A MIMO-OFDM Channel Estimation Approach Using Time of Arrivals

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***Abstract*—Channel estimation is critical in designing multiple-input multiple-output (MIMO) orthogonal frequency division multiplexing (OFDM) systems for coherent detection and decoding. We propose a channel estimation scheme based on time of arrivals (TOAs) estimation. The TOAs are first determined using a variant of probabilistic data association (PDA) and employing the minimum description length principle, then the PDA is augmented by group decision feedbacks to refine the TOA estimates. With the channels of typical urban and hilly terrain delay profiles, simulation results, compared with the alternating projection (AP) and the Fourier transform based methods, show that the proposed scheme provides a promising accuracy-complexity trade-off for MIMO OFDM channel estimation.**

***Index Terms*—Channel estimation, multiple-input multiple-output (MIMO), orthogonal frequency division multiplexing (OFDM), probabilistic data association (PDA), time of arrival (TOA).**

I. Introduction

THE multiple-input multiple-output (MIMO) orthogonal frequency division multiplexing (OFDM) is one of the most promising techniques for broad-band wireless communications. Channel estimation has been successfully used to improve the performance of OFDM systems. For instance, differential detection would result in a 3-dB loss in signal-to-noise ratio (SNR) compared with coherent detection, where channel parameters are required. Most diversity schemes are designed with the assumption that the channel information is available. For example, channel estimation is crucial for the receiver combining or decoding of space-time code. Therefore, channel estimation is essential in MIMO-OFDM system design.

Various OFDM channel estimation schemes have been proposed in the literature, mostly for single antenna system [14], [15]. In this paper, we consider channel estimation for transmit diversity using space time coding for OFDM systems. Assuming that the channel is quasi-stationary and the synchronization is perfect, we are interested in channel estimators based on a single block of OFDM data. The received signal is a superposition of different signals transmitted from different transmit antennas simultaneously. With the assumption of tolerable leakage, Fourier transform model based algorithms were studied in [1], [2], [16], and [17]. Later, a reduced complexity detection scheme was studied by exploiting the correlation of the adjacent subchannel responses [3]. A polynomial model based approach was developed in [12]. These typical schemes [2], [9], [10] assume a maximum delay profile and do not adapt to sparse channel conditions or higher delay profiles. Consequently, the estimation accuracy will be degraded under these conditions. Note that the channel impulse response is characterized by the delays of the paths, therefore, estimating time of arrivals (TOAs) is one way to improve channel estimation. A multidimensional maximum-likelihood (ML) search is one solution but a prohibitively complex task. A number of alternatives have been proposed to reduce the complexity. The alternating projection (AP) method [5] is interesting due to its good performance. A channel estimation scheme via near-ML TOA estimation, with its root in AP, was presented in [11] with good performances. However, the AP algorithm still suffers from high computational costs, especially when the number of paths is unknown.

Our goal is to present a TOA-based channel estimator with a good performance and a low complexity. We work on the matched filter outputs and propose a probabilistic data association (PDA) based TOA estimator. The basic idea of PDA is to approximate the interferences from other paths as Gaussian-distributed and iteratively update the covariance matrix [8]. The TOAs for the isolated delay paths are first determined using a variant of PDA and the minimum description length principle is employed to estimate the number of paths. Further, the TOA estimates are refined by group decision feedbacks (DF), in which we iteratively perform a local maximization with respect to a single delay time. Based on the estimated TOAs, we estimate the corresponding channel response for each path.

II. System and Problem Description

In OFDM, the entire channel is partitioned into subchannels and a block of data are modulated to a set of subcarriers. Transmit diversity has gained great interest, as the channel capacity is proved proportional to the number of transmitter or receiver antennas. We consider an OFDM system with m_T transmit and m_R receive antennas. At time n, an input data block is mapped into m_T complex constellation sequences $\{X_i[n,0], X_i[n,1], \ldots, X_i[n,K-1]\}$ for $i = 1, \ldots, m_T$, where K is the number of subchannels. With proper cyclic

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extension, the received signal after DFT process at receive antenna j is

$$r_j[n,k] = \sum_{i=1}^{m_T} H_{ij}[n,k] X_i[n,k] + w_j[n,k] \quad (1)$$

where $H_{ij}[n,k]$ indicates the channel frequency response from transmitter i to receiver j at the kth tone of the OFDM block at time n, and the noise $w_j[n,k]$ is assumed both spatially and temporally white, with zero mean and variance σ_n^2. Since channel estimation at each receiver is implemented independently, the index j will be omitted in the rest of the paper. The channel impulse response can be generally modeled as

$$h(t,\tau) = \sum_{k=1}^{p} \gamma_k(t)\delta(\tau - \tau_k) \quad (2)$$

where p is the total number of paths and τ_k is the corresponding delay of the kth path. In this paper, $\gamma_k(t)$'s are modeled as Rayleigh fading and assumed to have the same time correlation function. Therefore, the frequency response vector $\mathbf{H}_i[n]$ from transmitter i can be expressed as the weighted sum of complex sinusoids:

$$\begin{aligned}\mathbf{H}_i[n] &= [H_i[n,0], \ldots, H_i[n,K-1]]^T \\ &= [\mathbf{s}(\tau_1), \mathbf{s}(\tau_2), \ldots, \mathbf{s}(\tau_p)]\,\mathbf{a}_i = \mathbf{S}(\tau)\mathbf{a}_i \end{aligned} \quad (3)$$

where the vector $\mathbf{a}_i = [\gamma_1, \ldots, \gamma_p]^T$, the complex sinusoid $\mathbf{s}(\tau_k) = [1, e^{-j2\pi\tau_k/T_s}, \ldots, e^{-j2\pi\tau_k(K-1)/T_s}]^T$ with T_s being the symbol duration, and the delay vector $\tau = \{\tau_1, \ldots, \tau_p\}$.

Here we assume that the channels from different transmitters to the same receiver have the same delay and fading property (i.e., the same τ_k's) [2], [12], though the corresponding complex amplitudes are independent for different paths. It is a reasonable assumption because the transmit antennas are close to each other in practice. We consider the channel estimation based on the training pilots. We apply the simple training strategy proposed in [9] to effectively shift multiple antenna's channels into nonoverlapped regions by choosing the pilots signal as

$$X_i[k] = X_1[k] e^{-\frac{j2\pi k(i-1)T_0}{T_s}} \quad \text{with } k = 0, 1, \ldots, K-1 \quad (4)$$

for $i = 2, \ldots, m_T$, where the shift T_0 is larger than the maximum delay, to ensure that TOAs from different channels are nonoverlapped. Define $\mathbf{X}_1 = [X_1[0], \ldots, X_1(K-1)]$. Now, omitting the time index n, we have the received vector $\mathbf{r} = [r[0], \ldots, r[K-1]]$ in (1) as

$$\mathbf{r} = \mathbf{X_1} \odot (\mathbf{S}(\theta)\mathbf{a}) + \mathbf{w} = \mathbf{S}_1(\theta)\mathbf{a} + \mathbf{w} \quad (5)$$

where $\mathbf{w} = [w[1], \ldots, w[K-1]]$, the combined vector $\mathbf{a} = [\mathbf{a}_1^T, \ldots, \mathbf{a}_{m_T}^T]^T$, the combined delays after shifting $\boldsymbol{\theta} = \{[\tau_k, \tau_k + T_0, \ldots, \tau_k + (m_T - 1)T_0]_{k=1}^p\}$, the symbol $\odot$ represents the Hadamard product by multiplying component-wise, and each column of $\mathbf{S}_1$ is the Hadamard product of $\mathbf{X}_1$ and the corresponding column of $\mathbf{S}$. Our goal is to estimate the delay vector τ and the gains $\mathbf{a}$, based on the observations $\mathbf{r}$. Note that the above assumptions about the channel profiles and the training strategy can be relaxed in the algorithm developed later[1] and the process defined in the proposed scheme.

III. Proposed Scheme

From the model (5), the channel estimation problem is mathematically modeled as the estimation of superimposed signals $\{\mathbf{s}(\tau_k) \odot \mathbf{X}_1\}$. The channel estimation problem is equivalent to the problem of estimating TOAs, a problem faced in many application areas such as radar, sonar, and geophysics. Many approaches were proposed to estimate TOAs, and one popular solution is the ML estimator computed by the AP algorithm, which is similar to the coordinate descent (CD) algorithm [5]. However, AP still suffers a high computational cost for a high-dimensional problem, and the situation is even worse when the number of delay paths is unknown. Therefore, our motivation is to develop algorithms having a high accuracy and a low computational cost. Here we propose an approach from a different perspective to reduce the complexity in TOA estimation. Overall, our proposed scheme includes three stages: preprocessing, PDA-based searching, and refinement via decision feedback, as presented in more details in the following subsections.

A. Preprocessing

The goal of preprocessing is to decrease the problem dimension and thus reduce the computational cost. We choose to work in the matched filter (MF) domain instead of the raw data domain. Suppose we allow only $\{t_k\}$, for $k = 1, \ldots, N$, as the possible values of the path delays where N is the total number of t_k, we can consider $\{\mathbf{s}(t_k) \odot \mathbf{X}_1\}$ as all possible signatures. Hence with referring to the observation model in (5), the MF output vector $\mathbf{y} = [y_1 \ldots y_N]^T$ at the receiver is expressed by

$$\mathbf{y} = \mathbf{RAb} + \mathbf{n} = \mathbf{RBa} + \mathbf{n} \quad (6)$$

where the vector $\mathbf{b} \in \{0,1\}^N$ indicates the delays of paths with $b_i = 1$ meaning there is a path at delay t_i. Therefore, if there are p paths, the number of 1 elements in $\mathbf{b}$ is p and the corresponding $\{t_i\}$'s indicate the real path delays τ. $\mathbf{B}$ and $\mathbf{A}$ are diagonal matrices whose diagonal elements are $\{b_i\}$'s and $\{a_i\}$'s respectively, $\mathbf{R}$ is the N-by-N signature covariance matrix, and $\mathbf{n}$ is a noise vector following a $CN(0, \sigma_n^2\mathbf{R})$ distribution, with $CN(0, \sigma_n^2\mathbf{R})$ representing the complex Gaussian vector distribution with zero mean and covariance matrix $\sigma_n^2\mathbf{R}$. In our problem, the amplitudes $\{a_i\}$ are assumed unknown, but follow an i.i.d. $CN(0, \sigma_s^2)$ where σ_s^2 is known.[2] It is clear that the number of paths can vary between 0 and N. The possible

[1]When considering that the channels have different delay property (i.e., τ_k's are different for each link), we solve the problem with dimension N instead in Section III (e.g., in (8)). When a training strategy different from the phase-shifting one in (4) is applied (i.e., different $\mathbf{X}_i$'s are observed), the possible signatures will be modified correspondingly. Specifically, in Section III, for each delay t_k, we consider the signal signatures from different antennas as $\{\mathbf{s}(t_k) \odot \mathbf{X}_i\}$, for $i = 1, \ldots, m_T$.

[2]In practice, $\mathbf{a}_i$'s are independent complex Gaussian processes with different but unknown variances. We choose a prior that all variances are equally chosen based on the powers of observations. The results here can easily be generalized to nonidentical models. However, our experience suggests that the performance is not sensitive to the values of variances.

path delays t_i's can either be chosen uniformly, or chosen via an amplitude-weighted way. We give a simple example of the later case as the following. Suppose at first $\{t_i\}$'s are uniformly spaced, then each new t_i is adjusted based on the MF amplitudes observed at the adjacent old t_i and t_{i+1}, therefore, $t_i^{new} = (|y_i|t_i + |y_{i+1}|t_{i+1})/(|y_i| + |y_{i+1}|)$. This amplitude-weighted approach is commonly employed in target location estimation for radar applications. To further efficiently reduce the dimension of N, we could compare the magnitude of $\mathbf{y}$ to a threshold and consider only values that are above the threshold, which gives the advantage of only working within the regions that have good SNRs. Because the TOAs from different transmitters are assumed to be the same and due to the training strategy given in (4), we further reduce the dimension from N to $N_1 = N/m_T$ by assuming $t_{(j-1)N_1+i} = t_i + (j-1)T_0$ and accordingly $b(i) = b((j-1)N_1 + i)$, for $j = 1, \ldots, m_T$ and $i = 1, \ldots, N_1$. Here without loss of generality, we assume N is dividable by m_T. We focus on this specific model in the following derivations.

B. PDA-Based Searching

As shown in (6), if we discretize the delays that a path can inhabit, and assign a binary variable to indicate the existences of delays, then the TOA problem becomes similar to the code division multiple access (CDMA) demodulation. This observation suggests us to adapt multiuser detection approaches in CDMA to address our channel estimation problem. For instance, the Fourier transform model based algorithm proposed in [2] can be regarded as a decorrelator in CDMA. In this paper, we draw the comparison, and focus on a very promising approach: PDA. The so-called PDA detector [7] for CDMA has its root in the popular PDA filter of target tracking [8], and provides a very good performance and an attractive computation cost. Encouraged by this, we apply the PDA concept to the channel estimation problems and carry out a PDA-based algorithm to obtain TOA estimates. Since the number of paths p is unknown, we also need to estimate the number of paths by applying information theoretic criteria, such as the MDL principle [6].

The goal of PDA-based searching is to locate TOAs with an affordable computational cost. The basic idea of PDA is to iteratively approximate the interference from other paths as Gaussian noise. Based on model (6), recall that the elements of $\mathbf{a}$ follow the i.i.d. $CN(0, \sigma_s^2)$ distribution, according to the properties of the vector-valued Gaussian distribution, we have

$$f(\mathbf{y}|\mathbf{b}) = CN\left(0, \mathbf{RB\Sigma}_s\mathbf{B}^H\mathbf{R}^H + \sigma_n^2\mathbf{R}\right) \tag{7}$$

where $\mathbf{\Sigma}_s = \sigma_s^2\mathbf{I}_N$, with $\mathbf{I}_N$ being the identity matrix of dimension N-by-N. We apply the PDA concept to estimate $\mathbf{b}$ given the observation $\mathbf{y}$. Define $P_b(i)$ as the probability that a path arrives at the delay t_i. The key in PDA is to iteratively update $P_b(i)$ based on the Gaussian approximation until convergence. By using the binary nature of b_i's and applying the Gaussian approximation based on moment-matching, for $i = 1, \ldots, N_1$, we can show that

$$\begin{aligned} f\left[\mathbf{y}|b(i) = 0, \{P_b(j)\}_{j\neq i, j\in[1,N_1]}\right] &= CN(0, \mathbf{\Sigma}_{0i}) \\ f\left[\mathbf{y}|b(i) = 1, \{P_b(j)\}_{j\neq i, j\in[1,N_1]}\right] &= CN(0, \mathbf{\Sigma}_{1i}) \end{aligned} \tag{8}$$

with

$$\begin{aligned} \mathbf{\Sigma}_{0i} &= \sigma_s^2 \sum_{j\neq i} P_b(j) \left(\sum_{m=1}^{m_T} \mathbf{R}_{(m-1)N_1+j}\mathbf{R}^H_{(m-1)N_1+j} \right) + \sigma_n^2 \mathbf{R} \\ \mathbf{\Sigma}_{1i} &= \mathbf{\Sigma}_{0i} + \sigma_s^2 \left(\sum_{m=1}^{m_T} \mathbf{R}_{(m-1)N_1+i}\mathbf{R}^H_{(m-1)N_1+i} \right) \end{aligned}$$

where $\mathbf{R}_j$ is the jth column of the matrix $\mathbf{R}$. Because of the special form of the covariance matrices $\mathbf{\Sigma}_{0i}$ and $\mathbf{\Sigma}_{1i}$, a lot computational cost can be saved by using the rank one matrix inverse formula. Now based on the above Gaussian approximation of the distribution, at each iteration q, $P_b(i)$ is updated according to the Bayesian formula as

$$P_b(i)^{\{q\}} = \frac{f\left(\mathbf{y}|b(i) = 1, \left\{P_b(j)^{\{q-1\}}\right\}_{j\neq i}\right) Pr\left(b(i) = 1\right)}{\sum_{b(i)} f\left(\mathbf{y}|b(i), \left\{P_b(j)^{\{q-1\}}\right\}_{j\neq i}\right) Pr\left(b(i)\right)} \tag{9}$$

for $i = 1, \ldots, N_1$, where $Pr(b(i) = 1)$ is the prior probability and we choose 0.5 in our problem. Normally, $\{P_b(i)\}$ converges within 2–4 iterations as shown in [7].

With the preparation of the above statistic analysis, now we apply the PDA idea and the MDL principle to estimate $\mathbf{b}$.

1) **Ordering of MF bins and updating** $\{P_b(i)\}$: We first initialize the probabilities $P_b(i) = 0.5, \forall i$. At the first iteration, the indexes i's are sorted in the descending order of magnitude of $\mathbf{y}$, and each $P_b(i)$ in the ordered index is updated according to (9). In the following iterations they are sorted in the descending order of $\{P_b(i)\}$, and $P_b(i)$'s are sequentially updated based on the current value of $\{P_b(j), j \neq i\}$. Repeat the process until each $P_b(i)$ converges.
2) **Determining the number of paths**: Based on the probabilities $\{P_b(i)\}$'s obtained above, we further proceed to decide $\mathbf{b}$. Since the number of active paths p is unknown, any attempt to estimate it by maximizing $f(\mathbf{y}|\mathbf{b})$ directly will yield as many paths as possible. Therefore, a suitable order selection algorithm should be included. A popular principle is MDL [6]. Starting from picking only one path whose delay yields the largest probability $P_b(i)$, we sequentially add one more path by applying the MDL principle to decide the number of paths p. Note that the penalty term in MDL has the basic form $n_p \ln(N)/2$ where n_p is the total number of parameters estimated. Since in our problem the total number of estimated parameters is p (e.g., $\mathbf{b}$ contains p nonzero elements), now we have

$$\text{MDL}(\mathbf{y}, p) = -\ln\left(f(\mathbf{y}|\hat{\mathbf{b}})\right) + \frac{p\ln(N)}{2}$$

where

$$\hat{b}(i) = \begin{cases} 1, & \text{if } P_b(i) \in \{\text{the } p \text{ largest } P_b(i)\}; \\ 0, & \text{otherwise} \end{cases} \tag{10}$$

for $p = 1, 2, \ldots, N_1$. Then p is estimated as

$$\hat{p} = \arg\min_p \left\{\text{MDL}(\mathbf{y}, p)\right\}.$$

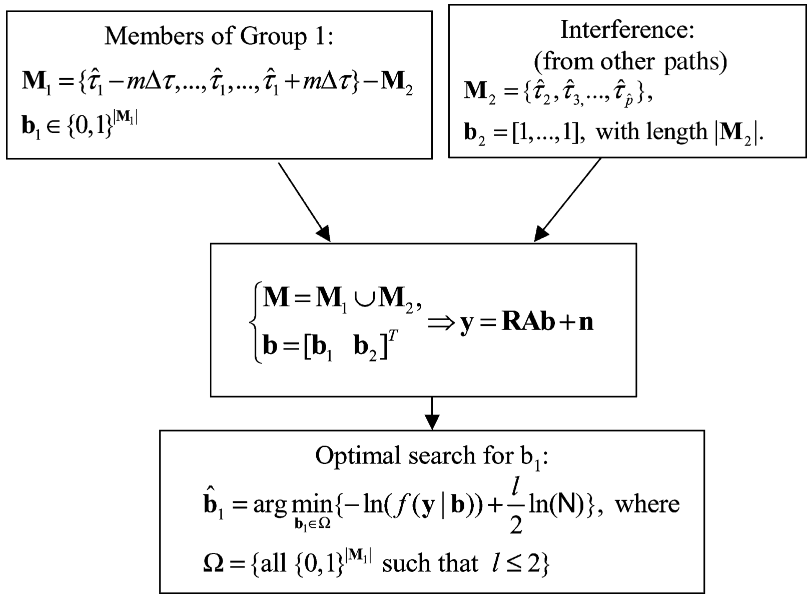

Fig. 1. Procedure of the refinement via DF idea within one iteration: the searching procedure demonstrated in group 1.

Based on the values of possible delays $\{t_i\}$, this Step-B usually yields a reasonably good resolution. To further improve the estimation accuracy, the following stage is applied, in which we apply the decision feedback idea and perform local estimation.

C. Refinement via Decision Feedback

Since we only have finite samples of $\mathbf{r}$ in a practical OFDM, the path arrival times $\boldsymbol{\tau}$ are roughly estimated in the above procedure, and we record the TOAs results as $\hat{\boldsymbol{\tau}} = \{\hat{\tau}_1, \ldots, \hat{\tau}_{\hat{p}}\}$. We improve the precision of estimates by performing a local minimization with respect to a single arriving time τ_i, while all other arriving times are held fixed. The process is performed iteratively. The idea behind is very similar to the decision feedback algorithm in CDMA. Since a minimization is performed at every sub-step, the value of the cost function $\mathrm{MDL}(\mathbf{y}, p)$ keeps decreasing with the iteration index, intuitively, this refinement process is to converge. The process is summarized in the following. We begin with the previously determined TOAs $\hat{\boldsymbol{\tau}}$, redefine $\mathbf{M} = \hat{\boldsymbol{\tau}}$, and then the following.

1) Sort the paths in the descending-power order. Assuming that the paths arrive at delays $\mathbf{M}$, the corresponding complex amplitudes of paths can be obtained by the ML estimate with referring to model (6).
2) For each path i, for $i = 1, \ldots, \hat{p}$, with $\hat{p}$ meaning the size of $\mathbf{M}$, we optimally search the nearby region (a group of delays) of $\hat{\tau}_i$ and record the updated estimates as $\{\hat{\tau}_i\}$ sequentially. We then update $\mathbf{M} = \{\{\hat{\tau}_1\}, \{\hat{\tau}_2\}, \ldots, \{\hat{\tau}_{\hat{p}}\}\}$. Here we illustrate the optimal search in group 1 in Fig. 1, where group 1 is characterized by $\hat{\tau}_1$ and paths arriving at other delays $\{\hat{\tau}_2, \ldots, \hat{\tau}_{\hat{p}}\}$ are regarded as interferences. Based on $\hat{\tau}_1$, the members of group 1 with size $(2m+1)$ are selected as the nearby delays around $\hat{\tau}_1$, which is in turn reasonably defined by the constant delay difference between the adjacent members $\Delta\tau$. This $\Delta\tau$ is referred to as the precision factor. We use $\mathbf{M}_1$ to indicate the members in group 1 but not part of the interference, and $\mathbf{M}_2$ to indicate the delay locations of interfering paths. We consider model (6), and apply the MDL principle to detect the number of paths in group 1

$$\hat{\mathbf{b}}_1 = \arg\min_{\mathbf{b}_1 \in \Omega} \left\{ -\ln\left(f(\mathbf{y}|\mathbf{b})\right) + \left(\frac{l}{2}\right) \ln(N) \right\} \qquad (11)$$

where $\mathbf{b} = [\mathbf{b}_1, \mathbf{b}_2]^T$, $\mathbf{b}_2 = [1, \ldots, 1]$ with length $|\mathbf{M}_2|$ indicating the interfering targets, and $\mathbf{b}_1 \in \{0,1\}^{|\mathbf{M}_1|}$ is used to indicate the locations and number of paths in $\mathbf{M}_1$. Since the purpose of this decision feedback process is to improve estimation of τ_1 through $\hat{\mathbf{b}}_1$, we only consider three possibilities: $l = 0$ (dropping one path), $l = 1$, or $l = 2$ (adding one path) in $\mathbf{M}_1$, indicating by Ω

$$\Omega = \{\text{all } \mathbf{b}_1 \text{ such that } l \le 2\}$$

where l means the number of nonzero elements (paths) in $\mathbf{b}_1$. Due to the small size of Ω, problem (11) can be solved by an exhaustive search. Based on $\hat{\mathbf{b}}_1$, we update $\{\hat{\tau}_1\}$. We similarly update $\{\hat{\tau}_i\}$, for $i = 2, \ldots, |\mathbf{M}|$. Note that two paths are possibly found at this stage, thus, a larger number of closely spaced paths can be detected by this iterative procedure.

We continue until the process converges. The final estimates of path delays are in the subset $\mathbf{M}$.

IV. Simulation Results

To demonstrate the performance of the proposed channel estimation approach, simulations have been conducted for the space-time code based OFDM. It has been shown that, in large cells with high base station antenna platforms, the multipath propagation of the radio channel in wireless communications is aptly modeled by a few dominant specular paths, typically two to six [13]. Thus the delay profiles studied are the well known

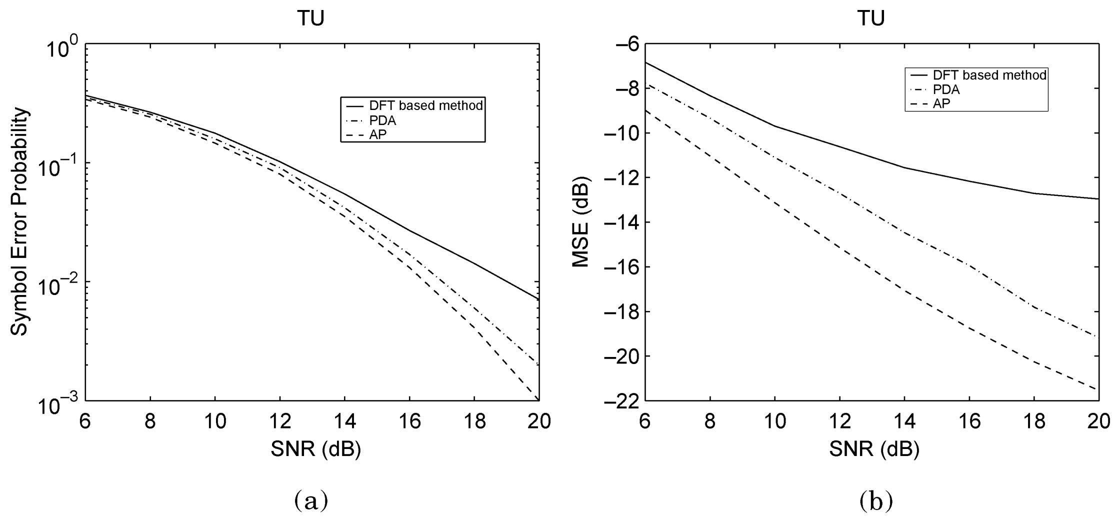

Fig. 2. Performance comparisons of different channel estimators for the TU channel with 40 Hz Doppler frequency. (a) Symbol error probability. (b) MSE.

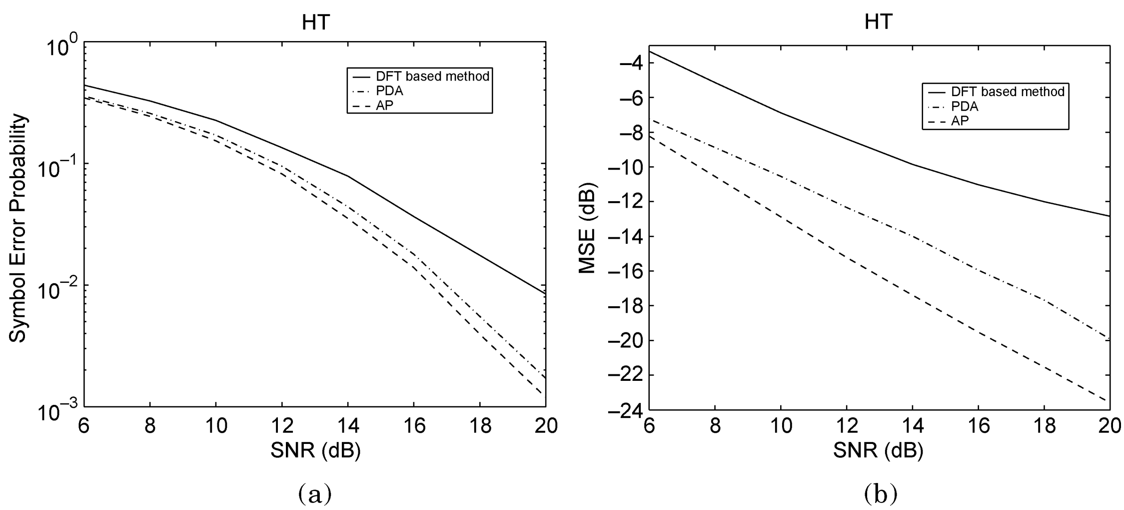

Fig. 3. Performance comparisons of different channel estimators for the HT channel with 40-Hz Doppler frequency. (a) Symbol error probability. (b) MSE.

typical urban (TU) and the hilly terrain (HT) delay profiles, as in [12], where the maximum delay is set as $T_d = 20\ \mu$s in HT case and $T_d = 8\ \mu$s in TU. The system bandwidth is 1.6 MHz and divided into 128 subchannels. The four subchannels on each boundary are used as guard tones. So totally 120 subchannels are used for transmission. To make the tones orthogonal to each other, the symbol duration is 80 μs. An additional 20 μs guard interval is used to avoid intersymbol interference due to channel delay spread. This results in a total block length as 100μs and a block rate as 10 kBd. A Doppler frequency of 40 Hz is used to represent the mobile environment, where the Rayleigh fading is generated using Jake's model. Two transmit and two receive antennas are used for diversity. The training sequence is designed as in (4). After the training block, the channel estimates are used to decode the next data block [1]. Recently, space-time coding at the transmitter equipped with an efficient decoder at the receiver has been shown to offer high code efficiency and good performance [4]. Here the space time block code using 8 PSK proposed in [4] is employed and the ML detection scheme is adopted for decoding. The described system can transmit data at a rate of 3.84 Mbits/s over an 1.6 MHz channel, i.e., the transmission efficiency is 2.4 bits/s/Hz.

The system performance is measured by symbol error probability and the mean-squared estimation error (MSE). Fig. 2 and Fig. 3 show the performance comparisons of the proposed scheme with the DFT based scheme in [2][3] and the AP method [5] for the TU and HT profile channels, respectively, where symbol error probability versus SNR and MSE versus SNR are plotted. In AP implementation, the knowledge of the number of paths in each channel link is assumed known. Therefore, AP serves as a bound of performance in terms of symbol error probability. It is clear that estimating TOAs via the proposed scheme yields a much better estimation performance than that of the

[3]We note that considering guard tones helps to improve the performance of the DFT-based scheme. In our implementation, the four subchannels at each end are used as guard tones. In addition, the number of taps K_0 is determined by the maximum delay in the corresponding delay profile.

Fourier transform based estimation, with the performance gap increases at larger SNR. For instance, the SNR different is larger than 2 dB for a 1% symbol error probability. We also note some minor performance degradations of our scheme compared with AP, e.g., less than 0.5 dB for $\mathrm{SNR} \leq 15$ dB. This degradation can be even smaller if the number of paths is also unknown in AP.

Now let us look at the computation complexity of different approaches, in terms of the number of complex multiplications. We note that the complexity of the Fourier transform based scheme is much lower than the proposed scheme and the AP method. Similar to the analysis in [15], the complexity of the Fourier transform based scheme is $O(K\log(K) + m_T^2 m^2)$, where m is the number of taps, depending on the delay profile and dispersion of the channel. Simulation results in [7] show that the complexity of the PDA approach is $O(N_1^3)$. The AP method has high complexity, demanding $O(K^2)$ operations at each search path and thus yielding a complexity as $O(pK^3)$. Since N_1, similar to m, is generally much smaller than K, the proposed scheme is more computationally efficient than the AP. For comparing the computational cost, we simulate the CPU time requirements of different approaches. For instance, at $\mathrm{SNR} = 10$ dB under the HT profile, the ratio of the average CPU time requirement of the DFT based scheme to that of the proposed scheme is 0.09, and the ratio of the proposed scheme to that of AP is 0.231. In addition, a much larger computational complexity will be required in AP if the number of paths needs to be estimated. Though the DFT based scheme is much more computationally efficient, as indicated in Fig. 2 and Fig. 3, its performance is much poorer especially when SNR is large. Therefore, we prefer the proposed scheme due to the significant performance gain. Overall, the proposed scheme is much faster than AP and has the comparable estimation accuracy.

V. Conclusion

In summary, the proposed TOA-based channel estimator incorporates the PDA and decision feedback methods to locate the path delays, with the number of paths determined via the MDL principle. It is illustrated that estimating TOAs via the proposed scheme yields a much better estimation performance than the DFT based estimation, with the gap increases at larger SNR. The scheme provides a comparable performance to that of AP, which serves as a performance upper bound. For the simulated system, the required SNR for a 1% symbol error rate for the proposed scheme is at least 2 dB less than that of the DFT based method, and about 0.5 dB more than that of the AP method. Moreover, our scheme requires a much lower computational cost than that of AP. Therefore, the proposed PDA based TOA estimation scheme provides a very promising technique for MIMO-OFDM channel estimation.

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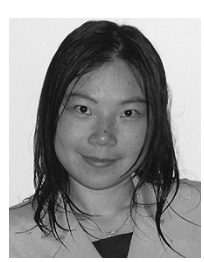

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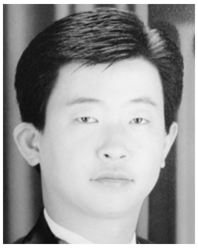

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