Abstract

This article reviews space-time modem technology for mobile radio applications. We begin with motivations for the use of space-time modems and then briefly discuss the challenges posed by wireless propagation. Next, we develop a signal model for the wireless environment. Channel estimation, equalization, and filtering techniques for space-time modems in the forward and reverse links are then discussed. Finally, we review applications of space-time modems to cellular systems and discuss industry trends.

Space-Time Modems for Wireless Personal Communications

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The goal of wireless personal communications is to allow users to communicate reliably in any form, at any time, and without regard to location and mobility. The expanding range of services that can be provided by digital transmission has led to increased air time usage and to a greater number of subscribers. This in turn has led to an increasing focus on developing new technologies that can provide a higher grade of service at a lower cost. Current projections of subscriber demands for wireless service put the growth rate at about 18 percent per year, and these trends are likely to continue into the new millennium [1]. Recent overviews of wireless personal communications services are given in [2, 3].

A wireless system designer is faced with a number of challenges. These include a complex multipath and time-varying propagation environment; limited availability of radio spectrum; limited energy storage capability of batteries in portable units; user demand for higher data rates, better voice quality, fewer dropped calls, enhanced in-building penetration, and longer talk times; and operator demand for greater area coverage by base stations, increased subscriber capacity, and lower infrastructure and operating costs. A number of different technologies have been used to meet such diverse requirements. These include advanced multiple access schemes such as slow frequency-hopped time-division multiple access (TDMA) and code-division multiple access (CDMA), bandwidth-efficient source coding (CELP and VSELP), and sophisticated signal processing techniques (diversity, adaptive equalization, and coding).

Current wireless modems use temporal signal processing methods. They have limited effectiveness against co-channel interference (CCI), which arises from cellular frequency reuse and thus limits the quality and capacity of wireless networks. Improved modem technology that combats CCI can have a significant impact on overall network performance. Smart antennas (or space-time processing) with multiple antennas in receive and transmit is a promising way of mitigating CCI by exploiting the spatial dimension. Space-time processing (STP) can improve network capacity, coverage, and quality by reducing CCI while also enhancing diversity and array gain.

A space-time receive modem operates simultaneously on all the antennas, processing signals in both space and time. This extra spatial dimension enables interference cancellation in a way that is not possible with single-antenna modems. The desired signal and CCI almost always arrive at the antenna array (even in complex multipath environments) with distinct and often well separated spatial signatures, thus allowing the modem to exploit such differences to reduce CCI. Likewise, the space-time transmit modems can use spatial selectivity to deliver signals to the desired mobile while minimizing interference for other mobiles.

The spatial dimension can also be used to enhance other aspects of modem performance. In the receiver, the antennas can be used to enhance received power, improve signal-to-thermal-noise ratio, and even suppress intersymbol interference (ISI). In the transmitter, the spatial dimension can be used to increase array gain through beamforming, improve transmit diversity through precoding, and reduce delay spread at the subscriber end (i.e., mobile).

This article presents an overview of space-time modem (also known as smart antenna) technology for wireless personal communications. Propagation issues are summarized in the next section. The next three sections will focus on vector signal models, space-time channel estimation techniques, and space-time modems (TDMA), respectively. We follow this with a section on space-time modems for direct sequence CDMA (DS-CDMA). We end with a review of applications of STP to cellular systems and a review of industry trends. We provide a large list of references for the interested reader to look up the details.

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Wireless Propagation

The propagation of radio signals on both the forward (base station to mobile) and reverse (mobile to base station) links is

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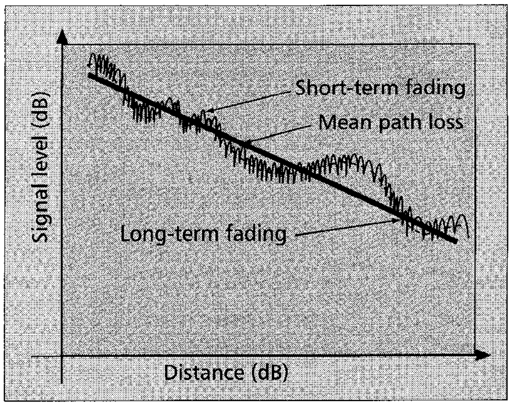
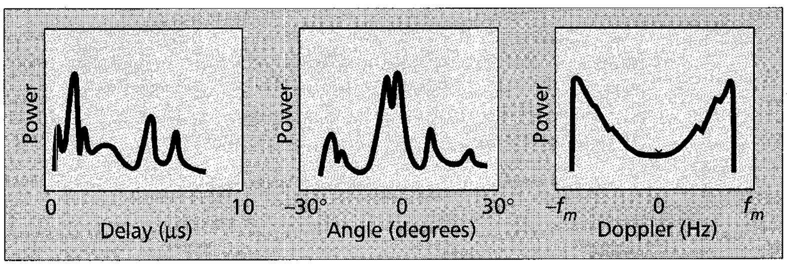
affected by the physical channel in several ways. In this section we review these effects and develop a model to describe channel behavior.

A signal propagating through the wireless channel usually arrives at the destination along a number of different paths, referred to as *multipath*. These paths arise from scattering, reflection, refraction, or diffraction of the radiated energy off objects in the environment. The received signal is much weaker than the transmitted signal due to mean propagation loss, and long- and short-term fading. The mean propagation loss arises from square law spreading, absorption by foliage, and the effect of ground-generated vertical multipath. Long-term fading, also known as *shadowing*, results from signal blocking by buildings and natural features. On the other hand, short-term fading results from multipath in the vicinity of the mobile. Figure 1 shows a typical variation in the received signal level as a function of the distance from the transmitter.



■ **Figure 1.** *Received signal level.*

Multipath propagation results in the spreading of the signal in different domains, including delay (or temporal) spread, Doppler (or frequency) spread, and angle spread. Figure 2 shows typical channel spreads in each domain. These spreads have significant effects on the signal. The mean path loss, long-term fading, short-term fading, delay spread, Doppler spread, and angle spread are the main channel effects. Detailed models for the mean path loss are described in [4, 5].



■ **Figure 2.** *The three spreads of the wireless channel.*

Fading

In addition to mean path loss, the received signal exhibits fluctuations in signal level called fading. Fading can be modeled statistically with probability distributions [4–12]. In addition to a statistical description of the fading channel, we can describe the *severity* of fading in the time, frequency, and spatial domains. These lead to different channel characterizations, namely time-, frequency-, and space-selective channels. These channel characterizations are not mutually exclusive. The selectivity of a channel can be quantified in terms of the envelope correlation function defined as [4, 13]

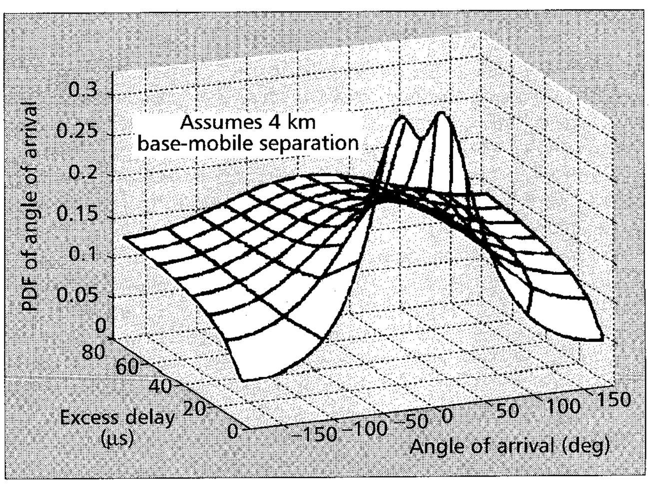
$$\rho(\Delta f, \Delta t, \Delta \mathbf{z}) = \frac{< r_1 r_2 > - < r_1 >< r_2 >}{\sqrt{\left[< r_1^2 > - < r_1 >^2\right]\left[< r_2^2 > - < r_2 >^2\right]}} \quad (1)$$

where $<\cdot>$ denotes the ensemble average, r_1 is the received signal envelope measured at frequency f_1, time t_1, and spatial location $\mathbf{z}_1$, and with a corresponding definition for r_2. The arguments of the correlation coefficient are the frequency separation $\Delta f = |f_1 - f_2|$, the time separation $\Delta t = |t_1 - t_2|$, and the spatial separation $\Delta \mathbf{z} = \|\mathbf{z}_1 - \mathbf{z}_2\|$.

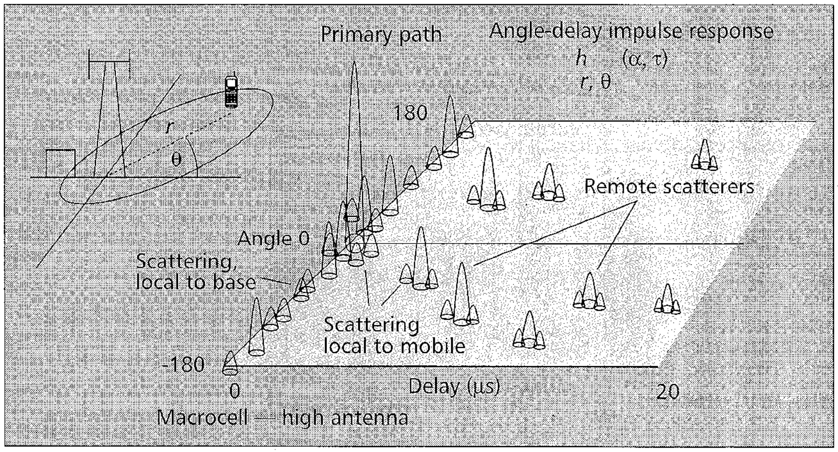
Doppler spread (or frequency dispersion) as a result of mobile motion causes time-selective fading in the channel. The coherence time of the channel can be used to characterize the time variation of the time-selective channel. It represents the time separation for which the correlation between the envelopes of the received signal at two time instants becomes 0.5 [13] and can be computed from Eq. 1 by setting Δf and $\Delta \mathbf{z}$ to zero. The coherence time is inversely proportional to the Doppler spread [14, 15] and is a measure of how fast the channel changes in time. Fast fading channels are characterized by a small coherence time.

Delay spread, on the other hand, causes ISI and is a result of a multipath propagation environment. The channel becomes frequency-selective, and the selectivity can be measured in terms of coherence bandwidth, which represents the maximum frequency separation for which the correlation of the signal amplitudes at two distinct frequencies becomes 0.5 [4, 13]. The coherence bandwidth is inversely proportional to the delay spread [14, 15]. A small ratio of coherence bandwidth to signal bandwidth indicates a frequency-selective channel.

Angle spread at the receivers refers to the spread of angles of arrival of the multipaths at the receiving antenna array. Likewise, angle spread at the transmitter refers to the spread of departure angles of the multipaths. The angle of arrival (or departure) of a path can be statistically related to the path delay based on a uniform distribution of scatterers on a constant delay ellipse assuming a single-bounce scattering model. The resulting joint angle of arrival and delay probability density function is shown in Fig. 3 (see [16] for further details of such a model). Angle spread causes space selective fading and is characterized by the coherence distance. The larger the angle spread, the shorter the coherence distance. As with the definitions of coherence time and bandwidth of a channel, we define the coherence distance as the maximum spatial separation for which the correlation between the received signal amplitudes at two antennas becomes 0.5 and can be computed from Eq. 1. Table 1 summarizes the different channel characteristics.



■ **Figure 3.** *Joint probability density function of angle of arrival and delay.*



■ **Figure 4.** *Macrocell impulse response.*

Multipath Propagation in Macrocells

In macrocells with high base station antenna elevation above the rooftop level, multipath scattering arises from three sources. These are scatterers local to the mobile, remote dominant scatterers, and scatterers local to the base. Scattering may include reflection and diffraction (see [17] for a discussion on propagation mechanisms). It is important to understand the different types of scatterers and their contribution to channel behavior. Our description below refers to the reverse link channel but applies equally to the forward link channel.

Scatterers Local to the Mobile – Scattering local to the mobile is caused by buildings and terrain features in the vicinity of the mobile (a few tens of meters). Mobile motion and local scattering give rise to Doppler spread which causes time-selective fading. For a mobile traveling at 65 mph, the Doppler spread is about 180 Hz in the 1900 MHz band. While local scatterers contribute to Doppler spread, the delay spread they contribute is usually insignificant because of the small scattering radius. Likewise, the angle spread induced is also small for mobiles distant from the base station (the majority of mobile users are in this class).

Remote Scatterers – The emerging wavefront from the local scatterers may then travel directly to the base or may be scattered or reflected toward the base by remote dominant scatterers, giving rise to specular multipath. These remote scatterers can be either terrain features or high-rise building complexes. Remote scattering can cause significant delay and angle spreads.

Scatterers Local to the Base Station– Once these multiple wavefronts reach the base station, they may be scattered further by local structures such as buildings or other structures in the vicinity of the base. Such scattering is less pronounced for antennas well above the rooftop. Scattering local to the base station can cause severe angle spread, which in turn causes space-selective fading.

A useful way of visualizing the channel characteristics (at a fixed time) of a macrocell is to plot the channel impulse response as a function of angle and delay. The impulse response itself is clearly a function of the geographical position of the mobile with respect to the base station. Figure 4 shows a typical angle-delay channel impulse response for a macrocell. The different impulses represent scatterers in the channel that contribute energy to the received signal. This response contains contributions from scatterers close to the mobile (shown as small impulses near the larger impulses), scatterers close to the base (shown at near zero delay but at wide angles), and remote scatterers at other locations.

Multipath Propagation in Microcells

The multipath propagation environment in a microcell is complicated since it is difficult to identify distinct classes of scatterers when the base station antenna is at a low elevation below the rooftop level. Figure 5 shows a typical propagation situation in a microcell environment. The channel impulse response is usually characterized by high angle spreads and small delay spreads, and may have Doppler spreads that can be as high as in macro-cell when the subscriber or base station is on a sidewalk located on roads with high-speed traffic. Figure 6 is a typical example of the angle-delay impulse response in a microcell environment. Note that there is no dominant impulse at the origin as in the macrocell case unless there is a line of sight from the mobile to the base station antenna.

Signal Model

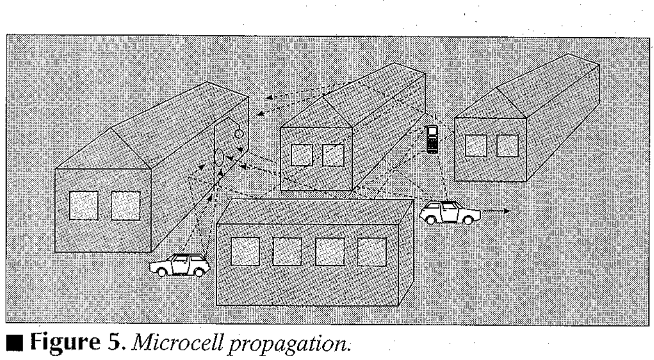
In the previous section, we discussed the physical wireless channel characteristics by examining various aspects of radio propagation. In this section, we focus on developing a signal model of the wireless channel for space-time processing applications. We assume that antenna arrays are used at the base stations and that the mobile has a single antenna. This leads to four interesting channel configurations.

Channel Configurations

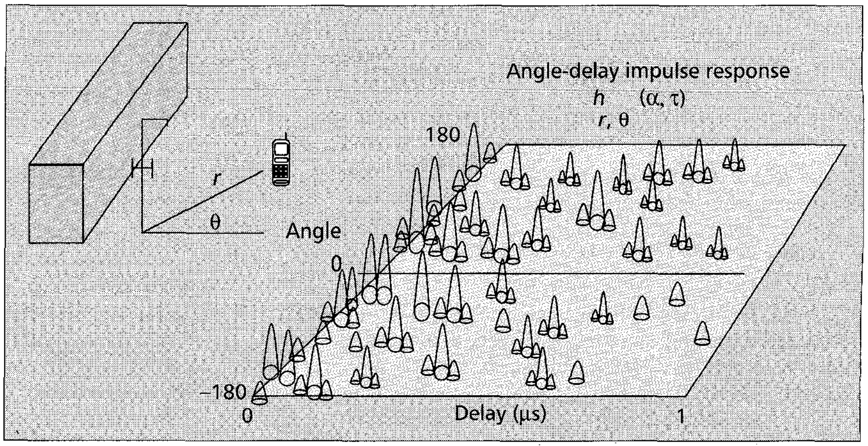
Before we begin discussing the signal models, some general remarks on the principle of reciprocity for the forward and reverse link channels are in order. This principle implies that the channels are identical on the forward and reverse links as long as the channels are measured at the same frequency and at the same time instant. In time-division duplexing (TDD) systems, the principle of reciprocity applies as long as the "ping-pong" time is very small compared to the channel coherence time. In frequency-division duplexing (FDD) systems (most macrocell wireless systems are FDD), the separa-

Channel spread	Channel selectivity	Coherence measure
Delay spread	Frequency-selective	Coherence bandwidth
Doppler spread	Time-selective	Coherence time
Angle spread	Space-selective	Coherence distance

■ **Table 1.** *Channel characteristics.*



■ **Figure 5.** *Microcell propagation.*



■ **Figure 6.** *Microcell impulse response.*

tion between the forward and reverse link frequencies is about 5 percent of the mean carrier frequency. This means that the principle of reciprocity must be used with care. Given the small frequency separation, the forward and reverse channels will share many common features. In a specular multipath channel as described earlier, the paths used by both links can be assumed to be identical. Therefore the number of paths, the path delays and path angles (arrival/ departure) are the same for both links. However the path amplitudes and phases (that is, the fading) will not be the same on both links and they will in fact be largely uncorrelated [4]. Also within any one link, the different paths fade independently. Since fading appears as a multiplicative gain, the symbol response channel appears to be uncorrelated between the forward and reverse links. We focus here on TDMA systems. DS-CDMA signal models are discussed in [18].

Reverse Link SU-SIMO – This configuration refers to a single-user (SU) with single antenna input (SI) at the mobile and multiple antenna output (MO) at the base (SU-SIMO). The signal model corresponds to the case when a single user transmits the information signal and it is received at a base station with m antennas. It can be shown that the received signal vector at the base station for a specular multipath channel is [19]

$$\mathbf{x}(t) = \sum_k \sum_{l=1}^{L} \mathbf{a}(\theta_l)\alpha_l^R(t) g(t - \tau_l - kT) s(k) \quad (2)$$

where $\mathbf{a}(\theta_l)$ is an m-dimensional complex vector representing the antenna array response to a signal arriving from direction θ_l, $|\alpha^R(t)|$ is the fade amplitude that can be modeled as a random variable with a probability distribution (e.g. Rayleigh), $g(t)$ is the pulse shaping waveform,[1] L is the number of multipath and $s(k)$ represents the user data.

Reverse Link MU-SIMO – This configuration refers to multi-user (MU) with single antenna input (SI) at each mobile and multiple antenna composite output (MO) at the base (MU-SIMO). The signal model is a generalization of the SU-SIMO case and refers to the case where multiple mobiles transmit their information signals and they arrive at a base station which uses an antenna array to separate individual signals. The MU-SIMO can easily be obtained from the SU-SIMO model. Assuming there are Q users, the composite received signal at the antenna array is a sum of the signals from Q mobiles and is given by

$$\mathbf{x}(t) = \sum_k \sum_{q=1}^{Q} \sum_{l=1}^{L_q} \mathbf{a}(\theta_{lq})\alpha_{lq}^R(t) g(t - \tau_{lq} - kT) s_q(k)$$

where we have indexed each user's signal, and corresponding path delay, angle, and fading parameters by the user index q and we have assumed that the users use the same pulse shaping filters.

[1] *We have assumed a linear modulation scheme in order to obtain Eq. 2. However, in the case of a nonlinear modulation scheme such as the Gaussian minimum shift keying (GMSK) signal in the GSM cellular radio system, an excellent linear approximation to the GMSK modulation can be obtained [20, 21], and Eq. 2 still holds. However, see [22] for a nonlinear signal model for the GSM system.*

Forward Link SU-MISO – This configuration refers to single-user (SU) with multiple antenna input (MI) at the base and single antenna output (SO) at the mobile unit (SU-MISO). In this model, the base station uses an antenna array to transmit an information signal to a single mobile. In the forward link the paths that couple the signal to the mobile will be the same as the paths available in the reverse link. However, the space-time processing of a user signal is carried out at the transmitter *before* the signal is launched into the channel. Therefore, due to the effect of base station antennas and transmit processing, the radiated signal will be *directional*, and therefore the transmit beam pattern will selectively weight the energy coupled into each of the multipaths. In an extreme case, some paths may not be excited at all. If we use space-only processing with a beamforming weight vector $\mathbf{w}$, the transmitted signal in each path will be the same, and the signal received by the mobile will be the sum of arrivals from different path signals.

With the simplifying assumption of space-only processing, the received baseband signal at the mobile station $x(t)$ is given by

$$x(t) = \sum_k \sum_{l=1}^{L} \mathbf{w}^H \mathbf{a}(\theta_l)\alpha_l^F(t) g(t - \tau_l - kT) s(k)$$

where $\mathbf{w}$ is the transmit weight vector that influences how the transmitted signal couples into the channel, and ^{H} denotes complex conjugate transpose. The path delay τ_l, and angle parameters θ_l, are the same as those of the reverse link. $\alpha_l^F(t)$ is the complex fading on the forward link which in (fast ping-pong time) TDD systems will be nearly identical to the reverse link complex fade amplitude $\alpha_l^R(t)$. In an FDD system $\alpha_l^F(t)$ and $\alpha_l^R(t)$ will have the same statistics but will, in general, be uncorrelated with each other.

Forward Link MU-MISO – This configuration refers to multi-user (MU) with multiple antennas composite input (MI) at the base and single antenna output (SO) at each mobile (MU-MISO). In this model, the information signals from a base station antenna array are transmitted to multiple mobiles. Once again the MU-SIMO model can be easily derived from the SU-SIMO model. Again, assuming that there are Q users, the signal received at the mth mobile is given by

$$x_m(t) = \sum_k \sum_{q=1}^{Q} \sum_{l=1}^{L_q} \mathbf{w}_q^H \mathbf{a}(\theta_{lm})\alpha_{lm}^F(t) g(t - \tau_{lm} - kT) s_q(k).$$

The Q different user data $\{s_q(k)\}$ couple into the L_m paths of the mth user through the corresponding weight vectors $\mathbf{w}_q$. As in SU-MISO, the forward link path parameters are related to the reverse link path parameters.

A Discrete Time Signal Model

When the received signal is sampled at the receiver at symbol rate or higher, it is more convenient to use a symbol response signal model. If we assume that the channel responses are of finite duration, such a signal model for the MU-SIMO case is given by

$$\mathbf{x}(k) = \sum_{q=1}^{Q} \mathbf{H}_q(k)\mathbf{s}_q(k) + \mathbf{n}(k) \tag{3}$$

where $\mathbf{H}_q(k)$ are the channel matrices for the Q users, $s_q(k)$ are the corresponding user data sequence vectors, and $\mathbf{n}(k)$ is a vector of additive noise. The signal model in Eq. 3 is a linear time-varying (LTV) model. There is a relationship between the elements of the channel matrices $\mathbf{H}_q(k)$ and the physical path parameters such as path angle of arrival, delay, fade amplitude, and the pulse shape $g(t)$ described earlier (see [23] for more details). The channel matrix offers a rich structure that can be exploited for improved algorithm design. Note that this model can also be used to model the case of a signal with CCI. The symbol response signal model can also be obtained for the forward link channels (SU-MISO and MU-MISO) where the channel matrices will include the weighting vectors.[2]

The time-varying channel matrices are a direct consequence of the time variation in the fading parameters $\alpha_l^R(t)$ or $\alpha_l^F(t)$ due to motion of the mobiles, CCI, or scatterers. When the time slot within a TDMA frame is small, compared to the coherence time of the channel (non-time-selective), the channel (as seen by the receiver or transmitter) can be regarded as time-invariant, and hence, the channel matrices $\mathbf{H}_q$ are not functions of time. In addition, if the signal bandwidth exceeds the coherence bandwidth of the channel (frequency selectivity), there will be significant ISI and this increases the overall channel length, and hence, the width of $\mathbf{H}_q$. A linear time-invariant (LTI) signal model is important because there exist numerous techniques in signal processing for blind channel estimation and equalization for this case. An example of where a LTI signal model can be used is the GSM system. We shall explore and discuss some of these techniques later.

When the channel is both time- and frequency-selective, adaptive equalization techniques must be used to enable channel tracking and data detection. However, the underlying structure of the channels enable new adaptive algorithms with improved performance. We shall briefly discuss this in the next section.

Spatial and Temporal Structure

A basic requirement for data detection is to estimate the channel. The underlying structure in the channel can be used to improve channel estimation. We briefly describe the channel and signal structures.

Spatial Structure – The spatial signature of a path arriving at an antenna array at an angle θ is captured by the array response vector $\mathbf{a}(\theta)$. If we know the array response for every θ, we need only to estimate a single parameter θ instead of $\mathbf{a}(\theta)$, a vector of length m. Spatial structure can be utilized effectively when the number of multipaths is small. Many algorithms have been developed for estimating θ; the interested reader is referred to [24–28]. We have assumed that the directions are time-invariant, which is reasonable since the change in direction of the mobile with respect to the base station is negligible during a small observation time such as a time slot in a TDMA frame.

Temporal Structure – The temporal structure here refers to the properties of the transmitted signal (which includes the pulse shape and modulation format). One common temporal structure found in some signals is a *constant modulus* (CM) envelope. Practical examples include the class of continuous-phase modulation (CPM) signals and the GMSK signal (which is a special case of a CPM signal). Blind techniques (i.e., techniques that do not require a training sequence) have been proposed for CM signals for applications ranging from direction finding to blind equalization. The constant modulus algorithm (CMA) was originally proposed for blind equalization [29] of phase-modulated signals, and was shown to be a special case of the Godard class of blind algorithms [30]. Other variants of the CMA can be found in [31–36].

Another popular temporal structure is the *finite alphabet* (FA) property of all digitally modulated signals. This refers to the finite number of constellation points in a chosen digital modulation scheme. A well-known technique using this property for data detection is the Viterbi algorithm (VA) for maximum likelihood sequence estimation (MLSE) (see [37]) in the presence of additive white Gaussian noise (AWGN). The VA assumes that the channel is known. Blind equalization techniques of multiple users using the FA property have also been proposed [38–41].

A less well known but powerful temporal structure is the pulse shaping function for a linear modulation scheme. For example, the IS-54 system uses pulse shapes that have a square root raised cosine spectrum for both the transmit and receive filters. Methods that exploit the knowledge of the transmit and receive pulse shaping filters for blind channel identification can be found in [42–44], and for nonblind channel estimation in [45]. An adaptive MLSE receiver for fast time-varying channels using prior knowledge of the pulse shape filters has also been proposed in [46].

Another temporal structure is the *cyclostationarity* of digital communication signals which can be exploited for non-time-selective channels. It was widely believed that blind channel identification was only possible using higher-order statistics-based techniques [47–49], since the phase of the channel is lost if second-order statistics of baud-spaced data samples are used for identifying a nonminimum phase channel. It was observed in [50] that a cyclostationary signal contains phase information that can be used to identify the channel. The work in [51] proved that blind channel identification can be achieved using second-order statistics of the *oversampled* (two or more samples per symbol) data. The temporal oversampling of a digital modulated signal results in a cyclostationary signal which preserves the channel phase information. Spatial oversampling of the signal using multiple antennas can also achieve cyclostationarity in the baud-rate sampled vector signal [52].

Channel Estimation

Channel estimation is an important step in signal detection. In the reverse link, channel estimation is needed for equalization, diversity, and CCI reduction. In the forward link, channel estimation is needed to design weight vectors to deliver energy to a selected user without causing significant CCI to other users.

Reverse Link Channel Estimation

We can broadly classify channel estimation techniques for the reverse link channel into two categories: nonblind and blind. The essential ingredient in nonblind channel estimation is the use of a known training sequence embedded in the data. On the other

[2] *Although the model in Eq. 3 is developed from the TDMA standpoint, it is readily clear that the discrete time signal model also applies to frequency-hopping multiple access (FHMA) schemes.*

hand, blind techniques do not need a training sequence and therefore eliminate this overhead. Also, using the rich underlying structure of the channels, improved channel estimation can be accomplished for both blind and nonblind methods.

Nonblind Channel Estimation – There are three methods to estimate the reverse link channel corresponding to different assumptions on the channel structure. We assume for now that the channel is time-invariant. The case when the channel is time-varying is deferred to the next section, where we will discuss joint channel and data estimation techniques.

- *Unstructured channel:*[3] In this method, we make no assumption on the channel other than a finite channel length. We can easily compute the least squares estimate of the reverse link channel H^R using the training sequence.
- *Structured channel:* In this method, we exploit the known pulse shaping filter to describe the channel. It can be shown that the channel lies in the subspace of a certain matrix $\mathbf{G}$ whose elements are the sampled values of the pulse shaping filter impulse response [45], that is, $\mathbf{h}^R = \mathbf{Gc}$. The channel depends only on the unknown coefficient vector $\mathbf{c}$ (which typically has a smaller number of elements than the channel itself). The vector $\mathbf{c}$ can be estimated via least squares using the training sequence.
- *Parametric channel:* Here we parameterize the channel in terms of the angles of arrival, delays, and complex path gains. It can be shown that the reverse link channel matrix $\mathbf{H}^R = \mathbf{A}(\theta)\mathbf{B}(\alpha)\mathbf{G}(\tau)$ [23], where $\mathbf{A}(\theta)$ is the spatial response matrix, $\mathbf{B}(\alpha)$ is a diagonal matrix containing the multipath gains, and $\mathbf{G}(\tau)$ is a matrix containing sampled (and delayed) versions of the pulse shaping waveform. Finding the parameters $\{\theta, \alpha, \tau\}$ is equivalent to estimating the channel. Again, using the training sequence, subspace-based algorithms can be used for estimating these parameters [23, 54].

Blind Channel Estimation – A significant amount of research effort has been focused lately on blind channel estimation[4] which we broadly categorize into three classes: higher-order statistics (HOS), second-order statistics (SOS), and maximum likelihood (ML) methods. We will summarize briefly some of the research results.

• *Higher-order statistics (HOS) methods:* Just as the autocorrelation function and power spectral density are important to the study of the second-order statistics of a stationary random process, the *cumulants* and their Fourier transforms, *polyspectra*, are the foundations for the study into the HOS of stationary random processes [55]. Two of the most important properties of HOS that distinguish it from second-order statistics are the preservation of phase information in the polyspectra and the fact that the polyspectra of a stationary Gaussian random process is zero. By virtue of these properties, methods based on the HOS of the channel output can be used to identify non-minimum-phase channels. Various techniques for blind channel identification using HOS can be found in [47, 49, 56, 57]. To obtain reliable estimates of the HOS of the received signal, a large amount of data is needed and the computational complexity can be high. Its usefulness for estimating wireless channels is thus limited.

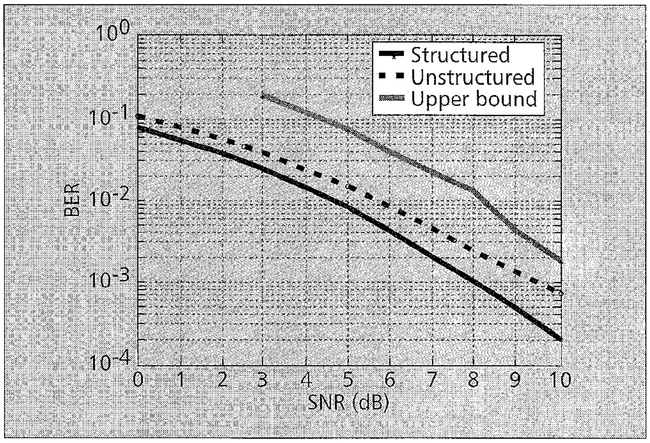
• *Second-order statistics (SOS) methods:* It was shown in [50] that the SOS of cyclostationary signals contain phase information that can be used to identify a non-minimum-phase channel. Loosely speaking, cyclostationary signals are signals whose statistical properties are invariant to time shifts by integral multiples of some constant T_o [58]. The pioneering work in [51] enabled blind channel identification based on the temporally *oversampled* channel output. It turned out that oversampling the channel output produces a cyclostationary sequence. From a different perspective, oversampling the received signal increases the number of samples in the signal and the number of phases in the channel per symbol period but does not change the data symbol value. Thus, oversampling results in a tall channel matrix $\mathbf{H}$. By making further use of the time invariance and finite length properties of the channel, special structures in the channel matrix (block Toeplitz) can be created to allow SOS-based blind channel identification. Motivated by subspace methods in array processing, blind subspace-based channel identification has been proposed in [59–61]. Frequency domain approaches using the cyclic spectra have been proposed in [62–64].

• *Maximum likelihood (ML) methods:* The principle of maximum likelihood is a popular method for statistical inference [65]. The ML method assumes that the probability density function of the received signal (conditioned on the channel) is known, and seeks to maximize the likelihood function (or the joint probability density function of the received signal) as a function of the channel parameters. For the AWGN case, the ML estimation for the channel parameters becomes a nonlinear optimization problem [66]. The complexity of the algorithm in [66] is $O(N^3P^3)$ where N is the length of the data sequence and P is the oversampling factor. It is clear that the implementation of the ML algorithm is computationally prohibitive except for very short data sequences.

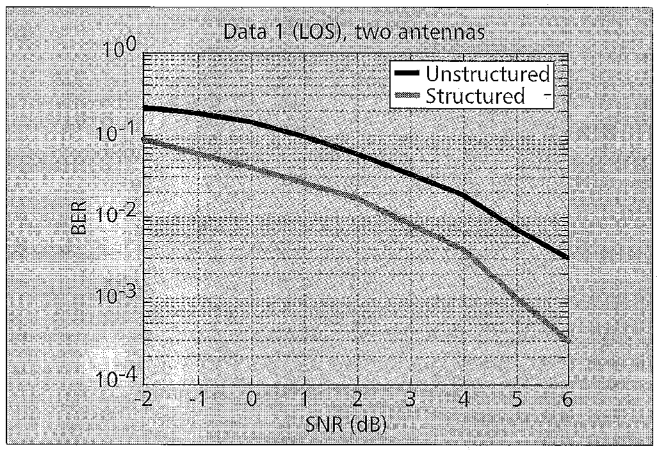
• *Channel identifiability:* Channel identifiability from the temporally oversampled channel output is an important issue. We assume for now that there is a single user ($Q = 1$) and a single antenna, and that the data vector $\mathbf{x}(k)$ in Eq. 3 is obtained from oversampling the received signal. Each row of the channel matrix $\mathbf{H}$ is then the discrete time impulse response for each of the P oversampled channels (these are sometimes known as the *polyphase* channels). It can be shown that the polyphase channels can be identified if the z-transforms of the polyphase channel impulse responses do not share any common roots [66–69]. An additional condition on the input data sequence for the case when the amount of data is small has also been found [70, 71]. For the case of a discrete multipath channel, it has been shown that temporal oversampling alone cannot identify the polyphase channels when the multipath delays are exactly integer multiples of the symbol period T or integer multiples of $T/2$ for an even number of polyphase channels (P is even) [69]. In addition, it was shown that band-limited multipath channels with frequency nulls in $[-(1-\beta)/2T, (1-\beta)/2T]$, where β is the excess bandwidth, also suffer from channel nonidentifiability. The introduction of multiple antennas has been shown to eliminate this class of identifiability problems [72]. When there are multiple users, the same condition of no common zeros among all the polyphase channels for all the different users is a necessary condition for channel identifiability. In addition, another condition is that the z-transform of the total channel matrix should be column-reduced [73]. However, there exists a more subtle ambiguity problem for SOS-based (or subspace-based)

[3] *A more traditional way to estimate the channel, such as in implementations of the MLSE receiver for the GSM system, is to use a filter that is matched to the sounding sequence (GMSK modulated training sequence). The estimated channel impulse response is then windowed to keep a modest number of states in the Viterbi equalizer [13]. This method of channel impulse response estimation is often used in time domain system identification applications [53] and is known as correlation analysis.*

[4] *There is a difference between channel estimation and equalization. Blind channel equalization or deconvolution attempts to estimate the data directly without estimating the unknown channel.*



■ **Figure 7.** *BER plots of the ST-MLSE for the GSM TU 12 ray channel model.*



■ **Figure 8.** *BER plots of the ST-MLSE for an indoor channel.*

channel estimation methods in that the channels can only be identified up to a $d \times d$ transformation matrix where d is the number of co-channel users [74]. As noted in [39, 75], it appears that this ambiguity cannot be resolved without resorting to some additional property (e.g., the FA property) of the user signals.

Forward Link Channel Estimation

We can estimate the forward link channel from the reverse link channel using the principle of reciprocity or from feedback from the receiver. We describe these approaches below.

Channel Estimation in TDD – In a TDD system, if the duplexing time is small compared to the coherence time of the channel, both channels are the same and the base-station can use its estimate of the reverse link channel to estimate the forward link channel. i.e., $\hat{\mathbf{H}}^F = \hat{\mathbf{H}}^R$, where $\hat{\mathbf{H}}^R$ is the reverse link channel estimate. It can be shown [13] that the coherence time is approximately $9/16\pi f_m$, where f_m is the maximum Doppler frequency.[5] As an example, for a mobile traveling at 65 mph, a mobile channel at 900 MHz exhibits a coherence time of approximately 2 ms. Thus, if the duplexing time is much smaller than 2 ms the forward link channel can be assumed to be similar to the reverse link channel.

Channel Estimation in FDD – In FDD systems, the forward and reverse link channels have different center frequencies causing a difference in the instantaneous complex path gains (i.e,. fading). However, the path angle of arrival and delay remain the same. Thus, it is still possible to approximately estimate the forward link channel from the reverse link channel. Since the difference in the up- and downlink carrier frequencies is about 5 percent of the carrier frequencies, we assume that the forward and reverse link array response vectors are similar for any direction of arrival/departure (see [76] for a discussion of the frequency dependencies of the array response vector). Depending on the angle and delay spreads of the channels, several methods can be used to estimate the forward link channel (see [18] for more details).

Channel Estimation Using Feedback – Another approach to estimate the forward link channel is to feedback the signal from the mobile unit and then use either a blind or nonblind method for estimating the channel. For time-invariant channels, a training signal is transmitted through each antenna, one at a time, from the base station to the mobile. Based on the received signals at the mobile, the total transmit channel can then be estimated as the solution to a least squares problem.

In LTV channels which need frequent tracking, more efficient probing methods can be used to reduce the overhead of multiple training signals. The common subspaces shared by the reverse and forward link channels can be used to minimize the amount of training needed (see [77] for details).

[5] *This assumes that the joint probability density function of the angle θ and delay τ is $p(\theta, \tau) = 1/2\pi\sigma(e^{-\tau/\sigma})$ where σ is the delay spread of the channel.*

Space-Time Modems for TDMA

Space-time modem (STM) techniques refer to the equalization (pre-equalization and coding) of the space-time channel observed at the receiver (transmitter) antenna array. Spatial processing offers CCI suppression, signal-to-thermal-noise enhancement, and spatial diversity against fading. Temporal processing, on the other hand, offers reduced ISI and temporal (path) diversity. The combination of space and time processing allows us to exploit the advantages of both dimensions.

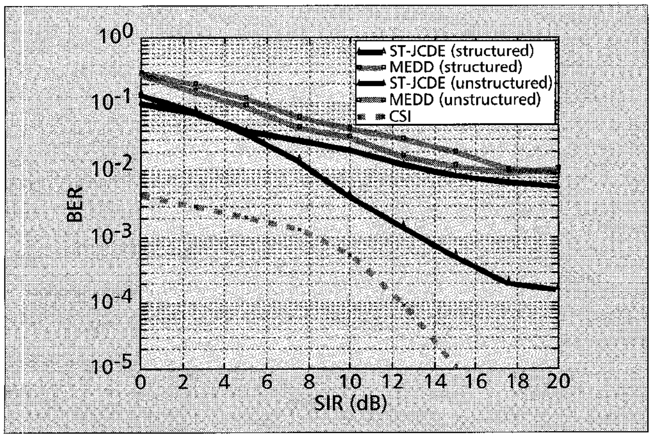
Nonblind ST Modems for Reverse Link

In nonblind STMs, we use training signals to estimate the channel. In GSM and IS-136 standards, training signals are provided inside each burst for this purpose. Training signals can be used for channel estimation or to determine the equalizer directly.

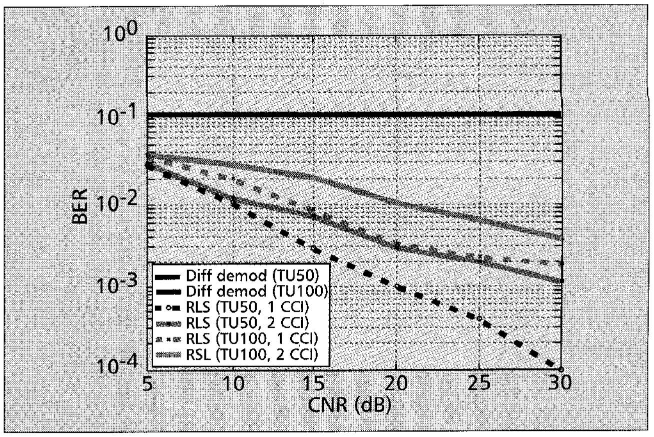
The standard MLSE seeks to estimate the transmitted data sequence that best describes the received signal given the channel estimate [37]. The extension to multiple antennas is straightforward and requires a multichannel MLSE along with an ST channel estimate. In most cases, the MLSE performance is limited by errors in channel estimate due to either the presence of noise or poor tracking of the time-varying channel during a data burst.

The optimum receiver in the presence of co-channel users is a multi-user ST-MLSE. This receiver decodes all the users jointly and in effect tries to estimate all the transmitted data sequences that best describe the received signal given the multiple ST channel estimates. The problem with multi-user methods is the exponential growth of complexity with the number of users and the need for accurate channel estimates for all co-channel users.

A computationally tractable ST-MLSE receiver structure uses a modified metric based on the covariance of the CCI plus noise with a single-user ST-MLSE structure [78, 79]. This is also known as an interference-whitening MLSE receiver. A much simpler receiver, which handles CCI robustly but is less optimum in handling ISI, is an ST-MMSE receiver. This receiver is discussed later. We also discuss later an interesting hybrid receiver [80], which combines the advantages of cancelling CCI in an ST filter followed by a scalar MLSE structure.



■ **Figure 9.** *BER for ST-JCDE receiver in a fast time-varying IS-54 channel with CCI.*



■ **Figure 10.** *BER plots of the RLS-DD ST-MMSE equalizer for an IS-54 mobile system.*

In the presence of LTV channels, we need to incorporate some form of channel tracking. Some approaches to handle this situation are discussed later. Furthermore, the use of channel structure can considerably improve channel estimation and tracking, and some examples that demonstrate this are also discussed in the following subsection.

ST-MLSE Receivers – Single-user ST-MLSE receivers are a straightforward extension of the scalar MLSE. Since we only have a finite training sequence, channel structure can be useful to improve channel estimation and therefore ST-MLSE performance [47]. This is shown in Fig. 7, where we plot the ST-MLSE performance with and without using channel structure for a GSM receiver. The simulation model uses two antennas and an oversampling factor of two. Figure 7 shows an improvement of 1 to 2 dB with structured methods at 1 percent BER. Another example of structured channel estimation is shown in Fig. 8. These results are plotted for an indoor channel with two antennas and use measurements made at 2.4 GHz (see [81] for details). Once again, structured methods offer a 2 dB gain in performance at a 1 percent BER.

In the presence of a time-varying channel, the ST-MLSE receiver must carry out joint channel and data estimation (ST-JCDE) [82–86]. These JCDE receivers can outperform conventional adaptive MLSE receivers [15, 87]. In the ST-JCDE receivers, the training sequence is used to obtain an initial estimate of the channel. Thereafter, the channel is tracked by associating a channel estimate (with fading memory) with each survivor sequence at each state in the search trellis.

In the presence of CCI, the ST-JCDE receiver can be modified if the CCI plus noise covariance is used in the metric (Mahalanobis distance) computation [88]. Furthermore, as seen above, the use of structured channels can further improve receiver performance. Figure 9 compares the performances of structured vs. unstructured receivers with and without the use of the CCI covariance metric. The plots can be compared to the receiver with perfect channel state information (CSI). We can see that a ST-JCDE receiver with channel structure information performs considerably better (6 dB) than unstructured and minimum Euclidean distance decoding (MEDD) receivers. However, CCI cancellation and channel tracking are not perfect as indicated by the difference between the error rates of the ST-JCDE receivers and the ST receiver with CSI. Despite its superior performance, the ST-MLSE receiver has a computational complexity that grows exponentially with channel length. Suboptimal techniques such as reduced-state sequence estimation (RSSE) [89], delayed decision feedback sequence estimation (DDFSE) [90], and channel memory truncation [91] have been proposed to reduce the computational complexity.

ST-MMSE Equalizer – In an ST-MMSE equalizer, the oversampled channel output for each antenna is weighted and summed to produce the desired output. The ST equalizer weight vector $\mathbf{w}$ is chosen to minimize the expected squared error, that is,

$$\mathbf{w}_D = \arg\min_{\mathbf{w}} E\ |\mathbf{w}^H\mathbf{x}(k) - s(k-D)|^2 \qquad (4)$$

where D is an integer delay. The subscript D on $\mathbf{w}$ indicates that it depends on the delay D in the reference signal. The optimal weight vector is given by the Wiener solution $\mathbf{w}_D = \mathbf{R}_{\mathbf{xx}}^{-1}\mathbf{r}_{\mathbf{x}s}(D)$, where $\mathbf{R}_{\mathbf{xx}}$ is the covariance matrix of the $\mathbf{x}(k)$ and $\mathbf{r}_{\mathbf{x}s}(D)$ is the cross-correlation vector between $\mathbf{x}(k)$ and $s(k-D)$ (see [18] for more details).

In practice, we compute the finite sample estimate of $\mathbf{R}_{\mathbf{xx}}$ and $\mathbf{r}_{\mathbf{x}s}(D)$ using the received samples during the training period. The optimal weight vector computed during the training period is then used for the entire time slot if the channel does not vary significantly over the slot period. For fast time-varying channels, the ST weight vector obtained during the training period should be tracked by using, for example, a decision-directed adaptive algorithm (see [92] for a tutorial on adaptive equalization).

Figure 10 shows BER plots of an ST recursive least squares decision-directed (RLS-DD) algorithm for a number of time-varying urban channel models in the presence of CCI for the IS-54 TDMA mobile system [93]. We observe that the conventional differential demodulator (detector) for the IS-54 is interference-limited (CCI is 7 dB below signal), and the BER does not improve as the SNR increases. Spatial filtering improves performance significantly (see also [94]). The ST-MMSE equalizer thus has a number of attractive advantages. It suppresses CCI effectively and performs adequately against ISI.

STF/MLSE – A hybrid two-stage CCI/ISI reduction structure with an ST filter (STF) followed by a scalar MLSE receiver has been proposed in [80]. The objective of the STF is to suppress CCI while capturing spatial diversity, and the MLSE is used to remove the residual ISI and capture temporal diversity. The filter weights and the target channel for the MLSE are jointly optimized to yield the maximum SINR. Figure 11 shows the BER plots of this hybrid receiver as a function of signal-to-interference ratio (SIR) for a GSM TU six-tap urban channel model. A two-element antenna array, with different numbers of STF tap weights, is used. The SNR is 20 dB. There is one signal and one CCI with a speed of 30 mph each. Both signal and CCI arrive at the array from random angles within a 120° sector, each with a 30° angle spread. We observe that the hybrid receivers with one and two taps per antenna outperform the ST-MLSE at low SIR (both with and without the incorporation of CCI statistics). For slow fading channels, adaptive implementations under an MMSE criterion

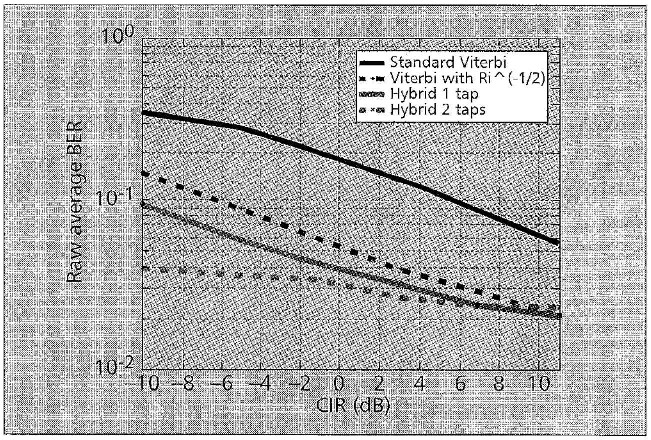


Figure 11. *BER for two-stage ST-MMSE/MLSE for a GSM system with CCI.*

have been proposed in [95]. The STF/MLSE receiver can be extended to cope with fast time-varying channels by using trellis search techniques as described previously.

Blind ST Modems for Reverse Link

In space-time blind equalization,[6] the objective is to recover the input data applied to unknown linear time-invariant (possibly non-minimum phase) channels, given only the output of the channels. Blind algorithms do not need any training signal and can be classified into block and adaptive methods.

Block ST Modems – In these methods, blind equalization is performed on a block of oversampled received channel data, corresponding to one time slot. These methods rely on the temporal structures of the input data.

Approaches that exploit the FA structure of the input data as well as the block Toeplitz property of the symbol matrix in a multi-user case have been proposed in [39, 40]. In these methods, the received ST signal is rearranged into a block Toeplitz matrix. The main observation is that the null space of the received signal matrix is also the null space of a block Toeplitz data symbol matrix. So by finding the null space of the received signal matrix, one could use the block Toeplitz structure in the symbol matrix as well as its FA property to estimate the multi-user data.

For small delay spread channels, approaches based on the FA property include the iterative least squares techniques (ILSP and ILSE) in [38], and an analytical CM algorithm (ACMA) based on the CM property of input signals in [36]. The ACMA finds the CM beamformer weights to separate multiple CM signals blindly. It is also able to detect the number of CM signals and to retrieve them while rejecting other non-CM signals.

Adaptive ST Modems – Adaptive schemes to equalize an unknown channel blindly have been the focus of intense research. One class of blind adaptive equalization algorithms is widely referred to as *Bussgang* algorithms. This class of algorithms are usually implemented by a transversal filter of adjustable tap weights followed by a memoryless nonlinear operator on the filter output.[7] The error between the nonlinear operator output and the filter output is then used to adjust the weights in the transversal filter by using a stochastic gradient adaptive algorithm [97]. The Sato [98], Godard [30], Benveniste-Goursat [99], and CM [29] algorithms are special cases of the Bussgang class of algorithms and are designed to deal with ISI in the single-user case. The differences lie in the implementation of the memoryless nonlinear operator. Extensions to deal with the blind equalization of multiple CM signals have been proposed in [31, 34, 100] by using multiple antennas. Another class of blind equalization techniques is based on the use of HOS of the input signal. The superexponential algorithms [101] are single-user methods based on the cumulants of the input signal and have a fast convergence rate. Both iterative and adaptive forms of the algorithms have been proposed in [101].

Recently, an approach that exploits "delay" diversity has been proposed based on the observation that a zero-forcing linear equalizer is a function of the delay chosen by the user (see Eq. 4 for the definition of the delay). Therefore, there exists a relationship between equalizers with different delays. This property can be exploited to obtain a bank of equalizers known as blind mutually referenced equalizers (MRE). This approach again requires either oversampling or multiple antennas [102].

ST Modems for the Forward Link

ST Pre-Equalizers – Space-time pre-equalization for the forward link refers to the design of an optimal ST weight vector at the base station to maximize the signal energy at the desired mobile while minimizing ISI at the desired mobile and CCI at other co-channel mobiles. The design of STM pre-equalization algorithms for the forward link represents significant challenges. The main difficulty lies in the fact that signal processing is done at the base station before the signal is emitted into a channel which may not be known exactly. Likewise, the channels to other co-channel mobiles H_F^n also may not be known. Several schemes can be proposed depending on the objective. Criteria such as the maximization of the SINR at the mobile [77], minimization of ISI subject to additional quadratic constraints on CCI to other mobiles [76], and the joint minimization of both the ISI and CCI at other mobiles [103] have been proposed. All STM pre-equalization schemes require some knowledge of the forward channels to the desired and co-channel mobiles.

Space-Time Coding – In FDD systems, the forward channel is usually unknown or only partially known. Therefore, even if we have multiple transmit antennas that exhibit low fade correlation, transmit diversity cannot be implemented directly as is possible in TDD systems. There is an emerging class of techniques which offers transmit diversity in FDD systems by using space-time channel coding. The diversity gain can then be translated into significant improvements in data rates or BER performance.

The basic approach in space-time coding (STC) is to split the encoded data into multiple data streams, each of which is modulated and simultaneously transmitted from a different antenna [104]. Different choices of data to antenna mapping can be used. All antennas can use the same modulation and carrier frequency. Alternatively, different modulations (symbol waveforms) or symbol delays can be used. Other approaches include the use of different carriers (multicarrier techniques) or spreading codes. The received signal is a superposition of the multiple transmitted signals. Channel decoding

[6] *In the signal processing literature, blind equalization is sometimes referred to as blind deconvolution.*

[7] *The reason why the algorithms are known as Bussgang algorithms is that the output of the transversal filter y(n) after convergence of the adaptive algorithm is approximately a Bussgang process, i.e., $Ey(n)y(n+k) \approx y(n)g(y(n+k))\ \forall k$ where $g(\cdot)$ is the memoryless nonlinear operator [96, 97].*

is used to recover the data sequence. Since the encoded data arrived over uncorrelated fading branches, diversity gain can be realized.

The key research issues in STC are optimum techniques for encoded data-to-antenna mapping and code design. The problem of mapping raises several issues and trade-offs such as receiver complexity, robustness to delay and Doppler spread in the channel, crest factor of transmitted waveforms, ease of receiver synchronization, and channel tracking. The code design problem relates to trading off code rate, diversity gain, constellation size, and trellis complexity.

Yet another important issue in exploiting transmit diversity is partitioning the resource, represented by multiple antennas, between co-channel interference reduction (through transmit null steering) and transmit diversity. Clearly transmit null steering needs accurate knowledge of the channel, in which case conventional transmit diversity can be implemented. The more likely situation is that we have approximate channel information; hence, the open problem is how to partition the antenna resource to balance co-channel interference reduction with transmit diversity.

In summary, STC offers a rich and promising area for research. Preliminary results [104, 105] show significant gains from this emerging technology.

Space-Time Modems for DS-CDMA

Direct sequence code-division multiple access (DS-CDMA) is a spread-spectrum multiple access scheme that is expected to gain a significant share of the cellular market. DS-CDMA has several attractive properties for personal communications, namely its efficient use of bandwidth, and its resistance to interference and casual eavesdropping. A good reference on DS-CDMA can be found in [106]. Other books on DS-CDMA include [107–109]. A DS-CDMA cellular system (IS-95) for North America has been standardized and is currently entering service. As in other multiple access systems, the use of multiple antennas in CDMA is expected to improve system capacity, quality, and coverage.

In CDMA, the users operate in the same frequency channel at the same time. In DS-CDMA, each user has a *unique* spreading code and the user's data is modulated by the code at a (chip) rate P times greater than the data rate. The value of P typically lies between 32 and 512. The DS-CDMA link is shared by multiple users and therefore needs a larger bandwidth channel than TDMA or FDMA. The user codes can be designed to be orthogonal or quasi-orthogonal. If there is no multipath, the use of orthogonal codes ensures no interference from other users. On the other hand, if multipath is present, the codes are no longer orthogonal and multiple access interference (MAI) results. The set of quasi-orthogonal codes is much larger than the set of orthogonal codes for a given P.

The optimum receiver in an AWGN channel is shown to consist of a bank of matched filters followed by a multi-user VA [110]. The computational complexity of this receiver grows exponentially with the number of users. Linear multi-user receivers for synchronous and asynchronous DS-CDMA have been proposed in [111, 112], where the computational complexity is linear with the number of users. These receivers exhibit the same degree of near-far resistance as the optimum multi-user receiver. They also have error rate performances comparable to the optimum multi-user receiver. These receivers also require knowledge of all the users' channels.

One difference between the DS-CDMA and TDMA radio links is that there is little ISI in the DS-CDMA channels. Instead, interchip interference (ICI) is often encountered. Since the spreading codes of the users are known, novel channel estimation techniques have been proposed [113, 114].

ST Receiver Modems

A popular single-user receiver in the presence of multipath is the RAKE combiner first proposed by Price and Green in 1958 [115]. The ST-RAKE is an extension of the RAKE receiver and consists of an MMSE beamformer for each path followed by a standard temporal RAKE receiver [116]. The beamformer weights are calculated based on the covariances of the received data and the channel vector for the desired path (finger). The ST-RAKE receiver reduces the amount of MAI and hence improves coverage and capacity. Other ST DS-CDMA receivers that have been proposed recently include [117–120].

ST Transmit Modems

On a DS-CDMA forward link, multiple antennas can be used for transmit beamforming to minimize interference generation to other users while maximizing the energy coupled to the intended user. In multipath environments, signal transmission must match the channel, and at the same time minimize generation of multi-user interference to other users. The problem of estimating the forward channel from the reverse channel is simpler in CDMA than in TDMA. This is because we can decouple the channel mapping for each path and therefore deal with a much lower angle spread. Beampattern optimization however is more complex in DS-CDMA. Several trade-offs exist between beamwidth, sidelobe level, cusping level, beam overlap, and beam diversity (from softer handoff). See [121] for more details.

Applications to Personal Communications Systems

In this section we review applications of space-time modems for PCS base stations and also discuss industry trends. One broad classification of space-time modem applications is based on channel reuse. In channel reuse between cells (RBC), the channel is used only once within a cell and is reused only in an external cell. On the other hand, in reuse within cell (RWC), also known as space-division multiple access (SDMA), the channel is used more than once within a cell and relies on spatial discrimination to allow channel reuse. We first discuss RBC applications followed by RWC applications.

Reuse Between Cells

In RBC applications, space-time modems are used to improve network performance without attempting to reuse a channel within a cell. The simplest approach to spatial processing is to use conventional beamforming followed by temporal processing. Typically a set of 4–8 antennas/sector are deployed. The antenna outputs are combined to form multiple preformed conventional beams. Butler matrix beamforming at RF is typically used. In FDMA or TDMA systems, there is only one subscriber per sector per channel (frequency or time slot). A "sniffer" circuit examines the beam outputs (usually for signal strength) to determine the best or two best beam(s). In order to reduce the probability of incorrect beam selection, the beam outputs are validated by checking the color code (e.g., CDVCC in IS-54 or SAT tone in AMPS) prior to selecting the best beam. A switch connects the selected beams to a two-branch diversity receiver.

The main application of such conventional beamformers, also known as *switched beam systems*, is the improvement in cell coverage by exploiting array gain. Since the selected beam is narrower than the sector, reduction in interference power can also be obtained when the desired signal and the interference fall into different beams. This SINR improvement can improve voice quality. In some cases, use of smaller reuse factor may also be possible if dynamic channel allocation can be used. This can therefore increase capacity.

In CDMA systems, subscribers are present in every beam, and therefore all the beams are fed to a bank of CDMA receivers through a switch. Beam selection is carried out to track an individual user as he moves across beams. This results in essentially a narrow sector system and reduces MAI. This advantage can be traded for increased capacity, coverage, or battery life. If multipath is present, a user's signal may arrive from more than one beam, and beam outputs are combined for improved diversity performance.

Beamforming concepts can be used in transmit also. In FDMA and TDMA systems, the receive beam with the best signal is used as the transmit beam, and energy is radiated in a narrow beam rather than across the entire sector. This results in reduced interference generation and higher EIRP for the desired mobile, although regulatory barriers may not allow the use of a higher EIRP. In CDMA systems, users are present in all beams, and therefore the signal to a particular user is connected to the appropriate beam. If more than one beam couples to the user, a signal can be transmitted on multiple beams. This is known as *softer handoff.*

More advanced applications for RBC will use space-time techniques described in the fourth and fifth sections. These approaches use joint space-time adaptive processing and offer improved performance to mitigate CCI and ISI while maximizing diversity. Joint space-time adaptive processing considerably improves its performance over conventional beamforming systems. In general, uncertainties in channel estimation for the forward link can degrade the performance in the link, particularly in large-angle-spread environments. Space-time modems have been developed for the IS-136 TDMA system primarily to improve link quality and coverage. To improve capacity, we need to incorporate dynamic channel allocation and forward link power control into the system, making it then possible to double the system capacity. Likewise, applications to GSM have also emerged. Again, improving link quality and coverage is relatively easy. Capacity improvements need the use of random frequency hopping, forward link power control, discontinuous transmission, soft blocking, and unity reuse factor, along with space-time processing. Simulations have shown that capacity gains of two to three are possible from the spatial dimension alone [122].

Reuse within Cell

RWC refers to the reuse of a channel *within* a cell by exploiting differences in the structure of the spatial channels. This is akin to spectrum reuse in cellular systems, where a channel or a spectrum resource used in one cell is reused in another cell based on differences in spatial locations of the users. RWC exploits differences in spatial channels between users to make CCI acceptably small via STP.

When RWC is used in conjunction with TDMA or FDMA, a cell supports two or more users in a given channel, as compared to a single user in RBC. Antenna arrays and STP are used for joint demodulation of multiple users, assuming such users are sufficiently separated in channel (direction). When the channels of two or more users become closely aligned, they are no longer separable, and one of the users should be handed off to another frequency or time slot. RWC needs to work on both the forward and reverse links; therefore, signal separability must be achieved on both links.

The principal challenge in RWC when used with TDMA or FDMA is to estimate and track the reverse and forward channels to a high degree of accuracy. The problem is further complicated by the near-far problem resulting in received power imbalance at the base between users. The ability to estimate and track the reverse link channel depends on angle, delay, and Doppler spreads. Channel estimation errors increase with these spreads. Therefore, flat rural environments with low angle and delay spreads offer advantages over urban applications and microcells, which often use antennas below the rooftop. Likewise, fixed wireless applications, which have low Doppler spreads, have a significant advantage over mobile applications. In the forward link, we need to once again predict the channel accurately. We can do this by an open loop method, that is, use the reverse link channel to predict the forward channel. Alternatively, we can use feedback from the mobile to estimate the forward channel. For open loop methods, the source of channel estimation error in FDD is angle spread, and in TDD it is Doppler spread. Due to the above, RWC appears to have limited applicability in TDMA and FDMA systems. Use of fast dynamic channel allocation and interference diversity methods such as frequency hopping may provide some relief from these problems.

The situation is different in CDMA systems due to the fact that the users are inherently separated by spreading codes. These spreading codes separate co-channel users by the processing gain (21 dB in IS-95). Also, in CDMA users are power-controlled, thus improving the power balance. These factors suggest that channel estimation errors may be less critical in CDMA and make it easy to implement RWC. In fact, CDMA air interfaces can use simple sector antennas to implement RWC. IS-95 uses three sectors in mobile applications and six or nine sectors in fixed applications. Each sector effectively reuses the radio spectrum. Therefore, a three-sector CDMA system offers nearly three times the capacity of an unsectored system. Field trial results in [123] have shown that using simple narrow antenna array beams can decrease mobile transmit power by 5–7 dB and increase the reverse link capacity by as much as 40 percent. Much higher gains in capacity appear possible but would require a careful redesign of the air interface.

Summary

Use of space-time modem technology is emerging as a useful tool for improving the performance of PCS networks. Successful field deployment of this technology is yet to emerge, and in the short term is expected to be limited to beamforming or space-time processing for modest (factor of two) improvements in cell coverage or capacity. Larger improvements will need substantial evolution of the current air interfaces or a new-generation air interface. These solutions must fully address the strengths and weaknesses of the spatial dimension. A review of the current state of the art in this technology can be found in [124–126].

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