, training (pilot)-aided methods can be found in the literature on various estimation problems, for example, References [28,29]. Maximum likelihood estimation can be found in Reference [30], where a reduced-rank multivariate linear regression problem was treated with some known input variables. Regression coefficients and equation noise were estimated through an ML estimator. Another training-aided technique can be found in Reference [31], where adaptive array processing was developed to track the channel and the interference covariance matrix using the initial estimates obtained with training symbols. More information about non-blind algorithms is provided in Reference [32].

Channel estimation in ST coded systems, however, is more challenging than that in single antenna systems since the number of unknown channel coefficients to be estimated increases proportionally to the number of transmit antennas. Therefore, effective and efficient channel estimation schemes are critically important. Although the recently proposed differential ST coding algorithms for frequency-nonselective channels (e.g. References [33,34] and references therein) obviate the requirement for channel estimation and, therefore, are particularly attractive in fast-fading environments when channel estimation becomes very difficult or even infeasible, differential decoding of ST codes suffers approximately a 3 dB penalty in signal-to-noise ratio (SNR) compared to coherent decoding, which requires channel information. Hence, channel estimation is well motivated, especially in cases when the channel experiences relatively slow fading, and channel estimation is more reliable.

Several optimum combining/processing schemes such as those considered in References [8,9,19] require CSI for *all* cochannel users, which may be difficult to obtain. Therefore, this paper investigates a combined transmit diversity, equalization, and CCI suppression strategy. It presents effective and computationally efficient CSI estimation and ISI and CCI suppression techniques by using the ML estimator and exploiting the structure of STBC for systems that involve two transmit antennas and N_r receive antennas along with N_i cochannel interferers. The results can be easily extended to more than two transmit antennas using general STBC discussed in Reference [14]. In Section 2, the data model for such systems is formulated. Then, an ML estimator is presented in Section 3, and the corresponding interference suppression and signal detection algorithm is proposed. A simplified computational method of matrix multiplication is given. Numerical examples are presented in Section 4 to illustrate the performance of the proposed channel estimator and linear receiver in multipath Rayleigh-fading channels. Finally, Section 5 gives the conclusions.

Notation. Vectors (matrices) are denoted by boldface lower (upper) case letters; all vectors are column vectors; superscripts $(\cdot)^*$, $(\cdot)^T$, and $(\cdot)^H$ denote the complex conjugate, the transpose, and the conjugate transpose, respectively; $\mathbf{I}_N$ denotes the $N \times N$ identity matrix; $\mathbf{0}$ denotes an all-zero vector (matrix); $|\cdot|$ and $\|\cdot\|$ denote the matrix determinant and the vector (matrix) 2-norm, respectively; $E[\cdot]$ denote statistical expectation; $\otimes$ denotes the matrix Kronecker product; $\text{diag}(\cdot)$ denotes a diagonal matrix; finally, $\lceil\cdot\rceil$ denotes the smallest integer no less than the argument.

2. Problem Formulation

2.1. System Model

Consider a wireless cellular system equipped with $N_t (N_t \geq 2)$ transmit antennas and $N_r (N_r > 1)$ receive antennas in frequency-selective fading channels. Alamouti's ST coding scheme [13] is assumed, which utilized $N_t = 2$ transmit antennas; extensions to other STBC schemes are straightforward. Figure 1 depicts a diagram of the baseband ST coded system. At the transmitter, the ST encoder (specified in Section 2.2) maps the incoming symbol stream $\{c(n)\}$, drawn from a certain constellation $\mathcal{B}$, into two ST coded symbol streams $\{s(n)\}$ and $\{\bar{s}(n)\}$. Then, the two coded symbol streams are sent out through transmit antenna 1 and transmit antenna 2, simultaneously. At the receive side, the channel estimator produces a channel estimate, which is then utilized by the detector for symbol detection and ST decoding.

The multipath channels including the physical channel and the transmit/receive filters between transmitter 1 and the N_r receivers are modeled as FIR (finite impulse response) filters [35] with a maximum order L and described by $\mathbf{h}_0, \ldots, \mathbf{h}_L$, where $\mathbf{h}_l = [h_1(l), h_2(l), \ldots, h_{N_r}(l)]^T \in \mathcal{C}^{N_r \times 1}$, $l = 0, \ldots, L$; and the multipath channels between transmitter 2 and the receivers are similarly described by $\bar{\mathbf{h}}_0, \ldots, \bar{\mathbf{h}}_L$, $\bar{\mathbf{h}}_l = [\bar{h}_1(l), \bar{h}_2(l), \ldots, \bar{h}_{N_r}(l)]^T \in \mathcal{C}^{N_r \times 1}$. It is assumed that the transmitting antennas at the transmit side are placed far apart. Similarly, the receiving antennas at the receive side are assumed to be sufficiently far apart. This ensures that the transmitted symbols from the antennas undergo effectively independent fading. Another assumption is that the channels are invariant within a data block, but allowed to be varying from block to block, independently.

We collect N_r samples from the output of the N_r receivers at time n: $\mathbf{y}(n) = [y_1(n), \ldots, y_{N_r}(n)]^T \in \mathcal{C}^{N_r \times 1}$. Then the complex baseband received signal is given by

$$\mathbf{y}(n) = \sum_{l=0}^{L} \mathbf{h}_l s(n-l) + \sum_{l=0}^{L} \bar{\mathbf{h}}_l \bar{s}(n-l) + \sum_{i=1}^{N_i} \sum_{l=0}^{L_i} \mathbf{g}_{i,l} s_i(n-l) + \mathbf{e}(n), \quad n = 0, \ldots, N-1 \tag{1}$$

where N is the received data length; $s(n-l)$ and $\bar{s}(n-l)$ are desired space-time block coded symbols

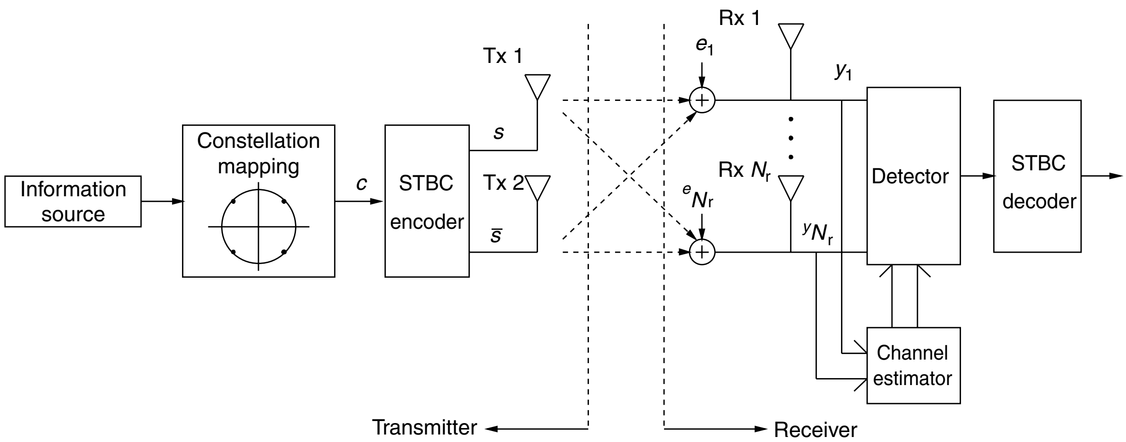

Fig. 1. Block diagram of a baseband ST coded system.

sent from transmit antenna 1 and 2, respectively; N_i is the number of the CCI users and $\mathbf{g}_{i,l} = [g_{i,1}(l), \ldots, g_{i,N_r}(l)]^T \in \mathcal{C}^{N_r \times 1}$, $i = 1, \ldots, N_i$, $l = 0, \ldots, L_i$ denotes the CCI channel of the interfering signal $s_i(n-l)$; and $\mathbf{e}(n)$ is the additive white Gaussian noise, which is formed from $e_1(n)$ to $e_{N_r}(n)$ with zero mean and variance σ_e^2. The problem of interest is to estimate the unknown channels $\{\mathbf{h}_l\}_{l=0}^{L}$ and $\{\overline{\mathbf{h}}_l\}_{l=0}^{L}$, demodulate coherently the symbols $\{s(n)\}$ and $\{\overline{s}(n)\}$, and suppress the interference existing in the systems.

Let $\sum_{i=1}^{N_i}\sum_{l=0}^{L_i} \mathbf{g}_{i,l} s_i(n-l) + \mathbf{e}(n) \triangleq \mathbf{w}(n)$. Though the exact distribution of $\mathbf{w}(n)$ is difficult to determine, we model it as a complex Gaussian vector with zero mean and $\mathrm{E}[\mathbf{w}(n)\mathbf{w}^H(m)] = \mathbf{Q}\delta(n-m)$, that is, the noise plus CCI is temporally white, $\mathbf{w}(n) \sim \mathcal{N}(\mathbf{0}, \mathbf{Q})$, where $\mathbf{Q}$ is the $N_r \times N_r$ covariance matrix of $\mathbf{w}(n)$ to be determined and $\delta(n)$ is the Kronecker delta function [36].

Let $\mathbf{H} \triangleq [\mathbf{h}_0, \mathbf{h}_1, \ldots, \mathbf{h}_L]$ and $\mathbf{s}(n) \triangleq [s(n), s(n-1), \ldots, s(n-L)]^T$. Let $\overline{\mathbf{H}}$ and $\overline{\mathbf{s}}(n)$ be similarly formed. We have the following input and output relation described in a compact vector/matrix form

$$\mathbf{y}(n) = \tilde{\mathbf{H}}\tilde{\mathbf{s}}(n) + \mathbf{w}(n),\ n = 0, 1, \ldots, M-1 \quad (2)$$

where $\tilde{\mathbf{H}} = [\mathbf{H}, \overline{\mathbf{H}}] \in \mathcal{C}^{N_r \times 2(L+1)}$ and $\tilde{\mathbf{s}}(n) = [\mathbf{s}^T(n), \overline{\mathbf{s}}^T(n)]^T \in \mathcal{C}^{2(L+1)\times 1}$. We assume that $\{s(-L), \ldots, s(M-1)\}$ and $\{\overline{s}(-L), \ldots, \overline{s}(M-1)\}$ are composed of known training symbols, and the total number $M+L$ of these training symbols is even, where M is the data length of the received symbols.

Let $\mathbf{Y} = [\mathbf{y}(0), \ldots, \mathbf{y}(M-1)] \in \mathcal{C}^{N_r \times M}$, $\tilde{\mathbf{S}} = [\tilde{\mathbf{s}}(0), \ldots, \tilde{\mathbf{s}}(M-1)] \in \mathcal{C}^{2(L+1)\times M}$, and $\mathbf{W} = [\mathbf{w}(0), \ldots, \mathbf{w}(M-1)] \in \mathcal{C}^{N_r \times M}$, the input and output relation can be expressed as

$$\mathbf{Y} = \tilde{\mathbf{H}}\tilde{\mathbf{S}} + \mathbf{W} \quad (3)$$

2.2. STBC Encoder

The STBC encoder in Figure 1 exploits the STBC scheme introduced in Reference [13]. Two adjacent symbols $c(2n)$ and $c(2n+1)$, $n = 0, 1, 2\ldots$, are grouped and input into the STBC encoder. Then the ST block coded symbols are output from the encoder, which may be expressed in the following matrix form:

$$\mathbf{D} \triangleq \begin{bmatrix} s(2n) & s(2n+1) \\ \overline{s}(2n) & \overline{s}(2n+1) \end{bmatrix}$$

where

$$\begin{aligned} s(2n) &= c(2n), & s(2n+1) &= -c^*(2n+1), \\ \overline{s}(2n) &= c(2n+1), & \overline{s}(2n+1) &= c^*(2n) \end{aligned} \quad (4)$$

The columns of $\mathbf{D}$ are then transmitted over two successive symbol intervals with the elements of each column sent from two transmit antennas, simultaneously.

Therefore, the task is to estimate the unknown channel coefficients $\{\mathbf{h}_l\}_{l=0}^{L}$ and $\{\overline{\mathbf{h}}_l\}_{l=0}^{L}$, and then to recover the transmitted information symbols $\{s(n)\}$ and $\{\overline{s}(n)\}$, and eventually $\{c(n)\}$ from the observations $\{\mathbf{y}(n)\}$ corrupted by CCI and noise.

3. Proposed Method

3.1. Maximum Likelihood (ML) Estimator

Given the Equation (3) derived in Section 2.1 under the Gaussian assumption of $\mathbf{w}(n)$, the log-likelihood function of $\{\mathbf{y}(n)\}_{n=0}^{M-1}$ is proportional to (within an additive constant) [30]

$$C_1 \triangleq -ln|\mathbf{Q}| - \frac{1}{M} tr\{\mathbf{Q}^{-1}(\mathbf{Y} - \tilde{\mathbf{H}}\tilde{\mathbf{S}})(\mathbf{Y} - \tilde{\mathbf{H}}\tilde{\mathbf{S}})^H\} \quad (5)$$

where $tr\{\cdot\}$ denotes the trace of a matrix. Maximizing C_1 with respect to $\mathbf{Q}$ yields

$$\hat{\mathbf{Q}} = \frac{1}{M}(\mathbf{Y} - \tilde{\mathbf{H}}\tilde{\mathbf{S}})(\mathbf{Y} - \tilde{\mathbf{H}}\tilde{\mathbf{S}})^H \quad (6)$$

Substituting Equation (6) into Equation (5), we see that maximizing C_1 is equivalent to minimizing

$$C_2 = \left| \frac{1}{M}(\mathbf{Y} - \tilde{\mathbf{H}}\tilde{\mathbf{S}})(\mathbf{Y} - \tilde{\mathbf{H}}\tilde{\mathbf{S}})^H \right| \quad (7)$$

Let $\hat{\mathbf{R}}_{\mathbf{YY}} = \frac{1}{M}\mathbf{Y}\mathbf{Y}^H$, $\hat{\mathbf{R}}_{\tilde{\mathbf{S}}\tilde{\mathbf{S}}} = \frac{1}{M}\tilde{\mathbf{S}}\tilde{\mathbf{S}}^H$, $\hat{\mathbf{R}}_{\tilde{\mathbf{S}}\mathbf{Y}} = \frac{1}{M}\tilde{\mathbf{S}}\mathbf{Y}^H$, and

$$\begin{aligned} \mathbf{F} &\triangleq \frac{1}{M}(\mathbf{Y} - \tilde{\mathbf{H}}\tilde{\mathbf{S}})(\mathbf{Y} - \tilde{\mathbf{H}}\tilde{\mathbf{S}})^H \\ &= [\tilde{\mathbf{H}} - \hat{\mathbf{R}}_{\tilde{\mathbf{S}}\mathbf{Y}}^H \hat{\mathbf{R}}_{\tilde{\mathbf{S}}\tilde{\mathbf{S}}}^{-1}]\hat{\mathbf{R}}_{\tilde{\mathbf{S}}\tilde{\mathbf{S}}}[\tilde{\mathbf{H}} - \hat{\mathbf{R}}_{\tilde{\mathbf{S}}\mathbf{Y}}^H \hat{\mathbf{R}}_{\tilde{\mathbf{S}}\tilde{\mathbf{S}}}^{-1}]^H \\ &\quad + \hat{\mathbf{R}}_{\mathbf{YY}} - \hat{\mathbf{R}}_{\tilde{\mathbf{S}}\mathbf{Y}}^H \hat{\mathbf{R}}_{\tilde{\mathbf{S}}\tilde{\mathbf{S}}}^{-1} \hat{\mathbf{R}}_{\tilde{\mathbf{S}}\mathbf{Y}} \end{aligned} \quad (8)$$

Since $\hat{\mathbf{R}}_{\tilde{\mathbf{S}}\tilde{\mathbf{S}}}$ is positive definite (therefore the first term is nonnegative), and the second and third terms do not depend on $\tilde{\mathbf{H}}$, it follows that

$$\mathbf{F} \geq \mathbf{F}|_{\tilde{\mathbf{H}} = \hat{\mathbf{R}}_{\tilde{\mathbf{S}}\mathbf{Y}}^H \hat{\mathbf{R}}_{\tilde{\mathbf{S}}\tilde{\mathbf{S}}}^{-1}} \quad (9)$$

The inequality expression here means that the difference matrix $\mathbf{F} - \mathbf{F}|_{\tilde{\mathbf{H}} = \hat{\mathbf{R}}_{\tilde{\mathbf{S}}\mathbf{Y}}^H \hat{\mathbf{R}}_{\tilde{\mathbf{S}}\tilde{\mathbf{S}}}^{-1}}$ is nonnegative definite.

When the whole sample covariance matrix $\mathbf{F}$ is minimized (in the sense that $\mathbf{x}^H(\mathbf{F} - \mathbf{F}_{min})\mathbf{x} \geq 0$, $\forall \mathbf{x} \in \mathcal{C}^{N_r \times 1}$), the estimate $\hat{\tilde{\mathbf{H}}}$ of $\tilde{\mathbf{H}}$ will minimize any nondecreasing function of $\mathbf{F}$ including the determinant of $\mathbf{F}$, which is C_2 in Equation (7). Hence, the ML estimate of $\tilde{\mathbf{H}}$ is given by

$$\hat{\tilde{\mathbf{H}}} = \hat{\mathbf{R}}_{\tilde{\mathbf{S}}\mathbf{Y}}^H \hat{\mathbf{R}}_{\tilde{\mathbf{S}}\tilde{\mathbf{S}}}^{-1} \tag{10}$$

It is easily seen that $\hat{\tilde{\mathbf{H}}}$ is a consistent estimate of $\tilde{\mathbf{H}}$.

Substituting Equation (10) back into Equation (6), we obtain the ML estimate of $\mathbf{Q}$,

$$\hat{\mathbf{Q}} = \hat{\mathbf{R}}_{\mathbf{YY}} - \hat{\mathbf{R}}_{\tilde{\mathbf{S}}\mathbf{Y}}^H \hat{\mathbf{R}}_{\tilde{\mathbf{S}}\tilde{\mathbf{S}}}^{-1} \hat{\mathbf{R}}_{\tilde{\mathbf{S}}\mathbf{Y}} \tag{11}$$

Equations (10) and (11) give the ML estimate of the channel $\tilde{\mathbf{H}}$ and the noise/interference covariance matrix $\mathbf{Q}$. The above ML estimates assume that $\hat{\mathbf{R}}_{\tilde{\mathbf{S}}\tilde{\mathbf{S}}}$ is invertible, which can be satisfied by choosing appropriate training symbols and $M \geq N_r$. It can be seen that our proposed estimation algorithm does not require any explicit knowledge about the interferers, for example, the total number of the interfering users and the coding information of the interfering signals.

3.2. Interference Suppression and Signal Detection

Now we describe how to use the estimates obtained above for signal detection and interference suppression. From now on, we assume $\tilde{\mathbf{H}}$ and $\mathbf{Q}$ are known.

Say, we want to detect a subframe of $K + L$ symbols:

$$\mathbf{y}(n) = \tilde{\mathbf{H}}\tilde{\mathbf{s}}(n) + \mathbf{w}(n),\ n = M, M+1, \ldots, N-1 \tag{12}$$

While an ML detector can be straightforwardly formulated, it will incur an exponential complexity with respect to the frame length and, hence, has limited practical use. We will instead focus on linear detectors. Specifically, we consider a Markov-like linear detector [37] as follows, in which we assume that the data within a subframe are correlated, but uncorrelated between subframes.

The data received after training symbols are denoted by $\{\mathbf{y}(n)\}_{n=M}^{N-1}$, from which nonoverlapping data vectors of length K are formed, that is, $\mathbf{y}_K(i) \triangleq [\mathbf{y}^T(iK+M), \ldots, \mathbf{y}^T(iK+K+M-1)]^T \in \mathcal{C}^{KN_r\times 1}$, $\mathbf{s}_K(i) \triangleq [s(iK+M-L), \ldots, s(iK+K+M-1)]^T \in \mathcal{C}^{(K+L)\times 1}$, $i = 0, \ldots, I-1$, where $I = \lceil (N-M)/K \rceil$. Let $\bar{\mathbf{s}}_K(i)$ be formed similarly to $\mathbf{s}_K(i)$ with $s(iK+M-L), \ldots, s(iK+K+M-1)$ replaced by $\bar{s}(iK+M-L), \ldots, \bar{s}(iK+K+M-1)$. The CCI and noise vector is defined as $\mathbf{w}_K(i) \triangleq [\mathbf{w}^T(iK+M), \ldots, \mathbf{w}^T(iK+K+M-1)]^T \in \mathcal{C}^{KN_r\times 1}$. The choice of the subframe length K is made by a compromise between performance and complexity: the larger the K, the better the performance, whereas the more complex the resulting detector [37]. And for an easy decoding in an ST coded system, $K + L$ is usually chosen to be even.

Let $\mathcal{H}_K$ define the $KN_r \times (K+L)$ block-Toeplitz CSI matrix

$$\mathcal{H}_K \triangleq \begin{bmatrix} \mathbf{h}_L & \mathbf{h}_{L-1} & \cdots & \mathbf{h}_0 & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{h}_L & \cdots & \mathbf{h}_1 & \mathbf{h}_0 & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{h}_L & \mathbf{h}_{L-1} & \cdots & \mathbf{h}_0 \end{bmatrix} \tag{13}$$

and let $\overline{\mathcal{H}}_K$ be similarly formed with $\bar{\mathbf{h}}_l$, $l = 0, \ldots, L$. Let $\tilde{\mathcal{H}}_K = [\mathcal{H}_K, \overline{\mathcal{H}}_K] \in \mathcal{C}^{KN_r\times 2(K+L)}$ and $\tilde{\mathbf{s}}_K(i) = [\mathbf{s}_K^T(i), \bar{\mathbf{s}}_K^T(i)]^T \in \mathcal{C}^{2(K+L)\times 1}$. Then, the total received symbols within a subframe can be expressed as

$$\mathbf{y}_K(i) = \tilde{\mathcal{H}}_K \tilde{\mathbf{s}}_K(i) + \mathbf{w}_K(i),\ \mathbf{w}_K(i) \sim \mathcal{N}(\mathbf{0}, \mathbf{I}_K \otimes \mathbf{Q}) \tag{14}$$

Therefore, the *soft* Markov-like estimate of $\tilde{\mathbf{s}}_K(i)$ is given by

$$\hat{\tilde{\mathbf{s}}}_K(i) = [\tilde{\mathcal{H}}_K^H (\mathbf{I}_K \otimes \mathbf{Q}^{-1}) \tilde{\mathcal{H}}_K]^{-1} \tilde{\mathcal{H}}_K^H (\mathbf{I}_K \otimes \mathbf{Q}^{-1}) \mathbf{y}_K(i) \tag{15}$$

The above equation resembles the structure of best linear unbiased estimation (BLUE) [24], but unlike the BLUE method, in which the true covariance values are exploited, the covariance matrix in Equation (15) is constructed with estimated values of $\mathbf{Q}$ obtained in Equation (11) of Section 3.1.

Our final estimate of $\mathbf{c}_K(i)$ is easily obtained by taking an arithmetic average of correlative points in $\mathbf{s}_K(i)$ and $\bar{\mathbf{s}}_K(i)$, respectively. The overlapping symbols of two continuous subframes due to block detection are obtained by an arithmetic average of the corresponding points in these two subframes. Specifically, form $\hat{\mathbf{c}}_K(i,k) = [\hat{s}_K(iK+M+k-L), \hat{s}_K(iK+M+k-L+1), \hat{\bar{s}}_K(iK+M+k-L), \hat{\bar{s}}_K(iK+M+k-L+1)]^T$, $k = 0, \ldots, K+L-1$ from the detector output $\hat{\tilde{\mathbf{s}}}_K(i)$ (see Equation 15). Assume that proper alignment/synchronization at the receiver has been performed such that estimates of the transmitted symbols can be made. Reversing the ST coding process, we obtain the *soft* estimates of $c_K(iK+M+k-L)$, $c_K(iK+M+k-L+1)$ as follows:

$$\begin{aligned} \hat{c}_K(iK+M+k-L) &= [\hat{s}_K(iK+M+k-L) \\ &\quad + \hat{\bar{s}}_K^*(iK+M+k-L+1)]/2, \\ \hat{c}_K(iK+M+k-L+1) &= [\hat{s}_K(iK+M+k-L) \\ &\quad - \hat{\bar{s}}_K^*(iK+M+k-L+1)]/2 \end{aligned} \tag{16}$$

Finally, the *hard* estimate $\hat{\hat{c}}_K(iK+M+k-L)$ is obtained by comparing the soft estimate $\hat{c}_K(iK+M+k-L)$ with every constellation point:

$$\hat{\hat{c}}_K(iK+M+k-L) = \arg\min_{c\in\mathcal{B}} |\hat{c}_K(iK+M+k-L)-c| \quad (17)$$

where $|\cdot|$ denotes the Euclidean distance. For a binary phase shift keying (BPSK), this reduces to $\hat{\hat{c}}_K(iK+M+k-L) = \text{sign}(\text{Re}(\hat{c}_K(iK+M+k-L)))$. The identical process can be applied to get the *hard* estimate $\hat{\hat{c}}_K(iK+M+k-L+1)$ of $\hat{c}_K(iK+M+k-L+1)$. Hence, the estimates of the grouped transmitted symbols can be acquired, and eventually, the estimates of the subframe of $K+L$ symbols.

Remark. The temporal structure of STBC is not explicitly used during channel estimation, although the spatial structure is inherent in Equations (2) and (3). Note that joint CCI/ISI suppression and decoding does require the STBC structure. The Markov-like detector given by Equation (15) can be viewed as a joint processor (i.e. equalizer, demodulator, and interference suppressor). Since $\mathbf{w}_K(i)$ is not modeled exactly, it may contain other unmodeled interference (in addition to CCI) and the *overall* interference is suppressed by the joint processor.

3.3. Matrix Multiplication and Inversion

Direct evaluation of Equation (15) is computationally inefficient and thus not recommended, particularly when the subframe size K is large. However, it is noticed that

$$\tilde{\mathcal{H}}_K^H(\mathbf{I}_K\otimes\mathbf{Q}^{-1})\tilde{\mathcal{H}}_K = \begin{bmatrix} \mathcal{H}_K^H(\mathbf{I}_K\otimes\mathbf{Q}^{-1})\mathcal{H}_K & \mathcal{H}_K^H(\mathbf{I}_K\otimes\mathbf{Q}^{-1})\overline{\mathcal{H}}_K \\ \overline{\mathcal{H}}_K^H(\mathbf{I}_K\otimes\mathbf{Q}^{-1})\mathcal{H}_K & \overline{\mathcal{H}}_K^H(\mathbf{I}_K\otimes\mathbf{Q}^{-1})\overline{\mathcal{H}}_K \end{bmatrix} \in \mathcal{C}^{2(K+L)\times 2(K+L)} \quad (18)$$

Therefore, the structure of $\mathcal{H}_K$ (or $\overline{\mathcal{H}}_K$) and $\mathbf{I}_K\otimes\mathbf{Q}^{-1}$ can be utilized to reduce the complexity significantly. We first note that

$$\mathcal{H}_K^H(\mathbf{I}_K\otimes\mathbf{Q}^{-1}) = \begin{bmatrix} \mathbf{Q}^{-1}\mathbf{h}_L & \cdots & \mathbf{Q}^{-1}\mathbf{h}_0 & & \mathbf{0} \\ & \ddots & \ddots & \ddots & \\ \mathbf{0} & & \mathbf{Q}^{-1}\mathbf{h}_L & \cdots & \mathbf{Q}^{-1}\mathbf{h}_0 \end{bmatrix}^H \quad (19)$$

which breaks down to the calculation of $L+1$ matrix-vector products of reduced dimension: $\{\mathbf{Q}^{-1}\mathbf{h}_l\}_{l=0}^L$. Let $\mathbf{\Phi} \triangleq \mathcal{H}_K^H(\mathbf{I}_K\otimes\mathbf{Q}^{-1})\mathcal{H}_K \in \mathcal{C}^{(K+L)\times(K+L)}$ and ϕ_{mn} denote its mnth element. Since $\mathbf{\Phi}$ is Hermitian symmetric, only the elements on and above the diagonal, that is, ϕ_{mn} for $n\geq m$, need to be evaluated. Furthermore, it can be verified by direct calculation that ϕ_{mn} for $n\geq m$ is given by

$$\phi_{mn} = \begin{cases} \sum_{i=1}^{m} \mathbf{h}_{L-i+1}^H\mathbf{Q}^{-1}\mathbf{h}_{L-i+(m-n+1)}, \\ \quad 1\leq m\leq L+1;\ m\leq n\leq m+L, \\ \sum_{i=1}^{L+1} \mathbf{h}_{L-i+1}^H\mathbf{Q}^{-1}\mathbf{h}_{L-i+(m-n+1)}, \\ \quad L+2\leq m\leq K;\ m\leq n\leq m+L, \\ \sum_{i=1}^{L+K-m+1} \mathbf{h}_{i-1}^H\mathbf{Q}^{-1}\mathbf{h}_{i-1+(m-n)}, \\ \quad K+1\leq m\leq K+L;\ m\leq n\leq K+L, \\ 0, \quad \text{otherwise} \end{cases} \quad (20)$$

where it was assumed that $K\geq L+1$ and $\mathbf{h}_i=\mathbf{0}$ for $i<0$. We see from Equation (20) that the calculation of $\mathbf{\Phi}$ reduces to a total of $(L+1)(L+2)/2$ quadratic terms $\{\mathbf{h}_i^H\mathbf{Q}^{-1}\mathbf{h}_j\}_{i,\ j=0}^L$ and their combinations, (note that $\mathbf{h}_i^H\mathbf{Q}^{-1}\mathbf{h}_j = (\mathbf{h}_j^H\mathbf{Q}^{-1}\mathbf{h}_i)^H$), and thus can be easily carried out. Similarly, $\overline{\mathcal{H}}_K^H(\mathbf{I}_K\otimes\mathbf{Q}^{-1})\overline{\mathcal{H}}_K$ can be obtained.

It is also noticed that

$$\mathcal{H}_K^H(\mathbf{I}_K\otimes\mathbf{Q}^{-1})\overline{\mathcal{H}}_K = (\overline{\mathcal{H}}_K^H(\mathbf{I}_K\otimes\mathbf{Q}^{-1})\mathcal{H}_K)^H \quad (21)$$

Hence, only the elements in the upper triangle of these two matrices need to be determined with the elements on the diagonal computed only once. This calculation can be implemented by using the method introduced in Equation (20). Therefore, the total computational load of $\tilde{\mathcal{H}}_K^H(\mathbf{I}_K\otimes\mathbf{Q}^{-1})\tilde{\mathcal{H}}_K$ is $(L+1)(2L+3)$ quadratic terms, their combinations and the corresponding conjugate transpose operations. The $2(K+L)\times 2(K+L)$ matrix of $\tilde{\mathcal{H}}_K^H(\mathbf{I}_K\otimes\mathbf{Q}^{-1})\tilde{\mathcal{H}}_K$ is inverted afterwards.

It is easy to see from Equation (18) that matrix $\tilde{\mathcal{H}}_K^H(\mathbf{I}_K\otimes\mathbf{Q}^{-1})\tilde{\mathcal{H}}_K$ is composed of four blocks $\mathcal{H}_K^H(\mathbf{I}_K\otimes\mathbf{Q}^{-1})\mathcal{H}_K$, $\mathcal{H}_K^H(\mathbf{I}_K\otimes\mathbf{Q}^{-1})\overline{\mathcal{H}}_K$, $\overline{\mathcal{H}}_K^H(\mathbf{I}_K\otimes\mathbf{Q}^{-1})\mathcal{H}_K$, and $\overline{\mathcal{H}}_K^H(\mathbf{I}_K\otimes\mathbf{Q}^{-1})\overline{\mathcal{H}}_K$ with reduced dimension $(K+L)\times(K+L)$. It is also noticed that from Equation (21),

$$(\mathcal{H}_K^H(\mathbf{I}_K\otimes\mathbf{Q}^{-1})\overline{\mathcal{H}}_K)^{-1} = ((\overline{\mathcal{H}}_K^H(\mathbf{I}_K\otimes\mathbf{Q}^{-1})\mathcal{H}_K)^{-1})^H \quad (22)$$

Therefore, inverse of $\tilde{\mathcal{H}}_K^H(\mathbf{I}_K \otimes \mathbf{Q}^{-1})\tilde{\mathcal{H}}_K$ can be easily carried out by doing inverse of these three blocks $\mathcal{H}_K^H(\mathbf{I}_K \otimes \mathbf{Q}^{-1})\mathcal{H}_K$, $\mathcal{H}_K^H(\mathbf{I}_K \otimes \mathbf{Q}^{-1})\overline{\mathcal{H}}_K$, and $\overline{\mathcal{H}}_K^H(\mathbf{I}_K \otimes \mathbf{Q}^{-1})\overline{\mathcal{H}}_K$ first, and then evaluating corresponding multiplications and combinations using the method introduced in Reference [36], which noticeably deduces the computational complexity compared with direct inverse calculation.

4. Simulation Results

In this section, we present simulation results for the proposed techniques. The performances of the ML estimation algorithm and the data detection scheme are illustrated.

We consider an ST coded TDMA system with a quaternary phase shift keying (QPSK) constellation and $N_r = 4$ receive antennas. Following a Rayleigh-fading assumption, the channel coefficients $\{h_{n_r}(l)\}$ and $\{\overline{h}_{n_r}(l)\}$ are generated as Gaussian random variables with zero mean and equal variance, which are independent for different n_r and/or l; also, $\{h_{n_r}(l)\}$ and $\{\overline{h}_{n_r}(l)\}$ are fixed within one frame and changed independently from frame to frame. In the following examples, we set $L = 1$ (a 2-ray channel), $N = 162$ (frame length), $M = 18$ (number of training symbols within a frame), $K = 17$ (received subframe size for detection), and the system is simulated with assumption of one cochannel interferer, which is generated similarly to the desired user. The SNR is defined as SNR $= 10 \log_{10} 1/\sigma_e^2$ dB, and the SIR (signal-to-inference ratio) is also similarly defined.

4.1. Channel Estimation

The performance measure of channel estimation is the average mean-squared error (MSE) of the channel estimates defined as $\mathrm{MSE}(\hat{\mathbf{H}}) = 1/(N_rN_t(L+1)) \sum_{m=1}^{N_rN_t} \mathrm{MSE}(\hat{\mathbf{h}}_m)/\|\mathbf{H}\|^2$, where $\hat{\mathbf{h}}_m$ includes all the multipath channels from each transmit-receive antenna pair. Because of the assumed quasi-static characteristic of the fading channel, the MSE results presented in Figure 2 are averaged over a large number of frames.

This figure depicts MSE of the channel estimates *versus* SNR given different SIRs. The channel estimates are obtained using Equation (10). It is noted that the estimation error calculated as defined drops rapidly with the increase of SIR, which demonstrates that our proposed scheme can provide an accurate estimate of the channel. It is noticed as well that the

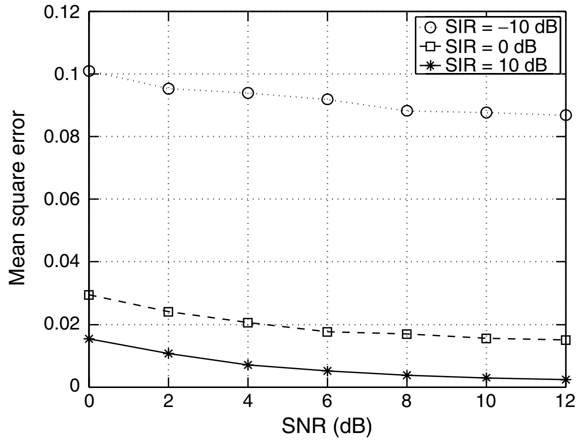

Fig. 2. MSE of channel estimate *versus* SNR.

channel estimates are consistent in the sense that MSE decreases monotonically with SNR increasing.

4.2. Symbol Detection

Next we examine the performance of the signal detector discussed in Section 3.2. The proposed scheme is compared with the ZF receiver. The scattering diagrams with the linear ZF receiver and the proposed scheme are depicted in Figure 3 with SNR = 12 dB and SIR = 0 dB. The ZF receiver is implemented as follows: first a channel estimate for the desired user is obtained *via* a least-squares (LS) fitting using the training symbols; the LS channel estimate is next substituted in the standard linear ZF receiver [35] for symbol demodulation. Note that with only the CSI of the desired user, the ZF receiver is able to suppress the ISI, but not the CCI.

Figure 4 shows the BER of the proposed scheme *versus* the SNR under several different values of SIR. It is also seen that when the CCI is weak, for example, SIR = 10 dB, the ZF receiver performs the best since it completely removes the ISI that dominates the overall interference in this case. When the CCI becomes stronger, that is, for SIR = 0 dB and −10 dB, the ZF fails because it is unable to cope with CCI, but the proposed scheme provides much better performance because it is capable of canceling both ISI and CCI.

4.3. Transmit Diversity Advantage

Finally, we consider the diversity advantage provided by ST coding. We compare the proposed ST coded system with the conventional system using receive diversity only without ST coding. Figure 5 gives the

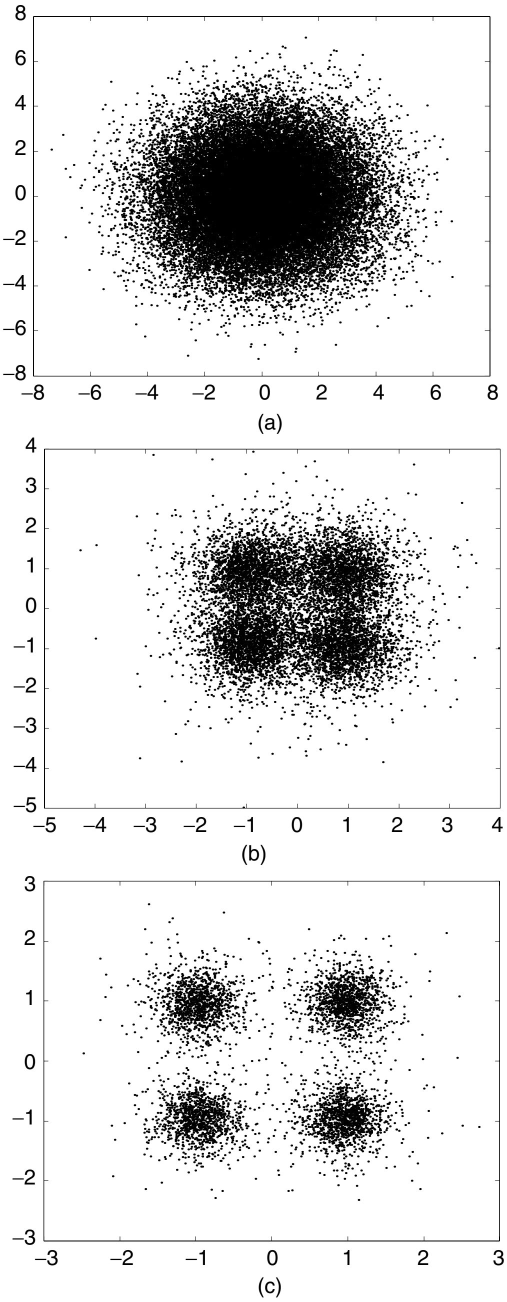

Fig. 3. Scattering diagrams (SNR = 12 dB, SIR = 0 dB) (a) no interference suppression; (b) ZF method; and (c) proposed method.

BER of these two systems. The CSI for the ST coded system is estimated by our proposed channel estimator while the channel estimate of one transmit antenna system is obtained exploiting a similar ML estimator [38,39]. It is seen that, compared to the cases with only one transmit antenna, better BERs are achieved as a result of the higher diversity gain provided by

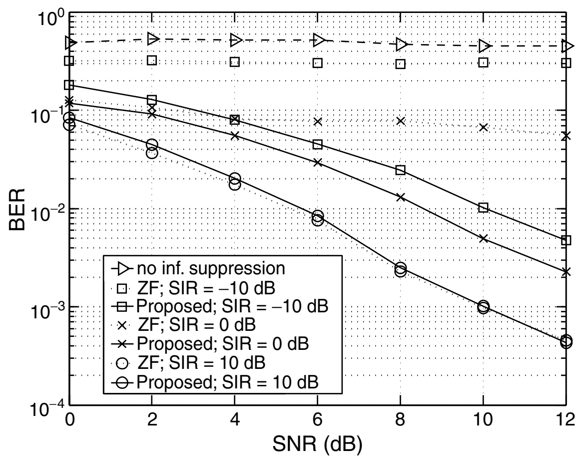

Fig. 4. BER *versus* SNR (2Tx).

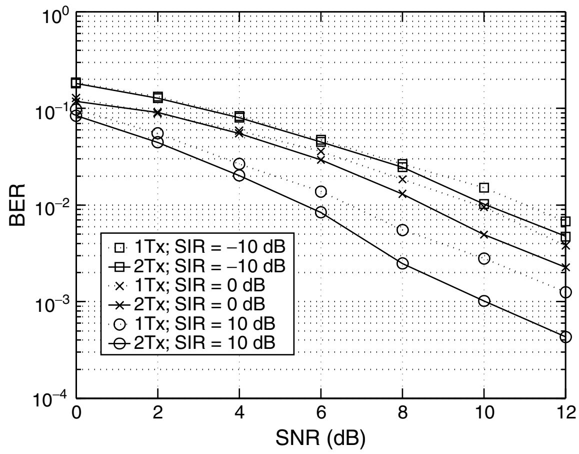

Fig. 5. BER *versus* SNR (2Tx *vs.* 1TX).

STBC and multiple transmit antennas. It clearly motivates the use of ST coding in conventional systems.

Simulation results shown above demonstrate the efficiency of our proposed method to estimate channels and suppress interference. Compared to the case without ST coding, significant performance improvements can be obtained.

5. Conclusion

We have investigated the problem of channel estimation and symbol detection for ST coded transmit diversity systems operating in frequency-selective fading environments. A channel estimation scheme is proposed, which yields consistent channel estimates. And the interference cancelation algorithm is explored for wireless cellular systems that utilize the spatial and temporal dimensions to suppress interference. The proposed schemes are simple to implement and able to deal with interference of various sources. The performance of the resulting receiver in multipath Rayleigh-fading channels has been shown and a comparison with the ZF receiver is given. The performance gain achieved by ST coding over conventional systems using receive diversity only has been demonstrated as well. Though the systems with only two transmit antennas are investigated here, it can be straightforwardly extended to systems with more transmit antennas.

Acknowledgement

This work was supported by the New Jersey Center for Wireless Telecommunications (NJCWT).

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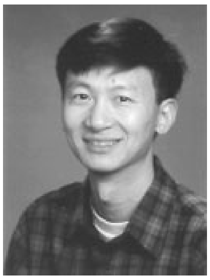

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