Joint Symbol Timing and Channel Estimation in Two-Way Multiple Antenna Relay Networks

Zhe Jiang*, Haiyan Wang* and Zhi Ding†
*School of Marine Engineering, Northwestern Polytechnical University
Xi'an 710072, P.R. China, Email: jzh1723@gmail.com, hywang@nwpu.edu.cn
†Department of Electrical and Computer Engineering, University of California
Davis, CA 95616, Email: zding@ucdavis.edu

***Abstract*—We present investigation results on joint estimation of symbol timing synchronization and channel response in two-way multiple antenna relay networks that utilize amplify-and-forward (AF) relay strategy. With practically unknown relay channel gains and timing offset, optimum maximum likelihood (ML) estimation for joint timing recovery and channel estimation can be prohibitively complex. We develop a new Bayesian based Markov chain Monte Carlo (MCMC) algorithm and generalize our previous principle to a multiple antenna relay network to accomplish joint symbol timing recovery and effective channel estimation. Simulation results are provided to demonstrate the performance of the proposed algorithm.**

I. Introduction

A great deal of of research has focused on two-way relay networks (TWRN) that use intermediate nodes to serve as relays between two communicating terminals. To support information exchange between two terminals, a TWRN can potentially achieve higher spectral efficiency over unidirectional relays under the practical half-duplex constraint [1], [2]. Instead of allocating 4 packet time slots to the relay to facilitate the transmission of 1 packet from each of the two transceiving terminals, a two-way AF relay can reduce the relay time to 2 packet time-slots by exploiting the broadcast nature of the wireless medium and by letting each terminal cancel its own transmission from the relay signal [1] as shown in Figure 1.

Most of existing works on TWRN are based on the assumption of perfect symbol level synchronization and channel state information (CSI) [3]. In practice, however, symbol timing recovery [4] as well as channel estimation [5] must be implemented at the receiver before demodulating its message of interest [3].

Our previous work [3] proposed a Bayesian based Markov chain Monte Carlo (MCMC) algorithm for joint symbol timing synchronization and channel estimation in TWRN with a single antenna 2-way relay. In this work, we generalize our approach to a multiple antenna relay system as discussed in [6]. With equal power allocation at every antenna, the relay amplifies and forwards the signals from both two terminals. Receiving the summed signals and self-interferences from multiple antenna relay, the receiver estimates the timing delays and composite channels before detecting unknown data from the other terminal.

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II. Problem Formation of Joint Symbol Timing Recovery and Channel Estimation

Consider a typical TWRN as shown in Fig. 1, consisting of two terminal nodes A and B to exchange information through a M-antenna relay node R. Using time-division duplex (TDD) mode, the link channels are reciprocal. Let h_i denote the baseband channel gain between node A and the i-th antenna of relay R, and let g_i denote the baseband channel gain between node B and the i-th antenna of R. All channels $h_i, i = 1, ...M$ and $g_i, i = 1, ...M$ are assumed to be independent, circular symmetric, complex Gaussian random variables with zero-mean and variance σ_h^2 and σ_g^2, respectively. Fig. 1 also show the timing delay of τ_{AR} between nodes A and R, as well as the timing delay τ_{BR} between nodes B and R.

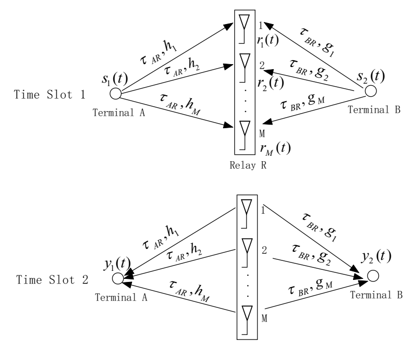

Fig. 1. A typical two-way multiple antenna relaying system with one relay node and working under AF mode.

Using AF, the TWRN can operate under the two-time-slot protocol. During time slot 1, terminals A and B transmit QAM signals $s_1(t)$ and $s_2(t)$, respectively, to the relay node at symbol interval T. The resulting complex baseband signal $r(t)$ received at the i-th antenna of R can be written as

$$\begin{aligned} r_i(t) =& \sqrt{E_{s1}} \cdot h_i \sum_m a_m q(t - mT - \tau_{AR}) \\ &+ \sqrt{E_{s2}} \cdot g_i \sum_m b_m q(t - mT - \tau_{BR}) + n_{ri}(t) \end{aligned} \tag{1}$$

in which $\{a_m\}$ is a sequence of i.i.d. QAM information symbols from node A whereas $\{b_m\}$ is a sequence of i.i.d. QAM information symbols from node B. $n_{ri}(t)$ is the complex-valued additive white Gaussian noise (AWGN) with variance σ_n^2 at the i-th antenna of R. Moreover, $q(t)$ is a unit-energy pulseshaping response which is typically a square-root raised-cosine rolloff pulse in practice. In addition to the unknown channel gains, τ_{AR} and τ_{BR} are unknown delays from terminals A and B to the relay, respectively.

Next in time slot 2, the AF relay scales $r_i(t)$ by a scalar α before broadcasting to both terminals A and B. Typically, the AF scalar α can be either determined a priori, or taken according to its received signal strength. In our formulation, we assume that α is chosen a priori that leads to a steady state average power output. Furthermore, we assume equal power allocation at all relay antennas, and α is computed via [7]

$$\alpha = \sqrt{\frac{E_{sr}}{M(\sigma_h^2 E_{s1} + \sigma_g^2 E_{s2} + \sigma_n^2)}} \tag{2}$$

Since both terminals A and B receive the same relayed signals, the same formulation of joint timing and channel estimation applies to both nodes. Thus, without loss of generality, we will only study the timing synchronization and channel estimation at the receiving terminal A. Supposing the relay processing delay from receiving to transmitting equals τ_p, then in time slot 2 the terminal A receives signal

$$\begin{aligned} y_1(t) =& \sqrt{E_{s1}}\alpha \sum_m a_m q(t - mT - \tau_1) \cdot \sum_{i=1}^{M} h_i^2 \\ &+ \sqrt{E_{s2}}\alpha \sum_m b_m q(t - mT - \tau_2) \cdot \sum_{i=1}^{M} h_i g_i \\ &+ \alpha \sum_{i=1}^{M} h_i n_{ri}(t) + n_1(t) \end{aligned}$$

where $n_1(t)$ represents the complex-valued AWGN at terminal A. In practical scenarios, wireless background noises $n_1(t)$ and $n_{ri}(t)$ are independent, with zero mean and spectrum $N_0/2$. The accumulative unknown timing delays equal

$$\begin{aligned} \tau_1 &= (2\tau_{AR} + \tau_p) \bmod T; \\ \tau_2 &= (\tau_{AR} + \tau_{BR} + \tau_p) \bmod T; \end{aligned}$$

The received signal $y_1(t)$ passes through a matched filter with impulse response $q(-t)$ before being sampled at rate $1/T_s$. The resulting signal samples are

$$\begin{aligned} z_k = z(kT_s) =& \sqrt{E_{s1}}\alpha \sum_m a_m p(kT_s - mT - \tau_1) \cdot \sum_{i=1}^{M} h_i^2 \\ &+ \sqrt{E_{s2}}\alpha \sum_m b_m p(kT_s - mT - \tau_2) \cdot \sum_{i=1}^{M} h_i g_i \\ &+ \underbrace{\alpha \sum_{i=1}^{M} h_i N_{rik}(t) + N_{1k}}_{\text{sumnoise } \nu_k} \end{aligned} \tag{3}$$

where the matched pulseshape equals $p(t) = q(t) * q(-t)$. Notice that the sum noise ν_k is Gaussian with zero-mean and autocorrelation function

$$\begin{aligned} R_\nu[\ell] &= (|\alpha|^2 \cdot \sum_{i=1}^{M} |h_i|^2 + 1) N_0/2 p(\ell T_s) \\ &= (|\alpha|^2 \cdot \sum_{i=1}^{M} |h_i|^2 + 1) \sigma_n^2 \int q(\ell T_s + u) q(u) du. \end{aligned} \tag{4}$$

Clearly, $R_\nu[\ell]$ depends on channel gains $|h|$, unlike in a typical synchronization and channel estimation problem.

In so far as detection of unknown symbols from terminal B, terminal A does not require the estimation of h_i and g_i directly. Instead, the composite channel response $\sum h_i^2$ and $\sum h_i g_i$ would suffice. For convenience, we define the two channel responses of interest as $u \triangleq \sum h_i^2$ and $v \triangleq \sum h_i g_i$, which we wish to estimate.

With known pilot data from terminal B and transmitted packet from terminal A itself, the receiver at A can estimate unknown parameters τ_1, τ_2, u and v jointly. For data detection, the matched filter output signal at terminal A is sampled at the estimated decision instants $kT_s + \hat{\tau}_2$ to maximize SNR. The resulting matched filter output samples must cancel the self-interference from in $z_k(\hat{\tau}_2)$ using known data $\{a[m]\}$ and estimated $\hat{\tau}_1$ and $\hat{u}$. The unknown data $\{b[m]\}$ of terminal B are recovered with help of channel estimate $\hat{v}$.

Compared with conventional symbol synchronization problem discussed in [8]–[10], our problem is more challenging as it is clear from the data sample z_k that the optimum (ML) detection of $b[m]$ at node A would be possible only with the estimates of all the unknown parameters $\Theta = [\tau_1, \tau_2, u, v]$. The nonlinear model of (3) with respect to both timing delays τ_1 and τ_2, and the dependency of $R_\nu[\ell]$ on channel gain $|h|$ further complicates the joint timing synchronization and channel estimation in TWRN.

III. Maximum Likelihood Joint Estimation

Let $u = |u|e^{j\psi_1}$ and $v = |v|e^{j\psi_2}$, $\mathbf{z}$, $\mathbf{a}$, $\mathbf{b}$ $\boldsymbol{\nu}$ be column vectors of length N containing a collection of received data samples, modulated data, and noise samples. Let $\mathbf{P}_1$ and $\mathbf{P}_2$ be matrices whose *km*-th entries equal $p(kT_s - mT - \tau_1)$ and $p(kT_s - mT - \tau_2)$, respectively. Then the conditional mean vector and conditional covariance matrix of vector $\mathbf{z}$ are respectively expressed by

$$E[\mathbf{z}|\Theta] = \sqrt{E_{s1}}|u|e^{j\varphi_1}\alpha \mathbf{P}_1 \mathbf{a} + \sqrt{E_{s2}}\,|v|\,e^{j\varphi_2}\alpha \mathbf{P}_2 \mathbf{b} \tag{5}$$

$$\mathrm{Cov}(\mathbf{z}|\Theta) = (|\alpha|^2|u| + 1)\frac{N_0}{2}\boldsymbol{\Lambda}. \tag{6}$$

For a nonsingular $\boldsymbol{\Lambda}$,the joint likelihood function given knowledge of $\mathbf{z}$ and pilot data $\mathbf{a}$ and $\mathbf{b}$ equals

$$\begin{aligned} L(\mathbf{z}|\boldsymbol{\Theta}) \quad \sim \quad & -N \log\left(\frac{N_0\left(\alpha^2\,|u| + 1\right)}{2}\right) - \log\det(\boldsymbol{\Lambda}) \\ & - \frac{(\mathbf{z} - E[\mathbf{z}|\boldsymbol{\Theta}])^H \cdot \boldsymbol{\Lambda}^{-1}\,(\mathbf{z} - E[\mathbf{z}|\Theta])}{N_0\left(\alpha^2\,|u| + 1\right)} \end{aligned} \tag{7}$$

It is therefore evident that ML estimates of parameters Θ at node A can be complex and computationally costly as it requires the search over six real variables.

The work of [7] presented a ML channel estimator assuming perfect timing synchronization among three nodes. Although our problem is more complex, one natural extension of this method is to assuming τ_1 and τ_2 to be known first before applying ML channel estimation in a two-step algorithm.

First, given the knowledge of τ_1 and τ_2, we can transform the pilot symbols via

$$\mathbf{a}(\tau_1) = \mathbf{P}_1 \cdot \mathbf{a}; \qquad \mathbf{b}(\tau_2) = \mathbf{P}_2 \cdot \mathbf{b}.$$

We can then define

$$\rho = \frac{\mathbf{a}^H(\tau_1)\mathbf{b}(\tau_2)}{\|\mathbf{a}(\tau_1)\|_2^2 \, \|\mathbf{b}(\tau_2)\|_2^2} \quad \text{and} \quad \mathbf{A} = \mathbf{I} - \frac{\mathbf{b}(\tau_2)\mathbf{b}^H(\tau_2)}{\|\mathbf{b}(\tau_2)\|_2^2}.$$

and further let

$$C_1 = \alpha^3 \left(1 - |\rho|^2\right) \|\mathbf{a}(\tau_1)\|_2^2 \tag{8}$$

$$C_2 = \alpha^3 N \cdot N_0^{-1} + 2\alpha \left(1 - |\rho|^2\right) \|\mathbf{a}(\tau_1)\|_2^2 \tag{9}$$

$$C_3 = \alpha N \cdot N_0^{-1} - \alpha \mathbf{z}^H \mathbf{A} \mathbf{z} + 2 \left|\mathbf{z}^H \mathbf{A} \mathbf{a}(\tau_1)\right|. \tag{10}$$

Then the angle of u can be obtained by

$$\widehat{\psi_{1\mathrm{ML}}}(\tau_1, \tau_2) = -\angle \left(\mathbf{z}^H \mathbf{A} \mathbf{a}(\tau_1)\right) \tag{11}$$

and the magnitude of $|u|$ is estimated from (12) on the top of next page.

The estimate of v can then be estimated via

$$\widehat{v}_{\mathrm{ML}}(\tau_1, \tau_2) = \frac{\mathbf{b}^H(\tau_2)}{\alpha \|\mathbf{b}(\tau_2)\|_2^2} \left(\mathbf{z} - \alpha \hat{u} \mathbf{a}(\tau_1)\right) \tag{13}$$

Nevertheless, τ_1 and τ_2 in practice are unknown and must also be estimated. We can find the ML estimates of τ_1 and τ_2 by maximizing the likelihood function (7) after substituting the ML estimates of $u_{\mathrm{ML}}(\tau_1, \tau_2)$ and $v_{\mathrm{ML}}(\tau_1, \tau_2)$. The second step of the ML estimation can be accomplished by an exhaustive search to maximize (7) as described in [8]–[10].

We note, however, that in this TWRN setup, each receiver must estimate all parameters in Θ. Therefore, the joint ML estimation algorithm described here must search over a 2-dimensional space for maximizing the likelihood function $L(\tau_1, \tau_2)$ in the rectangular area $(-T/2, T/2) \times (-T/2, T/2)$. Such an exhaustive search algorithm incurs high computation cost and is practically less attractive.

We will instead present a Bayes approximation to the joint ML estimation problem. The Bayesian MCMC algorithm has several advantages for this application. First, MCMC has modest complexity and is quite insensitive to the selection of initial estimates. It is also more robust to changing communication conditions than algorithms such as the expectation maximization (EM) technique [4], [11]. Most importantly, it is attractive to highly complex, nonlinear and high-dimensional space models [12], such as our TWRN joint estimation problem.

IV. BAYESIAN MCMC-BASED JOINT ESTIMATION

A. Basic Metropolis-Hastings Algorithm

Although the Gibbs sampler [12] is a popular algorithm for MCMC approach, it is rather tedious when applied in our framework since Gibbs sampler needs to drawn samples from $q_i\left(\phi_i|\Theta_i^{(j-1)}, \Theta_{-i}\right) = \pi\left(\phi_i|\Theta_{-i}\right)$. In this work, we develop a Metropolis-Hastings algorithm for joint channel estimation and timing synchronization.

Let $\pi(\Theta) = \pi(\tau_1, \tau_2, u, v) = \pi(\Theta_1, \Theta_2, \Theta_3, \Theta_4)$ be the target probability distribution from which we want to simulate random drawing. In basic Metropolis-Hastings (BMH) algorithm, at each time instant t, the next state $\Theta^{(t+1)}$ is chosen by first sampling a candidate point ϕ from a proposal distribution $q\left(\cdot|\Theta^{(t)}\right)$. Note that the proposal distribution may depend on the current point $\Theta^{(t)}$. The candidate point ϕ is then accepted with probability $\alpha\left(\Theta^{(t)}, \phi\right)$ where

$$\alpha(\Theta, \phi) = \min\left(1, \frac{\pi(\phi) q(\Theta|\phi)}{\pi(\Theta) q(\phi|\Theta)}\right). \tag{14}$$

If the candidate point is accepted, the next state moves to $\Theta^{(t+1)} = \phi$. If the candidate is rejected, the chain does not move and repeats for time instant $t+1$, i.e. $\Theta^{(t+1)} = \Theta^{(t)}$.

Instead of updating the whole of Θ *en bloc*, it is more convenient and computationally efficient to update components of Θ (τ_1, τ_2, u, v) one by one [13]. Let $\Theta_{-i} = [\Theta_1, ..., \Theta_{i-1}, \Theta_{i+1}, \Theta_n]$, i.e. Θ_{-i} comprise all of Θ except Θ_i. Starting with any configuration $\Theta^{(0)} = \left(\tau_1^{(0)}, \tau_2^{(0)}, u^{(0)}, v^{(0)}\right)$, our BMH algorithm is summarized in Algorithm 1 below.

Algorithm 1 Basic Metropolis-Hastings Algorithm

1. Set iteration counter to $j = 1$, and set the initialize value of the chain $\Theta^{(0)}$ randomly or deterministically.
2. Initial the component counter $i = 1$.
3. Move the ith component of the vector of states of the chain to a new value ϕ_i generated from the density $q_i(\phi_i|\Theta_i^{(j-1)}, \Theta_{-i})$.
4. Calculate the acceptance probability of the move $\alpha_i\left(\Theta_i^{(j-1)}, \Theta_{-i}, \phi_i\right)$ given by $\alpha_i\left(\Theta_i^{(j-1)}, \Theta_{-i}, \phi_i\right) = \min\left\{1, \frac{\pi_i(\phi_i|\Theta_{-i}) q_i\left(\Theta_i^{(j-1)}|\phi_i, \Theta_{-i}\right)}{\pi_i\left(\Theta_i^{(j-1)}|\Theta_{-i}\right) q_i\left(\phi_i|\Theta_i^{(j-1)}, \Theta_{-i}\right)}\right\}$. If the move is accepted, $\Theta_i^{(j)} = \phi_i$. If the move is rejected, set $\Theta_i^{(j)} = \Theta_i^{(j-1)}$.
5. Update component counter from i to $i+1$ and return to step 3 until $i = 4$. When $i = 4$, go to step 6.
6. Change iteration counter from j to $j+1$ and return to step 2 until convergence or maximum iteration.

As potential choices for the proposal kernel $q_i\left(\phi_i|\Theta_i^{(j-1)}, \Theta_{-i}\right)$, we can use symmetric, random walk or independent proposal. Specifically for our problem, we select the random walk sampler.

B. Metropolis-Hastings-ML Acceleration Algorithm

In order to accelerate the convergence of basic Metropolis-Hastings algorithm, as well as to improve the estimation per-

$$\widehat{|u|}_{\mathrm{ML}}(\tau_1,\tau_2)=\begin{cases}\max\{-C_3/C_2,0\} & \text{if } |\rho|=1;\\ \max\left\{\frac{-C_2+\sqrt{C_2^2-4C_1C_3}}{2C_1},0\right\} & \text{if } |\rho|<1 \text{ and } C_2^2-4C_1C_3\geq 0;\\ 0 & \text{if } |\rho|<1 \text{ and } C_2^2-4C_1C_3<0.\end{cases} \tag{12}$$

formance, we also propose to combine the basic Metropolis-Hastings algorithm with ML channel estimator. Specifically, for τ_1 and τ_2, we construct a Markov Chain, and then use ML algorithm [7] instead of constructing the Markov chain for two channels. Following the steps 1-4 of BMH algorithm, the steps of Metropolis-Hastings-ML (MH-ML) acceleration algorithm is detailed in Algorithm 2.

Algorithm 2 Metropolis-Hastings-ML Algorithm

1-4. Follow the steps 1-4 of basic Metropolis-Hastings algorithm.
5. Change the counter from $i=1$ to $i=2$ and return to step 3. Then go to step 6.
6. Estimate channels u and v based on ML channel estimator described in Section III.
7. Change the counter from j to $j+1$ and return to step 2 until convergence is reached.

C. Computation Complexity Analysis

Clearly, the major computation need of ML and MCMC algorithm arises from evaluating the log-likelihood function (7). To analyze the computational complexity of the three algorithms discussed thus far, we mainly focus on computation involving signals as matrices and vectors. We neglect the minimal cost of other low complexity operations such as Markov chain acceptance and rejection.

For search based algorithms, we have to divide the search space in grid. Let G be the number of grid points in each dimension of ML search. Recall that N is the number of training symbols. We can compare the computation complexity of the three joint estimation algorithms in Table I. The computational burden is measured in real-valued floating point operations (FLOPs). For BMH and MH-ML, we show the computational requirements of two algorithms per iteration. It is clear from the complexity comparison that the 2-D search algorithm of ML requires the highest number of computations while the BMH algorithm is the least demanding. The MH-ML algorithm naturally falls in between the two extremes.

TABLE I
COMPUTATIONAL REQUIREMENTS OF ML, BMH (PER ITERATION), AND MH-ML (PER ITERATION)

Algorithm	Real Flops	∼Real Flops
ML	$(20G^2+4N+19)N-G^2-4$	$O\left(G^2N+N^2\right)$
BMH	$8(20N-1)$	$O\left(N\right)$
MH-ML	$4N^2+99N-8$	$O\left(N^2\right)$

V. SIMULATION RESULTS

In this section, we numerically study the performance of the estimation algorithm presented thus far for TWRN. The estimation performance is measured in terms of MSE, estimation bias, and BER. To be fair, we cap the total signal energy from both terminals at a fixed $E_{sr}=(E_{s1}+E_{s2})/2$, and we let $E_{s1}=E_{s2}$. The training pilot sequence consists of three repeated and one more negative barker code with $N=11$. We assume the number of antennas on the relay is $M=2$, and rolloff factor is 0.1.

We fix two unknown delays as $\tau_1=T/4$ $\tau_2=-T/4$, and randomize the fading channels h and g with zero-mean and variance 1 circular symmetric, complex Gaussian random variables. Our performance result is measured for different values of average SNR at the terminal A receiver.

Figure 2 illustrates the resulting MSE of the τ_1 and τ_2 estimated by MH-ML at various levels of SNR. As shown in the figure, the MSE of τ_1 and τ_2 are similar for low SNR. Over SNR larger than $13dB$, the MSE of τ_2 is smaller than τ_1.

Figure 3 represents the mean of the estimates for the timing delay parameters τ_1 and τ_2 from MH-ML. Recall that $\tau_1=0.25T$ and $\tau_2=-0.25T$. We can see that for both τ_1 and τ_2, the estimation errors of our algorithm are below 1% of T over SNR larger than 6.5dB. Estimation errors in estimating both τ_1 and τ_2 are relatively small fractions of T over a large SNR range of interest.

Figure 4 shows the MSE of the estimates of random channel u and v. The MSE results of two channels are very similar over SNR of interest.

Another view is offered in Figure 5, where we show the BER achieved by the MH-ML versus SNR for BPSK modulation. For the sake of comparison, the BER of the perfectly synchronized receiver with known channel response (denoted as "Known Parameters") has also been plotted. It is clear that our algorithm enables to achieve the BER close to the receiver with perfect synchronization and channel information.

For MCMC-based algorithm, more iterations can improve the performance at the cost of larger computation burden.

VI. CONCLUSION

This work investigates the joint symbol timing synchronization and channel estimation in a two-way multiple antenna relay network. The amplify-and-forward relay makes it possible to conserve network bandwidth. However, the receiving terminals must accurately estimate the unknown channel and symbol timing delay in order to effectively demodulate and decode its signal of interest. We note that a classic ML joint estimation algorithm requires complex likelihood function evaluation and a 2-dimensional exhaustive search, thereby posing high computation burdens. We then apply a Bayesian

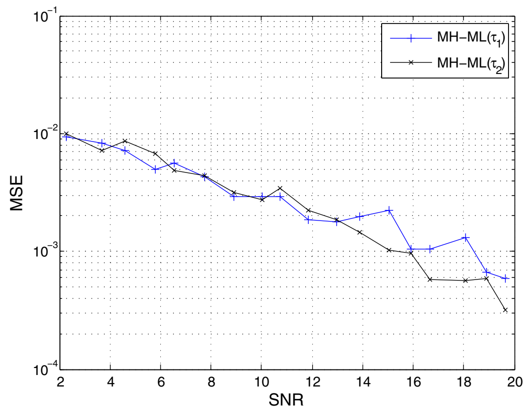

Fig. 2. MSE of τ_1 and τ_2 by MH-ML versus SNR.

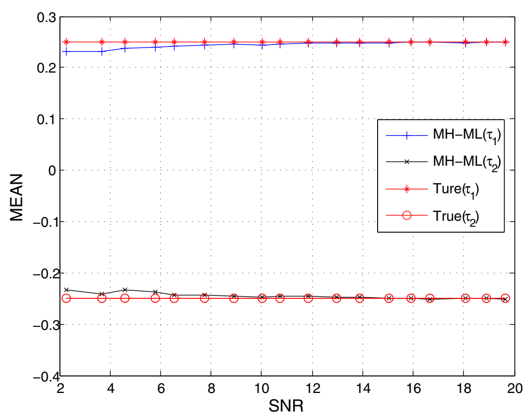

Fig. 3. MEAN of τ_1 and τ_2 by MH-ML versus SNR.

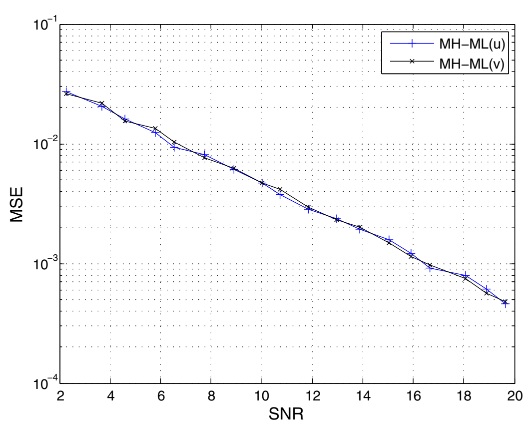

Fig. 4. MSE of u and v by MH-ML versus SNR.

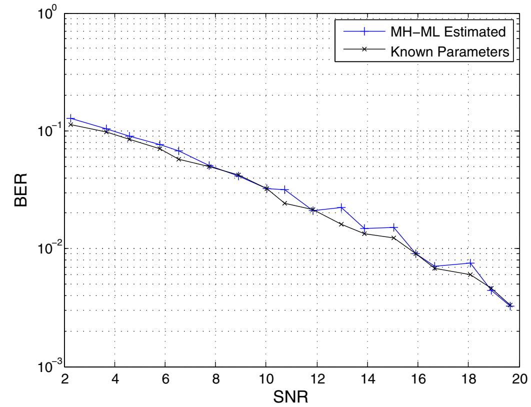

Fig. 5. BER achieved by MH-ML and receiver with perfect timing synchronization and channel information.

approach known as MCMC to simplify and approximate the ML approach. In particular, we present a basic Metropolis-Hastings algorithm and a Metropolis-Hastings-ML algorithm for the joint estimation and synchronization problem. Our results show that the proposed MCMC algorithms can substantially reduce the computation complexity with negligible performance loss in terms of MSE and bias. The BER performance achieved by our receiver is close to the receiver with perfect synchronization and channel information.

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