EFFICIENT BLIND DECODING OF MIMO USING SEQUENTIAL MONTE CARLO

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ABSTRACT

In this paper, blind decoding of OSTBC based MIMO systems using sequential Monte-Carlo methods is considered. Similar receivers developed earlier have suffered from the high computational complexity. By introducing some simplification and approximation techniques, we present a new decoding algorithm that requires much less computation. In addition to that, an efficient interlaced maximum likelihood estimator approach is developed to blindly estimate the statistical parameters of the channel. While a comparative analysis on the computational complexity shows significant computational savings, the simulation results show that the performance of the proposed algorithm is not compromised.

***Index Terms*—** MIMO, OSTBC, Kalman filter, Marginalized particle filter (MPF), Sequential Monte-Carlo (SMC)

1. INTRODUCTION

The focus of this paper is on blind signal detection at the receiver side of the MIMO system and hereafter this part will be called receiver in this paper. Among the different receivers for MIMO system marginalized particle filters (MPF) based receivers [1] received significant attention in the recent past. However, SMC methods are known for their intense computational requirement. The marginalization step employs Kalman filtering for each particle resulting in significant increase of computational complexity. It is shown in [2] that as the number of states in the Kalman filter(KF) increases, the achieved computational reduction will be lost and the technique will require more computation than the regular PF approach. This scenario is true for MIMO systems where the number of states in the Kalman filter increases with growing number of transmitting as well as receiving antennas since the number of states is proportional to the product of the number of transmitting and receiving antennas. Another dominant cause for computational load increase due to marginalization is the repeated likelihood calculations in the marginalization step.

Hence the objective of this paper is to introduce simplification as well as appropriate approximation techniques to develop computationally efficient MPF based MIMO receivers. The contributions of this paper towards the increased computational efficiency of the MPF based MIMO system receivers could be summarized as the following three: i)By assuming OSTBC's it is shown that significant simplification of the Kalman filtering step as well as the likelihood calculation step in MPF is possible with no loss in performance, ii) An approximation is introduced to use one Kalman filter (that is already simplified) instead of multiple Kalman filters in the marginalization step and iii) An interlaced maximum likelihood estimator (MLE) approach is developed to estimate the statistical parameters of the channel model.

2. BACKGROUND

Consider a MIMO system with N transmit and M receive antennas. In a time-varying flat-fading channel scenario, the discrete baseband received signal vector is given by

$$\mathbf{y}(n) = \mathbf{x}(n)\mathbf{H}(n) + \mathbf{v}(n) \tag{1}$$

where $\mathbf{H}(n)$ is the $N \times M$ channel matrix which is assumed constant during the transmission of the nth block of data and $\mathbf{y}(n) = [y_1(n)\ y_2(n)\ \ldots\ y_M(n)]$, $\mathbf{x}(n) = [x_1(n)\ x_2(n)\ \ldots\ x_N(n)]$, $\mathbf{v}(n) = [v_1(n)\ v_2(n)\ \ldots\ v_M(n)]$ are the row-vectors of the received signals, transmitted signals, and noise, respectively.The noise $\mathbf{v}(n)$ is assumed to be zero-mean complex Gaussian and spatio-temporally white with covariance matrix $\sigma_v^2\mathbf{I}_M$ where $\mathbf{I}_M$ is the identity matrix of dimension M.

We consider a block transmission scheme and assume that within the block period T, the channel is fixed. Based on such an assumption, the nth received block can be written as

$$\mathbf{Y}(n) = \mathbf{X}(n)\mathbf{H}(n) + \mathbf{V}(n) \tag{2}$$

where
$\mathbf{Y}(n) = \left[\mathbf{y}^T(nT-T+1), \mathbf{y}^T(nT-T+2), \ldots, \mathbf{y}^T(nT)\right]^T$
$\mathbf{X}(n) = \left[\mathbf{x}^T(nT-T+1), \mathbf{x}^T(nT-T+2), \ldots \mathbf{x}^T(nT)\right]^T$
$\mathbf{V}(n) = \left[\mathbf{v}^T(nT-T+1), \mathbf{v}^T(nT-T+2), \ldots \mathbf{v}^T(nT)\right]^T$ denote the received data, the transmitted data, and the measurement noise matrices respectively and $(.)^T$ denotes matrix transpose.

It should be emphasized that differential modulation should be employed in order to resolve the phase ambiguity that is inherent to any blind decoding scheme. The differential modulation scheme is summarized as $\mathbf{s}_0 = \mathbf{1}, \mathbf{s}_n = \mathbf{s}_{n-1} \circ \mathbf{d}_n$ where $\mathbf{1}$ is the column vector of length K containing all ones, $\circ$ denoted the element-by-element product and $\mathbf{d}_n$ is the data symbol vector for the nth block.

The matrix $\mathbf{X}(n)$ is a linear mapping that transforms $\mathbf{s}_n$ to a $T \times N$ matrix based on orthogonal space-time block coding (OSTBC, [3], [4]). Hereafter we replace $\mathbf{X}(n)$ with $\mathbf{X}(\mathbf{s}_n)$. It should be noted that $\mathbf{X}(n)$ satisfies $\mathbf{X}^H(\mathbf{s}_n)\mathbf{X}(\mathbf{s}_n) = \|\mathbf{s}_n\|^2\mathbf{I}_N$ [4], where $\|\cdot\|$ is the Euclidean norm and $(\cdot)^H$ denotes Hermitian transpose.

Let us re-write the nth received block (2) in the following format

$$\mathbf{y}_n = \mathbf{B}(\mathbf{s}_n)\mathbf{h}_n + \mathbf{v}_n \tag{3}$$

where $\mathbf{y}_n = \text{vec}\{\mathbf{Y}(n)\}, \mathbf{B}(\mathbf{s}_n) = \mathbf{I}_M \otimes \mathbf{X}(\mathbf{s}_n), \mathbf{h}_n = \text{vec}\{\mathbf{H}(n)\}, \mathbf{v}_n = \text{vec}\{\mathbf{V}(n)\}$, is the i.i.d Gaussian noise vector that has zero mean and covariance $\mathbf{\Sigma}_v = \sigma_v^2\mathbf{I}_{MT}$, $\otimes$ refers to the kronecker product and vec$\{\cdot\}$ refers to the vectorization operator which stacks all the columns of a matrix on top of each other. It can be easily verified that the matrix $\mathbf{B}(\mathbf{s}_n)$ satisfies $\mathbf{B}^H(\mathbf{s}_n)\mathbf{B}(\mathbf{s}_n) =$

$\|\mathbf{s}\|^2\mathbf{I}_{MN}$. This property will be shown later to be useful in the simplifications of the receiver.

The time-varying behaviour of the flat-fading mobile channel can be approximated as a first order auto-regressive (AR) channel [5]

$$\mathbf{h}_n = \mathbf{F}\mathbf{h}_{n-1} + \mathbf{w}_n \quad (4)$$

where, $\mathbf{F} = \alpha\mathbf{I}_{MN}$, $\mathbf{w}_n$ is the i.i.d Gaussian noise vector that has zero mean and covariance $\mathbf{\Sigma}_w = \sigma_w^2\mathbf{I}_{MN}$ and the channel parameter α is a function of doppler frequency of the (moving) wireless node F_d, sampling time T_s and carrier frequency F_c. Indeed α is given by $\alpha = J_0(0.2\pi F_d T_s)\exp\{j2\pi F_c T_s\}$ where $J_0(.)$ is the zeroth-order Bessel function of first kind.

3. BLIND MIMO DECODER FOR OSTBC

Given (3), the objective of blind decoding is to estimate the data symbols $\mathbf{s}_n$ without the knowledge of the channel. Assuming the knowledge of the noise variances the distribution of the unknowns $p(\mathbf{s}_n, \mathbf{h}_n)$ is called the *posterior density*. In [1] the linearity of the state space model (3)-(4) is exploited to marginalize the posterior distribution and particle filtering is used to track the posterior of the data symbols. The resulting algorithm (hereafter termed as the MPF receiver) is summarized below

Algorithm 1: MPF receiver (MPF) of [1]

1. FOR $i = 1 : N_s$
   - Compute KF predicts: $\mathbf{h}^i_{n|n-1}$, $\mathbf{P}^i_{n|n-1}$
   - FOR $j = 1 : |\mathcal{A}|$ Compute ψ^i_j (see (5))
   - Draw a sample $\mathbf{s}^i_n$ from the set $\mathcal{A}$ $= \{\mathbf{a}_1, \ldots, \mathbf{a}_{|\mathcal{A}|}\}$ with probability ψ^i_j
   - Compute weight update: $L^i = \sum_{j=1}^{|\mathcal{A}|}\psi^i_j$, $w^i_n = w^i_{n-1}L^i$
   - Compute KF updates: $\mathbf{h}^i_{n|n}$, $\mathbf{P}^i_{n|n}$
2. FOR $i = 1 : N_s$, $w^i_n = w^i_n / \sum_{i=1}^{N_s} w^i_n$
3. Compute (MAP symbol estimate:) $\hat{\mathbf{s}}_n = \arg\max_{\mathbf{a}_j \in A}\sum_{i=1}^{N_s} 1(\mathbf{s}^i_n \circ \mathbf{s}^{i*}_{n-1} = \mathbf{a}_j)w^i_n$
4. If $N_{eff} < N_{th}$ perform resampling

where $\mathcal{A} = \{\mathbf{a}_1, \ldots, \mathbf{a}_{|\mathcal{A}|}\}$ contains the possible set of data symbols for any $\mathbf{s}_n$ and the likelihood ψ^i_j is computed as

$$\begin{aligned}\psi^i_j &= p(\mathbf{y}_n|\mathbf{s}^i_n = \mathbf{a}_j, \mathbf{s}^i_{1:n-1}, \mathbf{y}_{1:n-1}) \\ &\quad p(\mathbf{s}^i_n = \mathbf{a}_j|\mathbf{s}^i_{1:n-1}, \mathbf{y}_{1:n-1})\end{aligned} \quad (5)$$

The first distribution in (5) is computed as [1]

$$\begin{aligned}&p(\mathbf{y}_n|\mathbf{s}^i_{1:n-1}, \mathbf{y}_{1:n-1}, \mathbf{s}_n = \mathbf{a}_j) \\ &= \mathcal{N}_c\left(\mathbf{y}_n; \mathbf{B}(\mathbf{a}_j)\mathbf{h}^i_{n|n-1}, \mathbf{\Omega}^i_{n,j}\right) \\ &= \pi^{-2MT}|\mathbf{\Omega}^i_{n,j}|^{-1}\exp\Big\{\left(\mathbf{y}_n - \mathbf{B}(\mathbf{a}_j)\mathbf{h}^i_{n|n-1}\right)^H \\ &\quad {\mathbf{\Omega}^i_{n,j}}^{-1}\left(\mathbf{y}_n - \mathbf{B}(\mathbf{a}_j)\mathbf{h}^i_{n|n-1}\right)\Big\}\end{aligned} \quad (6)$$

where $\mathbf{\Omega}^i_{n,j} = \mathbf{B}(\mathbf{a}_j)\mathbf{P}^i_{n|n-1}\mathbf{B}^H(\mathbf{a}_j) + \mathbf{\Sigma}_v$.

The second distribution in (5) is easily computed based on the differential encoding structure. It should be noted that the major computational complexity of the algorithm 1 above arises due to KF as well as the calculation of the likelihood ψ^i_j which involves finding $N_s|\mathcal{A}|$ number of determinants as well as inverses of $\mathbf{\Omega}^i_{n,j}$ for each iteration n. In the next section we introduce some simplification techniques for these calculations.

3.1. Simplification Techniques

First, assuming OSTBC and based on [6], the KF channel tracking could be efficiently computed as follows, i.e., given the KF estimate at time block $n-1$, $\mathbf{h}^i_{n-1|n-1}$ and the associated covariance $\delta^i_{n-1|n-1}$, the KF predicted state $\mathbf{h}^i_{n|n-1}$ and the prediction covariance $\mathbf{P}^i_{n|n-1} = \beta^i_{n|n-1}\mathbf{I}_{MN}$ are computed as

$$\mathbf{h}^i_{n|n-1} = \alpha\mathbf{h}^i_{n-1|n-1} \quad (7)$$

$$\beta^i_{n|n-1} = \delta^i_{n-1|n-1}\|\alpha\|^2 + \sigma_w^2 \quad (8)$$

and the KF update $\mathbf{h}^i_{n|n}$ and the associated covariance $\delta^i_{n|n}\mathbf{I}_{MN}$ is computed as

$$\mu^i_n = \frac{\beta^i_{n|n-1}}{\|\mathbf{s}^i_n\|^2\beta^i_{n|n-1} + \sigma_v^2} \quad (9)$$

$$\mathbf{h}^i_{n|n} = (1 - \mu^i_n\|\mathbf{s}^i_n\|^2)\mathbf{h}^i_{n|n-1} + \mu^i_n\mathbf{B}^H(\mathbf{s}^i_n)\tilde{\mathbf{y}}_n \quad (10)$$

$$\delta^i_{n|n} = \frac{\sigma_v^2\beta^i_{n|n-1}}{\|s^i_n\|^2\beta^i_{n|n-1} + \sigma_v^2}. \quad (11)$$

Second, by the use of *Sylvester's determinant theorem*, stated as $\left|\mathbf{I}_m + \mathbf{A}\mathbf{B}^H\right| = \left|\mathbf{I}_n + \mathbf{B}^H\mathbf{A}\right|$ where $\mathbf{I}_m$ and $\mathbf{I}_n$ are identity matrices of appropriate size and $|.|$ denotes matrix determinant, the determinant part of the likelihood is simplified, i.e.,

$$\begin{aligned}|\mathbf{\Omega}^i_{n,j}| &= \left|\sigma_v^2\mathbf{I}_{MT} + \beta^i_{n|n-1}\mathbf{B}(\mathbf{a}_j)\mathbf{B}(\mathbf{a}_j)^H\right| \\ &= (\sigma_v^2)^{MT}\left|\mathbf{I}_{MN} + \frac{\beta^i_{n|n-1}}{\sigma_v^2}\mathbf{B}(\mathbf{a}_j)^H\mathbf{B}(\mathbf{a}_j)\right| \\ &= (\sigma_v^2)^{MT}\left(1 + \frac{\beta^i_{n|n-1}\|\mathbf{a}_j\|^2}{\sigma_v^2}\right)^{MN}.\end{aligned} \quad (12)$$

Thirdly, by the use of matrix inversion lemma, the matrix inverse part of the likelihood is simplified as

$$\begin{aligned}{\mathbf{\Omega}^i_{n,j}}^{-1} &= \left[\mathbf{B}(\mathbf{a}_j)\mathbf{P}^i_{n|n-1}\mathbf{B}^H(\mathbf{a}_j) + \mathbf{\Sigma}_w\right]^{-1} \\ &= \left[\frac{2\mathbf{I}_{MT}}{\sigma_v^2} - \kappa^i_{n,j}\mathbf{B}(\mathbf{a}_j)\mathbf{B}^H(\mathbf{a}_j)\right]\end{aligned} \quad (13)$$

where $\kappa^i_{n,j} = \frac{\beta^i_{n|n-1}}{\|\mathbf{a}_j\|^2\beta^i_{n|n-1}\sigma_v^2 + \sigma_v^4}$.

3.2. Approximation Techniques

In an attempt to further reduce the computational complexity of the receiver, an approximation technique is introduced in this section and the resulting receiver is termed as modified MPF (MMPF) receiver. The idea is to replace N_s Kalman filters with a single one, i.e, at iteration n, the MAP data estimate $\hat{\mathbf{s}}_n$ is used to update the state and covariance values of the Kalman filter instead of updating them for each particle $\mathbf{s}^i_n$.

It should be noted that in the absence of source coding the marginalized distribution of the discrete state $\mathbf{s}_n$ will be uniform, however in practical systems the space-time coding block is preceded by source coding in order improve the communication system. In both scenarios the marginalized posterior would be closer to unimodal hence the single Kalman filter approximation of [7] is adopted in this section.

Algorithm 2: Modified MPF receiver (MMPF)

1. Kalman prediction: $\hat{\mathbf{h}}_{n|n-1}$, $\hat{\beta}_{n|n-1}$
2. FOR $i = 1 : N_s$
   - Compute $\hat{\psi}_j^i$
   - Draw $\mathbf{s}_n^i$ with probability ψ_j^i
   - Compute: $\hat{L}^i = \sum_{j=1}^{\mathcal{A}}$; $w_n^i = w_{n-1}^i \hat{L}^i$
3. FOR $i = 1 : N_s$ $w_n^i = w_n^i / \sum_{i=1}^{N_s} w_n^i$
4. Compute (MAP symbol estimate:) $\hat{\mathbf{s}}_n = \arg\max_{\mathbf{a}_j \in A} \sum_{i=1}^{N_s} 1(\mathbf{s}_n^i \circ \mathbf{s}_{n-1}^{i*} = \mathbf{a}_j) w_n^i$
5. Kalman update (use $\hat{\mathbf{s}}_n$): $\hat{\mathbf{h}}_{n|n}$, $\hat{\delta}_{n|n}$
6. If $N_{eff} < N_{th}$ perform resampling

It should be noted that the likelihood $\hat{\psi}_j^i$ above is calculated by replacing $\mathbf{h}_{n|n-1}^i$ and $\beta_{n|n-1}^i$ in (6) with $\hat{\mathbf{h}}_{n|n-1}$ and $\hat{\beta}_{n|n-1}$ respectively. Intuitively enough, starting from $\hat{\mathbf{h}}_{n-1|n-1}$ and $\hat{\delta}_{n-1|n-1}$ the KF procedure (7)–(11) is followed to get $\hat{\mathbf{h}}_{n|n-1}, \hat{\beta}_{n|n-1}, \hat{\mathbf{h}}_{n|n}$ and $\hat{\delta}_{n|n}$.

3.3. Efficient Blind Estimation

In this section we present an interlaced maximum likelihood (ML) estimation approach to blindly estimate the channel parameter α. A natural solution to estimate this parameter would be to use it as a part of the state in the MPF algorithm, however, doing so will require complex analytical derivations for marginalization and some of the gains due to marginalization will be lost as well. Further, expanding the state dimension will demand more particles to achieve the same performance. The proposed algorithm is based on the interlacing approach for spacecraft angular rate and inertia estimation reported in [8]. In this paper, by exploiting the nature of the data model, we have much simplified the algorithm, analytically and by introducing approximations.

The idea behind this approach is to interlace the regular PF with ML estimate of α. The ML approach is implemented as a secondary PF by maximizing the likelihood function given by $\mathcal{L}(\alpha|\mathbf{y}_{1:n}) \triangleq p(\mathbf{y}_{1:n}|\alpha)$ where

$$\begin{aligned}
p(\mathbf{y}_{1:n}|\alpha) &= \prod_{k=1}^{n} p(\mathbf{y}_k|\mathbf{y}_{1:k-1}, \alpha) \\
&= \prod_{k=1}^{n} \int_{-\infty}^{\infty} p\left(\mathbf{y}_k|\mathbf{h}_k, \mathbf{y}_{1:k-1}, \alpha\right) p\left(\mathbf{h}_k|\mathbf{y}_{1:k-1}, \alpha\right) d\mathbf{h}_k \\
&\propto \prod_{k=1}^{n} \sum_{j=1}^{|\mathcal{A}|} \int_{-\infty}^{\infty} p\left(\mathbf{y}_k|\mathbf{a}_j, \mathbf{h}_k, \mathbf{y}_{1:k-1}, \alpha\right) \\
&\quad p\left(\mathbf{h}_k|\mathbf{y}_{1:k-1}, \alpha\right) d\mathbf{h}_k
\end{aligned} \tag{14}$$

It could be realized from (3) that $p\left(\mathbf{y}_k|\mathbf{a}_j, \mathbf{h}_k, \mathbf{y}_{1:k-1}, \alpha\right) \sim \mathcal{N}\left(\mathbf{y}_k; \mathbf{B}(\mathbf{a}_j)\mathbf{h}_k, \mathbf{\Sigma}_v\right)$ and from Kalman prediction that $p\left(\mathbf{h}_k|\mathbf{y}_{1:k-1}, \alpha^l\right) \sim \mathcal{N}\left(\mathbf{h}_k; \mathbf{h}_{k|k-1}, \mathbf{P}_{k|k-1}\right)$ hence the integration reduces to $\mathcal{N}\left(\mathbf{y}_k; \mathbf{B}(\mathbf{a}_j)\mathbf{h}_{k|k-1}, \bar{\mathbf{\Omega}}_k\right)$ where $\bar{\mathbf{\Omega}}_k = \mathbf{B}(\mathbf{a}_j)\mathbf{P}_{k|k-1}\mathbf{B}^H(\mathbf{a}_j) + \mathbf{\Sigma}_v$. It should be noted that $\mathbf{h}_{k|k-1}$ and $\mathbf{P}_{k|k-1}$ are KF predicts obtained by following (7)–(11).

Now, by calculating the product only for $k = 1$, an approximation for the above likelihood is obtained as

$$\begin{aligned}
\Phi_n^l \triangleq \Phi(\alpha^l) &\approx \pi^{-2MT} \sum_{j=1}^{|\mathcal{A}|} |\bar{\mathbf{\Omega}}_k|^{-1} \exp\Big\{ \big(\mathbf{y}_k - \\
&\mathbf{B}(\mathbf{a}_j)\mathbf{h}_{k|k-1}\big)^H \bar{\mathbf{\Omega}}_k^{-1} \left(\mathbf{y}_k - \mathbf{B}(\mathbf{a}_j)\mathbf{h}_{k|k-1}\right) \Big\}
\end{aligned} \tag{15}$$

It is also notable that the above is an approximation only for an α that remains constant over time whereas for time varying parameter (15) is more suitable than (14).

Now, assuming that the likelihood (15) is estimated for $l = N_a$ samples, the ML estimate of α is obtained as

$$\hat{\alpha}_n^{\mathrm{ML}} = \arg\max_l \Phi_n^l, \quad l = 1, \ldots, N_a \tag{16}$$

A block diagram describing the interlaced approach is illustrated in Figure. 1 and the corresponding algorithm is summarized below.

Algorithm 3: Interlaced MMPF receiver (IMMPF)

1. FOR $l = 1 : N_a$
   - Assign: $\alpha_n^l = \alpha_{n-1}^l$
   - Use $\hat{\mathbf{h}}_{n|n-1}$ and $\hat{\delta}_{n|n-1}$ to compute Φ_n^l for each α_n^l
2. Compute (the ML estimate:) $\hat{\alpha}_n^{\mathrm{ML}} = \arg\max_l \Phi_n^l$
3. Use $\alpha = \hat{\alpha}_n^{\mathrm{ML}}$ on the MMPF and find $\hat{\mathbf{s}}_n$
4. If $N_{eff} < N_{th}$ for α^ls resample them

Remark: It should be noted that the dominant computational load in the MMPF algorithm comes from the likelihood calculation and all other computations including that of KF could be neglected. Indeed, blind decoding of each block n by MMPF requires $N_s|\mathcal{A}|$ likelihood calculations. Now, assuming perfect knowledge of the channel coefficients, the ML decoding requires the computation of $|\mathcal{A}|$ likelihoods. Hence the following relationship could be established $\mathcal{C}_{\mathrm{MMPF}} = N_s\mathcal{C}_{\mathrm{ML}}$ where $\mathcal{C}$ denotes complexity and the subscript denotes the type of the algorithm. Further, assuming $N_s = N_a$, it could be said that $\mathcal{C}_{\mathrm{IMMPF}} = 2N_s\mathcal{C}_{\mathrm{ML}}$.

4. SIMULATION RESULTS AND DISCUSSIONS

In simulations, we consider the full rate Alamouti's code of [3] with $N = M = T = 2$ and $K = 2$. The channel coefficients $\mathbf{H}(n)$ are generated according to Jakes model [9] for $F_sT_s = 0.005$. The channel parameters are generated based on the block fading assumption. Each element of the data symbols $\mathbf{s}_n$ is generated from BPSK symbols, i.e., $\mathbf{s}_n \in \{-1, +1\}^K$.

The normalized SNR at the receiver is defined as $\mathrm{SNR} = \frac{\sigma_h^2}{MN\sigma_v^2}$ and the normalized mean squared error (NMSE) is defined as $\mathrm{NMSE} = E\left\{\frac{\|\alpha - \hat{\alpha}_{n,\mathrm{ML}}\|^2}{\|\alpha\|^2}\right\}$ and was used to compare the performance of the channel parameter estimate.

Assuming the first block of data at the receiver, the Kalman filter in each particle is initialized based on the maximum likelihood channel estimates that can be obtained based on the measurement model (3). As for the initialization of the interlacing part, for each sample $l, l = 1, \ldots N_a$, the absolute and angle values of the alpha are initialized from uniform distribution spanning their possible range, i.e., $|\alpha_0^i| \sim \mathcal{U}[0, 1]$, $\angle\alpha_0^i \sim \mathcal{U}[-\pi/2,\ \pi/2]$ where $\mathcal{U}[a, b]$ is a uniformly distributed number between a and b. Further, a small drift introduced after the resampling procedure is found to help the ML estimates to maintain diversity in order to shift towards the true values. The variance of the drift is decreased with number of blocks n, i.e., after each resampling step at the nth block, the following is executed $|\alpha_n^i| = |\alpha_n^i| + \mathcal{N}(0, \frac{1}{n^2})$, $\angle\alpha_n^i = \angle\alpha_n^i + \mathcal{N}(0, \frac{\pi}{2n^2})$ where $\mathcal{N}(0, \rho)$ is a normal distributed number with zero mean and standard deviation ρ^2. The number of particles used in all the simulations is kept as $N_s = 100$ and the number of samples for the interlaced ML estimator is kept at $N_a = 100$.

Figure 2 shows the SER vs. SNR performance of the proposed IMMPF receiver for unknown α. For comparison, the receiver based only on simplification, i.e. MPF receiver with N_s Kalman filters (termed as ISMPF) is also shown. It confirms that the single KF assumption does not result in performance loss. In Figure 3 an overlay plot of 100 snapshots of the estimated α by the IMMPF algorithm is shown. As the figure suggests, regardless of the initial values, the estimates are found quickly moving towards the true values for both ISMPF and IMMPF. Hence, after $n = 200$ iterations the interlacing MLE could be shut down without affecting the performance of the receiver in order to save computation, provided that the true α remains constant.

5. CONCLUSIONS

Computationally efficient blind sequential Monte Carlo receivers for MIMO systems were presented in this paper. First, by assuming Orthogonal space time block codes, a simplified MIMO receiver without any compromise in performance was developed based on the marginalized particle filtering algorithm. Then an approximation technique was employed to further reduce the complexity of the simplified receiver resulting in a modified MPF receiver. Finally, an interlacing approach was developed to estimate the channel parameter α.

6. REFERENCES

[1] Dong Guo and Xiaodong Wang, "Blind detection in MIMO systems via sequential Monte Carlo," *IEEE Journal on Selected Areas in Communications*, vol. 21, no. 3, pp. 464–473, 2003.

[2] R. Karlsson, T. Schon, and F. Gustafsson, "Complexity analysis of the marginalized particle filter," *IEEE Transactions on Signal Processing*, vol. 53, no. 11, pp. 4408–4411, 2005.

[3] S.M. Alamouti, "A simple transmit diversity technique for wireless communications," *IEEE Journal on Selected Areas in Communications*, vol. 16, no. 8, pp. 1451–1458, 1998.

[4] V. Tarokh, H. Jafarkhani, and A.R. Calderbank, "Space-time block codes from orthogonal designs," *IEEE Transactions on Information Theory*, vol. 45, no. 5, pp. 1456–1467, 1999.

[5] Hong Shen Wang and Pao-Chi Chang, "On verifying the first-order Markovian assumption for a Rayleigh fading channel model," *IEEE Transactions on Vehicular Technology*, vol. 45, no. 2, pp. 353–357, 1996.

[6] B. Balakumar, S. Shahbazpanahi, and T. Kirubarajan, "Joint MIMO channel tracking and symbol decoding using Kalman filtering," *IEEE Transactions on Signal Processing*, vol. 55, no. 12, pp. 5873–5879, 2007.

[7] F. Mustiere, M. Bolic, and M. Bouchard, "A modified Rao-Blackwellised particle filter," in *IEEE International Conference on Acoustics, Speech and Signal Processing*, 2006, vol. 3, pp. 21–24.

[8] Avishy Carmi and Yaakov Oshman, "Robust spacecraft angular rate estimation from vector observations using interlaced particle filtering," *Journal of Guidance, Control, and Dynamics*, vol. 30, no. 6, pp. 1729–1741, 2007.

[9] WC Jakes Jr, *Microwave Moble Communication*, John Wiley & Sons, Inc., New York, 1974.

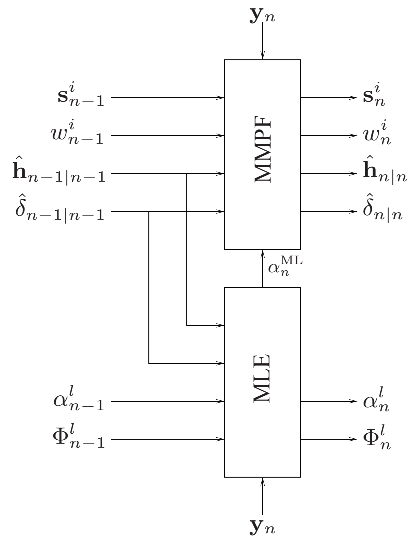

Fig. 1. The block diagram of the interlacing approach to estimate α.

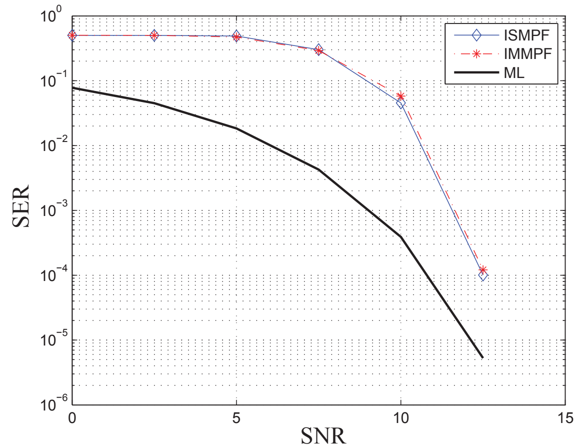

Fig. 2. The SER vs. SNR for unknown α at $F_dT_s = 0.005$ and $N = M = T = 2$.

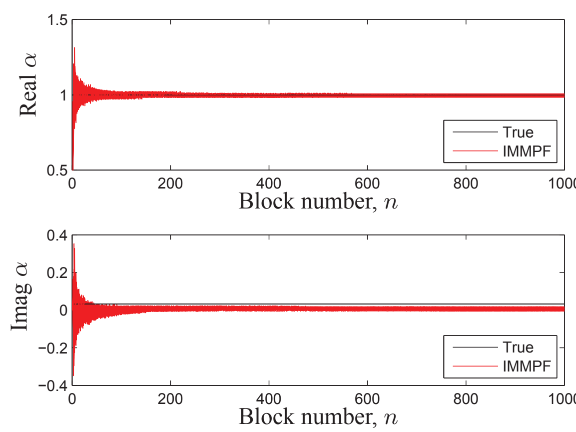

Fig. 3. 100 overlay plots of the performances of α estimates by IMMPF.