Optimal SP Training and Precoding Designs for Channel Estimation and Symbol Detection in MIMO-OFDM Systems

Nguyen N. Tran, Dang L. Khoa, Vo T. Tri, and Ha X. Nguyen

Abstract—Based on convex programming for optimization, a closed-form solution of superimposed (SP) training on linearly precoded data for jointly optimal channel estimation and symbol detection is proposed in this paper for MIMO-OFDM systems. The newly designed method not only efficiently identifies the frequency-selective fading channel but also effectively enhances the symbol detection. Although linearly precoding technique is employed and protects the transmitted data over the multi-path MIMO wireless channels, the precoded data is always arithmetically added to the training sequence to prevail transmission bandwidth. Analytical and numerical results confirm that the proposed design efficiently estimates the wireless fading channel and effectively recovers the source data symbols.

Index Terms—MIMO-OFDM, channel estimation, superimposed training, precoding technique, convex optimization.

1. Introduction

M ultiple-input multiple-output (MIMO) communications systems are capable of achieving very high data rates over wireless links [1], while orthogonal frequency-division multiplexing (OFDM) is an effective technique to cope with inter-symbol interference (ISI) over multi-path fading channels. Combined MIMO-OFDM is a research topic of great interest in recent years.

Channel state information (CST) and data symbol recovery are major challenges in the implementation of a communications system operating over a frequency-selective fading wireless channel. A training sequence (also known as pilot tones or preamble symbols) is often used for the identification of an unknown channel [2]–[5]. A linear precoder is needed to guard against the effects of frequency distortion and spectrum nulls of a multi-path fading channel in order to enhance the data symbol recovery.

Over the last decade, various designs of training signals [6]–[10] and linear precoders [11]–[15] have been proposed. The two simplest training sequences for OFDM channel estimation are illustrated in Fig. 1. The training signal and linearly precoded data are sent separately in time. The bandwidth is consumed for both training signals and redundancy introduced by linear precoding. Affine precoding that superimposes training signals on linearly precoded data [16]–[22] is an alternative to save the bandwidth. The post-multiplying based precoder was employed in [16],[18] but the post-multiplying based precoder proposed in [19],[20],[22] has been shown to be much superior in general frequency-selective fading channels. The pilot-embedded data-bearing approach [21], which is based on Walsh-Hadamard (WH) matrix, is actually a special case of the approach in [20],[22]. References [19],[20],[22] also examine the optimal power allocation between training and data signals.

In this paper, the approach proposed in [19],[20],[22] is applied for jointly optimal channel estimation and data detection in wireless MIMO-OFDM. Although a similar design as that in [19],[20],[22] is proposed in this paper, the application of SP training and precoding designs to MIMO-OFDM is really necessary as MIMO-OFDM is now a key technique for current (4G, LTE) and new (5G) generations of wireless cellular networks. The guard interval by zero padding in [19],[20],[22] is replaced by the cyclic prefix (CP) as it is a stan-

Fig. 1: Two simplest types of training signal arrangement for OFDM channel estimation.
standard technique for OFDM. Instead of two block-type and comb-type training signal arrangements as in Fig. 1, our proposed training method for MIMO-OFDM is illustrated in Fig. 2. Similar to [19], [20], [22], it will be shown that this proposed affine precoder is capable of efficiently identifying the MIMO-OFDM wireless channel and effectively recover the OFDM data symbols.

The paper is organized as follows. Section 2 describes the system model and affine precoded data. The optimal superimposed training signal, post-multiplying based linear precoding matrix as well as the optimal power allocation are presented in Section 3. Simulation results are provided in Section 4 and Section 5 concludes the paper.

Notation: Boldface upper and lower cases denote matrices and column vectors. Superscripts T, H and * mean transposition, Hermitian adjoint and complex conjugate operators, respectively. I_N is the N×N identity matrix. E{x} is the expectation of the random variable x while tr{A} is the trace of the matrix A. The vectorization operator on a matrix to form a column vector by vertically stacking the matrix columns is denoted as vec(·).

2. System model and affine precoded data

Consider a MIMO-OFDM system with t transmit and r receive antennas. These antennas are assumed uncorrelated at both the transmitter and receiver. Let S ∈ C^{Nt×K} denote the source symbol matrix, where N is the number of subcarriers and K is the number of source symbol vectors. Let M be the number of transmitted data vectors. The symbol matrix S is post-multiplying by the K×M linear precoder P, and then arithmetically added to the Nt×M training matrix C = CQ_E^H to form the following equivalent Nt×M OFDM symbol matrix:

\[ U = SP + C \]

The design of matrices P, C and Q_E is given in the next section. Since the linear precoder introduces redundancy, the number of transmitted data vectors after linear precoding is greater than the number of source symbol vectors, i.e., M > K. Each equivalent OFDM symbol matrix U is then transmitted across t transmit antennas.

The frequency-selective fading channel is represented by L most significant taps between any antenna pair. The channel taps are assumed to remain constant during one OFDM symbol block (of duration M), but may change independently from block to block (i.e., quasi-static or block fading). For notational simplicity, the block index is omitted. The channel impulse response vector from the jth (j = 1, ..., r) receive antenna to the ith (i = 1, ..., t) transmit antenna in one OFDM block is

\[ h_{ji} = [h_{ji}(0), h_{ji}(1), ..., h_{ji}(L - 1)]^T, \]

where entries of h_{ji} are independent and identically distributed (i.i.d.) circularly symmetric complex Gaussian random variables of variance \( \sigma_h^2 \), i.e., \( CN(0, \sigma_h^2) \).

Define the CP removal matrix of dimensions \( N \times (N + L) \) as \( R_{CP} = [0_{N \times L}; I_N] \), and the \( N \times N \) discrete Fourier transform (DFT) matrix as

\[ F_N = \left\{ 1/\sqrt{N} \cdot \exp(-j2\pi pk/N) \right\}_{p,k=0}^{N-1}. \]

Define \( F_L \) is the matrix that contains the 1st to \( L \)th columns of \( F_N \). Under tolerable power leakage and perfect time/frequency synchronization and after performing the inverse discrete Fourier transform (IDFT), CP insertion, transmission over the fading channel and CP removal, the equivalent input/output relationship corresponding to the transmission of one OFDM block is

\[ Y = DU + (I_r \otimes (F_N R_{CP}))N \]

\[ = DSP + DC + (I_r \otimes (F_N R_{CP}))N, \]

where \( Y \), \( N \in C^{Nr \times M} \) are the received signal and the additive white Gaussian noise (AWGN), respectively, and \( D \) is the \( Nr \times Nt \) channel matrix in the frequency domain, give by

\[ D = \begin{bmatrix}
D_{11} & \cdots & D_{1t} \\
\vdots & \ddots & \vdots \\
D_{r1} & \cdots & D_{rt}
\end{bmatrix}, \text{ with } D_{ji} = \text{diag}\{d_{ji}\}, \]

and

\[ d_{ji} = [d_{ji}(0), ..., d_{ji}(N - 1)]^T = \sqrt{N}F_L h_{ji}. \]

The following assumptions are made:

A1). The source symbol S ∈ C^{Nt×K} has zero-mean i.i.d. elements with variance \( \sigma_s^2 \), i.e.,

\[ E\{SS^H\} = \sum_{i=1}^{K} E\{s_is_i^H\} = K\sigma_s^2 I_{Nt}. \]

A2). The noise matrix N ∈ C^{Nr×M} has zero-mean i.i.d. elements with variance \( \sigma_n^2 \), i.e.,

\[ E\{NN^H\} = \sum_{i=1}^{M} E\{n_in_i^H\} = M\sigma_n^2 I_{Nr}. \]

A3). The channel is Rayleigh fading with \( E\{h_{ji}h_{ji}^H\} = \sigma_h^2 I_L \), where \( \sigma_h^2 = \frac{1}{L}. \)
Furthermore, the following classes of training and precoding matrices are considered:

B1. The average training power, defined as $\sigma_T^2 = \text{tr}(CC^H)/MNt$, satisfies $\sigma_T^2 + \sigma_c^2 = 1$. Hence, the training power is constrained by

$$P_T = \text{tr}(CC^H) = \sigma_T^2 MNt.$$  

B2. The matrix $P$ is full rank (i.e., $PP^H$ is nonsingular) and $\text{tr}(PP^H) = M$.

Condition B1 is just the normalization for the transmitted symbols, which include the training sequence and source symbols. On the other hand, Condition B2 guarantees that the average power of the source is unchanged after precoding, which can be verified as:

$$\sigma_S^2 = \frac{\text{tr}(E[SPHSH])}{MNT} = \frac{NT\sigma_T^2 \text{tr}(PP^H)}{MNT} = \sigma_T^2.$$

3. Optimal affine precoder design

The affine precoder consists of the superimposed training matrix $C$ and the linear precoding matrix $P$. The aim is to design the jointly optimal training signal and post-multiplying precoding matrix to estimate the unknown MIMO channel and recover the OFDM source symbols from the received signal $Y$ in (2). To this end, following [20], [22], the received signal is first post multiplied by the decoding matrix $Q_E \in \mathbb{C}^{M \times q}$ such that

$$PQ_E = 0_{K \times q} \quad \text{and} \quad Q_E^H Q_E = I_q.$$  

The first condition is for the separation of training signal and precoded data, while the second condition ensures that the noise power and noise statistic remain unchanged after the decoding. The decoding operation yields the following:

$$YQ_E = DUQ_E + (I_t \odot (F_NR_{CP}))NQ_E = DCQ_E + (I_t \odot (F_NR_{CP}))NQ_E.$$  

As previously mentioned, the training matrix $C$ is factorized as $C = \hat{C}C_E^H$. Hence, the training matrix after decoding by $Q_E$ is $CQ_E = \hat{C}Q_E^HQ = \hat{C} \in \mathbb{C}^{Nt \times q}$. It can be seen that there is no unwanted presence of the data in the decoded signal in the channel estimation process. With knowledge of the channel and noise statistics in (5), the channel gains, either in the frequency time domain, can be estimated based on the equivalent training matrix $\hat{C}$.

To recover the source symbols, the training matrix $C$ is removed from the received data by post multiplying it with another decoding matrix for detection [20], [22], namely

$$Q_D = P^H (PP^H)^{-1}$$  

with $P \in \mathbb{C}^{K \times M}$ designed such that

$$Q_D^H P^H = 0_{q \times K} \Leftrightarrow PQ_E = 0_{K \times q}.$$  

By this choice, the two following desired conditions are simultaneously satisfied:

$$Q_D^H Q_D = 0_{q \times K} \quad \text{and} \quad PQ_D = I_K.$$  

The first condition in (8) enables the superimposed training signal $C = \hat{C}Q_E^H$ to be easily removed from the received signal, while the second condition reverse the effect of the precoding matrix $P$ in order to obtain the source symbol matrix $S$. Specifically, the system for source detection is

$$YQ_D = DS + (I_r \odot (F_NR_{CP}))NQ_D.$$  

3.1. Optimal training signal design

By changing the variables $\tilde{Y} = YQ_E \in \mathbb{C}^{Nr \times q}$, $\tilde{N} = (I_r \odot (F_NR_{CP}))NQ_E \in \mathbb{C}^{Nr \times q}$, (5) can be rewritten as

$$\tilde{Y} = DC \tilde{C} + \tilde{N}.$$  

where $\tilde{C}$ is constrained by the training power as

$$\text{tr}(\tilde{C}C^H) = \text{tr}(\tilde{C}Q_E^H Q_E C^H) = \text{tr}(C^H) = P_T.$$  

Decompose $\tilde{C}$ as

$$\tilde{C} = \begin{bmatrix} \tilde{c}_{11} & \cdots & \tilde{c}_{1q} \\ \vdots & \ddots & \vdots \\ \tilde{c}_{11} & \cdots & \tilde{c}_{1q} \end{bmatrix},$$

where $\tilde{c}_{im} \in \mathbb{C}^{N \times 1}$, $i = 1, \ldots, t$; $m = 1, \ldots, q$. Define $\tilde{y} = \text{vec}(\tilde{Y})$, $\tilde{d} = [d_1^T, \ldots, d_t^T, d_1^T, \ldots, d_t^T]^T$, $\tilde{n} = \text{vec}(\tilde{N})$, $\tilde{h} = [h_1^T, \ldots, h_{tr}^T, h_{tr}^T, \ldots, h_t^T]^T$, $\tilde{C}_{im} = \text{diag}(\tilde{c}_{im}), \tilde{C}_{m} = [\tilde{C}_{1m}, \ldots, \tilde{C}_{tm}] \in \mathbb{C}^{N \times Nt}$, and

$$\tilde{C} = \begin{bmatrix} I_r \odot \tilde{C}_{1} \\ \vdots \\ I_r \odot \tilde{C}_{q} \end{bmatrix} \in \mathbb{C}^{Nrq \times Nrt}.$$  

Equation (10) is rewritten in a compact form as

$$\tilde{y} = \tilde{C} \tilde{d} + \tilde{n}.$$  

From (3), it is obvious that

$$\tilde{d} = \tilde{F}h,$$  

and (13) becomes

$$\tilde{y} = \tilde{C}\tilde{F}h + \tilde{n}.$$  

Since the elements of $h$ are i.i.d. $CN(0, \sigma_h^2)$, the channel vector $h$ is zero-mean and has covariance $R_h = \sigma_h^2 I_{Ltr}$. Also, $\tilde{n} = \text{vec}(\tilde{N}) = \text{vec}(I_r \odot (F_NR_{CP}))NQ_E = (Q_E^H \odot (I_r \odot (F_NR_{CP})))n$, with $n = \text{vec}(N)$. By assumption A2, $E(nH) = \sigma_n^2 I_{NMr}$ and the covariance of $\tilde{n}$ is $R_{\tilde{n}} = \sigma_n^2 I_{NMr}$. Employing the linear minimum
mean square error (LMMSE) estimation, the estimated channel response vector is
\[
\hat{h} = (R_h^{-1} + \sum_i F_i H_i C_i^{-1} \tilde{F}_i C_i H_i)^{-1} \sum_i F_i H_i C_i^{-1} \tilde{F}_i C_i H_i y_i
\]
(16)
The channel estimation error is
\[
\epsilon_h = \text{tr} \left( \left( \frac{1}{\sigma_n^2} L + \sum_i \tilde{F}_i C_i H_i \right) \right.
\]
(17)
From (12),
\[
\tilde{C}_i = (I_r \otimes \tilde{C}_i), \quad \tilde{Q}_i = (I_r \otimes \tilde{Q}_i)
\]
and
\[
\text{tr} \{C H C \} = r \cdot P_T.
\]
(19)
The problem is now to design the training matrix \( C \) such that the channel estimation error is minimized:
\[
\min C_{I_r} \text{ s.t. } \text{tr} \{C H C \} \leq r \cdot P_T.
\]
(20)
Following the same derivations in [20], [22], the optimal solution to this convex optimization satisfies
\[
\tilde{C}_i = \frac{P_T}{N t} \sigma_2 I_{N t}
\]
and the minimum channel estimation error is
\[
\epsilon_h = \frac{L^2 s_2^4}{\sigma_n^2} + \frac{L r T^2}{\sigma_n^2} = \frac{L r T^2}{\sigma_n^2} + N M \sigma_2^2.
\]
(21)
Note that, one solution of \( C \) is such that \( C C^H = C Q_E H C \), where \( Q_E = \frac{P_T}{N t} \sigma_2 I_{N t} \) is the optimal matrix \( C \) according to
\[
\text{C} = \sigma_c \sqrt{M} O(1 : N t, :) \in C^{N \times M}, \quad \tilde{C} = I_q
\]
(22)
where \( O(1 : N t, :) \) denotes the 1st to \( N t \)th rows of \( O \).

3.2. Optimal post-multiplying linear precoding design
We now design the optimal precoding matrix \( P \) to efficiently recover the source symbols from the received signal in (9). Instead of designing the precoder to maximize the effective signal to noise (SNR) as indicated in [20], [22], the linear precoder shall be designed to minimize the symbol estimation error of the system in (9).

Let \( \tilde{y}_i \) and \( q_{D_i} \), \( i = 1, \ldots, K \) be the \( i \)th column of \( YQ_D \) and \( Q_D \). One has
\[
\tilde{y}_i = D q_i + (I_r \otimes (F_N R_{CP})) N q_{D_i},
\]
(24)
From assumption A1, the covariance of \( s_i \) is \( R_{s i} = E \{ s_i s_i^H \} = \sigma_s^2 I_{N t} \). Also the covariance of \( (I_r \otimes (F_N R_{CP})) N q_{D_i} \) is \( \sigma^2 \| q_{D_i} \|^2 I_{N t} \), where assumption A2 has been used.

The channel response was estimated in (16) with \( \hat{h} = \hat{h}_r \). Hence, the channel estimate in the frequency domain \( \tilde{D} \) can be obtained as
\[
\tilde{D} = \left[ \begin{array}{ccc}
D_{11} & \cdots & D_{1t} \\
\vdots & \ddots & \vdots \\
D_{t1} & \cdots & D_{tt}
\end{array} \right],
\]
where \( D_{ji} = \text{diag} \{ \sqrt{N} F_L \} \).

Based on this channel estimate \( \tilde{D} \), the \( i \)th source symbol vector \( s_i \) is recovered from the \( i \)th decoded signal \( \tilde{y}_i \), by the following MMSE detector [23]
\[
\hat{s}_i = \left( R_{s i} + \sum_i H_i M_i \tilde{D}^{-1} H_i^H y_i \right)^{-1} \tilde{D}^{-1} H_i^H y_i
\]
(25)
The MSE of the source detection is
\[
\varepsilon_{s_i} = \text{tr} \{ E \{ s_i \hat{s}_i^H \} \} = \text{tr} \left( \frac{1}{\sigma_n^2} I + \frac{1}{\sigma_2^2 \| q_{D_i} \|^2} \tilde{D}^H \tilde{D} \right)^{-1}
\]
(26)
The total source MSE is thus
\[
\varepsilon_s(Q_D) = \sum_i K \left\{ \frac{1}{\sigma_s^2} I + \frac{1}{\sigma_2^2 \| q_{D_i} \|^2} \tilde{D}^H \tilde{D} \right)^{-1}
\]
(27)
As \( Q_D = (P P^H)^{-1} \), the problem under condition B2, is how to design the precoding matrix \( P \) such that
\[
\min_{\| Q_D \|^{-1}} \sum_i K \left\{ \frac{1}{\sigma_s^2} I + \frac{1}{\sigma_2^2 \| q_{D_i} \|^2} \tilde{D}^H \tilde{D} \right)^{-1}
\]
(28)
As in [20], [22], the optimal \( Q_D \) is such that
\[
P P^H = \left( Q_D^H Q_D \right)^{-1} \frac{M}{K} I_K.
\]
(29)
Like in [20], [22], with the same orthogonal matrix \( O \in C^{M \times M} \) defined by (22), let \( O(N t + 1; N t + K, :) \) denote the \( (N t + 1) \)th to \( (N t + K) \)th rows of \( O \). It is clear that
\[
P = \sqrt{\frac{M}{K}} O(N t + 1; N t + K, :), \quad O(1 : N t, :)
\]
(30)
satisfies the desired conditions (4), (8), and (29). Moreover, with this very simple solution of \( P \) in (30), implementing the precoding matrix does not significantly increase the complexity of the system.

According to (25), the corresponding estimate of the source matrix \( s_i \) is
\[
\hat{S} = \left( \frac{1}{\sigma_s^2} I + \frac{M}{K} \tilde{D}^H \tilde{D} \right)^{-1} \frac{M}{K} \tilde{D}^H Y Q_D
\]
(31)
. Actually, the equality \( E \{ N X N H \} = \sigma_s^2 \text{tr}(X) I_{N_t} \) holds true for any Hermitian matrix \( X \), while \( (I_r \otimes (F_N R_{CP})) (I_r \otimes (F_N R_{CP}))^H = I_{N t} \).
Similarly, according to (27), the total source symbol error is

\[
\varepsilon_{S_1} = \sum_{i=1}^{K} \text{tr}\left\{ \left( \frac{1}{\sigma_s^2} I + \frac{1}{\sigma_n^2} \|q_{Di}\|^2 \hat{D}^H \hat{D} \right)^{-1} \right\}
\]

\[
= K \cdot \text{tr} \left\{ \left( \frac{1}{\sigma_s^2} I + \frac{M}{\sigma_n^2} \hat{D}^H \hat{D} \right)^{-1} \right\}, \quad M > (32)
\]

To see that the MIMO-OFDM system employing the post-multiplying based precoder is superior than the MIMO-OFDM system without a precoder, calculate the total source symbol error of the latter system as follows. First, the equation for symbol detection is

\[
\tilde{Y} = DS + W,
\]

where \( W \in \mathbb{C}^{Nt \times K} \) represents AWGN whose elements have the same distribution as that of \( N \). The matrices \( D \) and \( S \) are the same as those described in Section 2. Based on the channel estimate \( \hat{D} \), the total source symbol error is

\[
\varepsilon_{S_2} = \sum_{i=1}^{K} \text{tr} \left\{ \left( \frac{1}{\sigma_s^2} I + \frac{1}{\sigma_n^2} \hat{D}^H \hat{D} \right)^{-1} \right\}
\]

\[
= K \cdot \text{tr} \left\{ \left( \frac{1}{\sigma_s^2} I + \frac{1}{\sigma_n^2} \hat{D}^H \hat{D} \right)^{-1} \right\}. \quad (33)
\]

By comparing the two expressions in (32) to (33), it is simple to see that the total source symbol error of the proposed affine precoding is always less than that of the system without precoding, though both systems consume the same bandwidth.

3.3. Power allocation

With \( \hat{D} \) denoting the estimate of \( D \), the channel error is \( \hat{D} = D - \hat{D} \). Rewrite (9) as

\[
YQ_D = (\hat{D} + \hat{D})S + (I_r \otimes (F_N R_{CP}))NQ_D
\]

\[
= \hat{D}S + \hat{D}S + (I_r \otimes (F_N R_{CP}))NQ_D. \quad (34)
\]

Define the effective signal-to-noise ratio of the system in (34) as

\[
\text{SNR}_{(34)} = \frac{E\{||\hat{D}S||^2\}}{E\{||Z||^2\}}, \quad (35)
\]

where \( Z = \hat{D}S + (I_r \otimes (F_N R_{CP}))NQ_D \).

As discussed in [20], [22], the performance of the source detection can be improved by maximizing this effective SNR as a function of the training power. The optimal \( \sigma_c^2 \) is

\[
\sigma_c^2 = \frac{(NL_{rt}\sigma_n^2 + L\gamma\sigma_n^2 - \beta)}{N(L_{rt}\sigma_n^2 - M\gamma)^2}, \quad (36)
\]

where

\[
\beta = [L\gamma L\sigma_n^2(L\sigma_n^2 + NM)(N_{rt} + \gamma)]^{1/2}, \quad (37)
\]

and

\[
\gamma = KN_{rt}\sigma_n^2/M. \quad (38)
\]

4. Simulation results

First, the power allocation expression in (36) is verified in Figure 3. The MIMO-OFDM system has 2 transmit and 2 receiver antennas, channel length \( L = 3 \) an 4 subcarriers. The source symbol matrix has \( K = 8 \) column vectors drawn from the quadrature phase-shift keying (QPSK) constellation \( \{ \pm \sqrt{\sigma_s^2/2} \pm j \sqrt{\sigma_s^2/2} \} \). The precoder has size \( 8 \times 160 \). It can be seen that there is a trade-off between training and data powers. A larger training power does not always lead to a better bit-error-rate (BER) performance. It can also be observed from Figure 3 that the optimal power allocations computed by (36), namely \( \sigma_c^2 = 0.1182 \) for SNR=5dB, \( \sigma_c^2 = 0.1172 \) for SNR=15dB, and \( \sigma_c^2 = 0.1171 \) for SNR=30dB, all agree well with the values found by simulation. Moreover, Figure 3 shows that the optimal power allocation is quite insensitive to the SNR value.

Next, the error performance of the proposed scheme is illustrated in Figure 4 for two systems: \( 2 \times 2 \)-OFDM and \( 4 \times 4 \)-OFDM. The \( 2 \times 2 \) system has the channel length \( L = 3 \) and 8 subcarriers, while the \( 4 \times 4 \) system has \( L = 3 \) and 4 subcarriers. In both cases, the same source symbol matrix having \( K = 8 \) column vectors, the same precoding matrix having size \( 8 \times 160 \), and the same training matrix having size \( 16 \times 160 \) are used. Furthermore, for comparison, the error performance of two MIMO-OFDM systems having the same system parameters but without affine precoding, with perfect channel estimation and full symbol power \( \sigma_s^2 = 1 \), is also presented. It is remarkable to observe that, although having perfect channel estimation and full power \( \sigma_s^2 = 1 \), the error performance of the systems that do not implement precoding is always inferior.

5. Conclusion

This paper proposed a new design for jointly optimal channel estimation and symbol detection in MIMO-OFDM systems. The training signal is superimposed on the linearly precoded data, hence both SP training and
precoding matrix can share the same transmission bandwidth. It was demonstrated that the proposed superimposed training helps the receiver to efficiently identify the unknown wireless channel while the precoder can combat the frequency-selective fading and effectively recover the OFDM source symbols.

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References

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