TEMPORAL PARTITION PARTICLE FILTERING FOR MULTIUSER DETECTORS WITH MUTUALLY ORTHOGONAL SEQUENCES

Soner Özgür and Douglas B. Williams

Center for Signal and Image Processing
School of Electrical and Computer Engineering
Georgia Institute of Technology, Atlanta, Georgia 30332–0250
E-mail: {ozgur, dbw}@ece.gatech.edu

ABSTRACT

We propose a blind multiuser detector based on Monte Carlo Markov chain (MCMC) techniques. The detector exploits mutually orthogonal complementary sequences to distinguish between transmitting users and space-time codes to take advantage of the available spatial diversity. We propose a partitioning scheme for the symbol draws in the MCMC algorithm that reduces the complexity without any degradation in performance. The detector's performance is simulated in an iterative receiver that utilizes an outer coder. The simulations display some loss in coding gain because of the blind nature of the system; however, diversity gain is preserved.

1. INTRODUCTION

A sequential Monte Carlo (SMC) framework has been developed and a wide range of applications have been discussed in [1]. This Bayesian technique is primarily utilized in target tracking algorithms [2]; however, other applications also exist. Blind receivers are one application of this technique in the telecommunications field, and an adaptive scheme has been proposed in [3]. Here we extend this SMC technique for efficient blind detection of multiple users in multi-antenna scenarios.

Our approach utilizes mutually orthogonal (MO) sets rather than pseudo-noise (PN) sequences. MO sets introduce minimal bandwidth expansion since the chip-rate is equal to the bit-rate. MO sets are also suitable for multi-user applications where uncoupled parallel communication channels exist. A soft multi-user detector was introduced and utilized in an iterative receiver in [4], where the channel was assumed known at the receiver. In this work the channel is unknown at the receiver, however a slow fading rate is assumed.

The contribution in this work is in the partitioning of the symbol space. Partitioning has been applied previously to visual and acoustic tracking problems with particle filters [5,6]. Here, though, we take advantage of the conditional independence of the received signal vectors. Instead of drawing symbols from the entire symbol space, we partition it, draw "sub-symbols" from the subspaces and then merge the results. This technique reduces the complexity of the algorithm significantly without any performance loss or additional error propagation. We display the performance of the detector in an iterative receiver utilizing an outer channel code.

2. SYSTEM DESCRIPTION

A detailed discussion on the construction and properties of MO complementary sets can be found in [7]. Use of these sets in multiuser communications has been discussed in [4]. Let us elaborate on the signaling at the transmitter in Fig. 1. The channel coded symbols c_k are differentially encoded into d_k and then convolved with the mutually orthogonal set A_{km} assigned to the kth user:

$$d_k[n] = d_k[n-1]c_k[n] \tag{1}$$

$$s_{km}[n] = d_k[n] * A_{km}[n], \tag{2}$$

where $(*)$ denotes convolution. We stack $s_{km}[n]$

$$\mathbf{s}_k[n] \triangleq [s_{k1}[n] \ \ldots \ s_{kM}[n]]^T. \tag{3}$$

We define the following quantities by stacking each user's successive samples of the coded data vectors. The goal here is to obtain a transmitter model that will account for all K users. Then, the symbols in the vector $\mathbf{s}_k$ are mapped to the space-time block code matrix $\mathbf{S}_k[n]$. Here a code matrix designed by Tarokh is chosen [8].

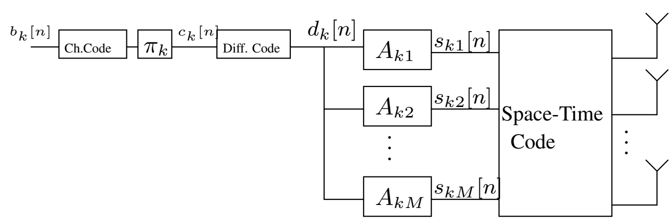

Fig. 1. Transmitter Model

3. A BLIND MULTIUSER DETECTOR

To simplify notation we stack $\mathbf{S}_k$s, $\mathbf{h}_k$s, c_ks and d_ks as follows: $\mathbf{c}[n] = [c_1[n] \ldots c_K[n]]^T$, $\mathbf{d}[n] = [d_1[n] \ldots d_K[n]]^T$, $\mathbf{S}[n] = [\mathbf{S}_1[n] \ldots \mathbf{S}_K[n]]$, $\mathbf{h}[n] = [\mathbf{h}_1[n]^T \ldots \mathbf{h}_K[n]^T]^T$. Here, $\mathbf{h}_k[n]$ is a column vector containing the complex amplitudes of each channel. Subscripts for the remainder of the paper will indicate time epoch rather than user number or a sequence number within a set.

$$\mathbf{d}_{n_1:n_2} \triangleq [\mathbf{d}[n_1]^T, \mathbf{d}[n_1+1]^T, ..., \mathbf{d}[n_2]^T]^T, \quad n_2 > n_1 \tag{4}$$

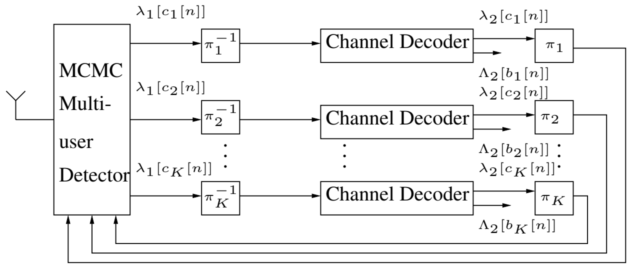

Fig. 2. Iterative Receiver Model

and similarly $\mathbf{r}_n \triangleq \mathbf{r}[n]$.

The received signal vector can be described as:

$$\mathbf{r}_n = \mathbf{S}_n \mathbf{h}_n + \eta_n, \tag{5}$$

where η_n is receiver noise, which is additive white Gaussian noise with zero mean and σ^2 variance. In this paper we assume that the noise power is known and in practice it can be easily estimated.

Our goal is to calculate the a posteriori distribution $p(\mathbf{c}_n|\mathbf{r}_{0:n+L-1})$ of all users' coded symbols $\mathbf{c}$ without knowledge of the channel $\mathbf{h}$.

4. THE SMC DETECTOR

The MO complementary codes disperse the symbol $\mathbf{d}_n$ in the transmitted signal throughout L consecutive time epochs, where L is the length of the MO sequences. In other words, the symbols $\mathbf{d}_{n-(L-1):n}$ contribute to the received signal $\mathbf{r}_n$. Therefore,

$$p(\mathbf{r}_n|\mathbf{d}_{n-L+1:n}, \mathbf{h}_n) \sim \mathcal{N}(\mathbf{S}_n \mathbf{h}_n, \sigma^2 \mathbf{I}). \tag{6}$$

Similarly,

$$\begin{aligned} &p(\mathbf{d}_n, \mathbf{h}_n|\mathbf{r}_{n:n+L-1}) \propto \\ &p(\mathbf{r}_{n:n+L-1}|\mathbf{d}_{n-(L-1):n+L-1}, \mathbf{h}_{n:n+L-1}) \\ &p(\mathbf{h}_{n:n+L-1}|\mathbf{d}_{n-(L-1):n+L-1}) p(\mathbf{d}_{n-(L-1):n+L-1}). \end{aligned} \tag{7}$$

Let $\{\mathbf{d}_n^{(i)}, w_n^{(i)}\},_{i=1}^{N_s}$ denote a random measure that characterizes the a posteriori distribution $p(\mathbf{d}_n|\mathbf{d}_{0:n-1}\mathbf{r}_{n:n+L-1})$. Let $\mathbf{d}_n^{(i)}, i = 1, \ldots, N_s$ be a sample draw. Our goal is to obtain samples of the transmitted symbols $\{\mathbf{d}_n^{(i)}, w_n^{(i)}\}$, properly weighted with respect to the distribution $p(\mathbf{d}_n|\mathbf{d}_{0:n-1}, \mathbf{r}_{n:n+L-1})$.

The weights are defined as:

$$w_n^{(i)} \propto \frac{p(\mathbf{d}_{0:n}^{(i)}|\mathbf{r}_{1:n+L-1})}{q(\mathbf{d}_{0:n}^{(i)}|\mathbf{r}_{1:n+L-1})}. \tag{8}$$

We choose a proposal density:

$$q(\mathbf{d}_n|\mathbf{d}_{0:n-1}, \mathbf{r}_{1:n+L-1}) \triangleq p(\mathbf{d}_n|\mathbf{d}_{0:n-1}, \mathbf{r}_{1:n+L-1}). \tag{9}$$

As a result the weight update simplifies:

$$w_n^{(i)} \propto w_{n-1}^{(i)} p(\mathbf{r}_{n+L-1}|\mathbf{r}_{1:n+L-2}, \mathbf{d}_{0:n-1}^{(i)}). \tag{10}$$

We cannot compute the above probability directly. We need to include $\mathbf{d}_{n:n+L-1}$ and then marginalize it out. Also notice that consecutive received vectors are conditionally independent.

$$\begin{aligned} w_n^{(i)} &\propto w_{n-1}^{(i)} \\ &\sum_{\mathbf{sym}_{n:n+L-1}} p(\mathbf{r}_{n:n+L-1}, (\mathbf{d}_{n:n+L-1}^{(i)} = \mathbf{sym}_{n:n+L-1})|\mathbf{d}_{0:n-1}^{(i)}) \\ &\quad p(\mathbf{c}_n = \mathbf{d}_{n-1}^{(i)} \odot \mathbf{sym}_n), \end{aligned} \tag{11}$$

where the symbol $\odot$ denotes Schur (element-wise) vector product and $\mathbf{sym}$ denotes the symbol drawn from the posterior distribution. So far we have not included the channel effect in the above distribution.

$$\begin{aligned} &p(\mathbf{r}_{n:n+L-1}, (\mathbf{d}_{n:n+L-1}^{(i)} = \mathbf{sym}_{n:n+L-1})|\mathbf{d}_{0:n-1}^{(i)}) = \\ &\int p(\mathbf{r}_{n:n+L-1}, (\mathbf{d}_{n:n+L-1}^{(i)} = \mathbf{sym}_{n:n+L-1})|\mathbf{d}_{0:n-1}^{(i)}, \mathbf{h}_{n:n+L-1}) \\ &\quad p(\mathbf{h}_{n:n+L-1}|\mathbf{d}_{0:n-1}^{(i)}, \mathbf{r}_{1:n+L-2}) d\mathbf{h}_{n:n+L-1} \end{aligned} \tag{12}$$

The first distribution in the integrant is Gaussian. The second distribution describes the channel. The channel is a flat Rayleigh fading channel, and its distribution is that of a complex Gaussian random process. Hence, the above integral is also a complex Gaussian pdf.

$$p(\mathbf{r}_{n:n+L-1}, (\mathbf{d}_{n:n+L-1}^{(i)} = \mathbf{sym}_{n:n+L-1})|\mathbf{d}_{0:n-1}^{(i)}) \sim \mathcal{N}(\mu_{n,j}^{(i)}, \mathbf{P}_{n,j}^{(i)}) \tag{13}$$

$$\mu_{n,j}^{(i)} = \begin{bmatrix} S_{n,j}^{(i)} & 0 & \cdots & 0 \\ 0 & S_{n+1,j}^{(i)} & \cdots & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & \cdots & 0 & S_{n+L-1,j}^{(i)} \end{bmatrix} \begin{bmatrix} h_n^{(i)} \\ h_{n+1}^{(i)} \\ \vdots \\ h_{n+L-1}^{(i)} \end{bmatrix} \tag{14}$$

The elements in the main diagonal are space-time code matrices associated with the ith particle and jth symbol in the alphabet $\mathcal{A}^{KL}$. For shorter notation:

$$\mu_{n,j}^{(i)} = \mathbf{\Xi}_{n,j}^{(i)} \mathbf{h}_{n:n+L-1}^{(i)}. \tag{15}$$

Each particle $\mathbf{h}_{n:n+L-1}^{(i)}$ for the channel also has a covariance matrix $\mathbf{\Sigma}_{n-1,j}^{(i)}$ associated with it. It is defined recursively in equation (18). The covariance of the distribution in (13) is

$$\mathbf{P}_{n,j}^{(i)} = \sigma^2 \mathbf{I} + \mathbf{\Xi}_{n,j}^{(i)} \mathbf{\Sigma}_{n-1,j}^{(i)} \mathbf{\Xi}_{n,j}^{(i)\,H}. \tag{16}$$

With $\mu_{n,j}^{(i)}$ and $\mathbf{P}_{n,j}^{(i)}$ known, the channel state can be updated with a Kalman filter:

$$\mathbf{h}_{n:n+L-1}^{(i)} = \mathbf{h}_{n-1:n+L-2}^{(i)} + \mathbf{K}_n^{(i)} (\mathbf{r}_{n:n+L-1} - \mu_{n,j}^{(i)}) \tag{17}$$

$$\mathbf{\Sigma}_{n,j}^{(i)} = (\mathbf{I} - \mathbf{K}_n^{(i)}) \mathbf{\Xi}_{n,j}^{(i)} \mathbf{\Sigma}_{n-1,j}^{(i)}, \tag{18}$$

where the Kalman gain is:

$$\mathbf{K}_n^{(i)} = \mathbf{\Sigma}_{n-1,j}^{(i)} \mathbf{\Xi}_{n,j}^{(i)\,H} (\mathbf{P}_{n,j}^{(i)})^{-1} \tag{19}$$

Let us summarize our Monte Carlo Markov Chain (MCMC) blind detector:

- Initialization
- Compute $\mu_{n:n+L-1,j}^{(i)}$,$\mathbf{P}_{n:n+L-1,j}^{(i)}$ and $\beta_{n:n+L-1,j}^{(i)}$ for each possible $\mathbf{sym}_{n:n+L-1} \in \mathcal{A}^{KL}$
- Draw a sample $\mathbf{sym}_{n:n+L-1}^{(i)} \in \mathcal{A}^{KL}$ from the distribution below:

$$p(\mathbf{d}_{n:n+L-1}^{(i)} = \mathbf{sym}_{n:n+L-1}|\mathbf{d}_{0:n-1}, \mathbf{r}_{1:n+L-1}) \propto \beta_{n:n+L-1,j}^{(i)} \tag{20}$$

- Update and normalize the weights:

$$w_n^{(i)} \propto w_{n-1}^{(i)} \beta_{n:n+L-1,j}^{(i)} \tag{21}$$

$$w_n^{(i)} = \frac{w_n^{(i)}}{\sum_{i=1}^{N_s} w_n^{(i)}} \tag{22}$$

- Update the a posteriori mean and covariance of the channel: $\mathbf{h}_{n:n+L-1}^{(i)}$ and $\mathbf{\Sigma}_{n,j}^{(i)}$ using (17-19) for the particular drawn symbol. Update the mean and covariance of the received signal vector $\mu_{n:n+L-1,j}^{(i)}$ and $\mathbf{P}_{n:n+L-1,j}^{(i)}$ using (15-16)
- Compute the a posteriori probability for the drawn symbol $\mathbf{c}_n$.
- Re-sample to increase particle efficiency.

5. TEMPORAL PARTITION PARTICLE FILTER (TPPF)

The algorithm described in the previous section requires the computation of a weight update that involves $2ML$ long vectors. This increases the complexity of the algorithm even further in equation (16). 2^{KL} matrices must be computed, each of which requires multiplication of $2ML \times LMK$ sized matrices. Moreover, in equation (19) the inverse of a $2ML \times 2ML$ sized matrix must be calculated. The primary contribution of this work is in the simplification of this process. We propose a partitioning scheme for the symbol draws that reduces the complexity of the algorithm and preserves the performance.

Our goal is to draw samples from the following distribution:

$$\begin{aligned} &p(\mathbf{d}_n, \mathbf{h}_n | \mathbf{r}_{n:n+L-1}) \propto \\ &\quad p(\mathbf{r}_{n:n+L-1} | \mathbf{d}_{n-(L-1):n+L-1}, \mathbf{h}_{n:n+L-1}) \\ &\quad p(\mathbf{h}_{n:n+L-1} | \mathbf{d}_{n-(L-1):n+L-1}) p(\mathbf{d}_{n-(L-1):n+L-1}) \end{aligned} \tag{23}$$

However, the received vectors are conditionally independent:

$$\begin{aligned} &p(\mathbf{d}_n, \mathbf{h}_n | \mathbf{r}_{n:n+L-1}) \propto \\ &\quad \prod_{l=0}^{L-1} [p(\mathbf{r}_{n+l} | \mathbf{d}_{n-(L-1)+l:n+l}, \mathbf{h}_{n+l}) \\ &\quad p(\mathbf{h}_{n+l} | \mathbf{d}_{n-(L-1)+l:n+l})] p(\mathbf{d}_{n-(L-1):n+L-1}) \end{aligned} \tag{24}$$

As a result of this partitioning, we get L distributions $\beta\_\mathbf{l}_{n,j}^{(i)}(\cdot), \quad l = 0, \ldots, L-1$ whose product is proportional to the incremental weight update.

$$\begin{aligned} &\beta\_\mathbf{0}_{n,j}^{(i)}(\mathbf{r}_n | \mathbf{h}_n) = |\mathbf{P}_{n,j}^{(i)}|^{-1} \exp\{-(\mathbf{r}_n - \mu_{n,j}^{(i)})^H \\ &\quad (\mathbf{P}_{n,j}^{(i)})^{-1} (\mathbf{r}_n - \mu_{n,j}^{(i)})\} p(\mathbf{c}_n = \mathbf{d}_{n-1}^{(i)} \odot \mathbf{d}_n) \end{aligned} \tag{25}$$

$$\begin{aligned} &\beta\_\mathbf{1}_{n,j}^{(i)}(\mathbf{r}_{n+1} | \mathbf{h}_{n+1}, \mathbf{d}_{n+1}) = |\mathbf{P}_{n+1,j}^{(i)}|^{-1} \\ &\exp\{-(\mathbf{r}_{n+1} - \mu_{n+1,j}^{(i)})^H (\mathbf{P}_{n+1,j}^{(i)})^{-1} (\mathbf{r}_{n+1} - \mu_{n+1,j}^{(i)})\} \\ &p(\mathbf{c}_n = \mathbf{d}_{n-1}^{(i)} \odot \mathbf{d}_n) \end{aligned} \tag{26}$$

$$\begin{aligned} &\beta\_\mathbf{L} - \mathbf{1}_{n,j}^{(i)}(\mathbf{r}_{n+L-1} | \mathbf{h}_{n+L-1}, \mathbf{d}_{n+1:n+L-1}) = |\mathbf{P}_{n+L-1,j}^{(i)}|^{-1} \\ &\quad \exp\{-(\mathbf{r}_n - \mu_{n,j}^{(i)})^H (\mathbf{P}_{n+L-1,j}^{(i)})^{-1} (\mathbf{r}_n - \mu_{n,j}^{(i)})\} \\ &\quad p(\mathbf{c}_n = \mathbf{d}_{n-1}^{(i)} \odot \mathbf{d}_n) \end{aligned} \tag{27}$$

It seems that we are making the process more complex, but actually the computational complexity is relieved significantly because the matrix $\mathbf{P}_{n,j}^{(i)}$ has to be evaluated N_{symb}^L times less. The matrix itself is L times smaller in each dimension, hence computation of its inverse is also easier. N_{symb} above is the cardinality of the symbol constellation.

Let us summarize our TPPF blind detector:

- Initialization
- Compute

$$\mu_{n,j}^{(i)} = \mathbf{S}_{n,j}^{(i)} \mathbf{h}_n^{(i)} \tag{28}$$

$$\mathbf{P}_{n,j}^{(i)} = \sigma^2 \mathbf{I} + \mathbf{S}_{n,j}^{(i)} \mathbf{\Sigma}_{n-1,j}^{(i)} \mathbf{S}_{n,j}^{(i)\,H} \tag{29}$$

$$\beta\_\mathbf{0}_{n,j}^{(i)}, \beta\_\mathbf{1}_{n,j}^{(i)}, \ldots, \beta\_\mathbf{L} - \mathbf{1}_{n,j}^{(i)} \tag{30}$$

  for each possible $\mathbf{sym}_{n:n+L-1} \in \mathcal{A}^{KL}$

- Draw a sample $\mathbf{sym}_{n+L-1}^{(i)} \in \mathcal{A}^K$ from the distribution:

$$\begin{aligned} &p(\mathbf{d}_{n+L-1}^{(i)} = \mathbf{sym}_{n+L-1}^{(i)} | \mathbf{d}_{0:n-1}, \mathbf{r}_{n+L-1}) \propto \\ &\int \quad p(\mathbf{r}_{n+L-1} | \mathbf{d}_{n:n+L-1}, \mathbf{h}_{n+L-1}) \\ &p(\mathbf{h}_{n+L-1} | \mathbf{d}_{n:n+L-1}) p(\mathbf{d}_{n:n+L-1}) \mathrm{d}\mathbf{d}_{n:n+L-2} \propto \\ &\int \beta\_L - 1_{n,j}^{(i)} \mathrm{d}\mathbf{d}_{n:n+L-2} \end{aligned} \tag{31}$$

- For $p = L-2, L-3, \ldots, 2$ draw a sample $\mathbf{sym}_{n+p}^{(i)} \in \mathcal{A}^K$ from the distribution:

$$\begin{aligned} &p(\mathbf{d}_{n+p}^{(i)} = \mathbf{sym}_{n+p}^{(i)} | \mathbf{d}_{0:n-1}, \mathbf{r}_{n+p:n+L-1}, \mathbf{sym}_{n+p:n+L-1}) \propto \\ &\int \prod_{l=p}^{L-1} p(\mathbf{r}_{n+l} | \mathbf{d}_{n:n+p-1}, \mathbf{h}_{n+p}, \mathbf{sym}_{n+p:n+L-1}) \\ &p(\mathbf{h}_{n+p} | \mathbf{d}_{n:n+p-1}, \mathbf{sym}_{n+p:n+L-1}) \\ &p(\mathbf{d}_{n:n+p-1}) \mathrm{d}\mathbf{d}_{n:n+p-1} \propto \\ &\int \prod_{l=p}^{L-1} \beta\_l_{n,j}^{(i)} \mathrm{d}\mathbf{d}_{n:n+p-1} \end{aligned} \tag{32}$$

- Draw a sample $\mathbf{sym}_n^{(i)} \in \mathcal{A}^K$ from the distribution:

$$\begin{aligned} &p(\mathbf{d}_n^{(i)} = \mathbf{sym}_n^{(i)} | \mathbf{d}_{0:n-1}, \mathbf{r}_{n:n+L-1}, \mathbf{sym}_{n+L-1}) \propto \\ &\prod_{l=0}^{L-1} p(\mathbf{r}_{n+l} | \mathbf{d}_n, \mathbf{h}_{n+l}, \mathbf{sym}_{n+1:n+L-1}) \\ &p(\mathbf{h}_{n+l} | \mathbf{d}_n, \mathbf{sym}_{n+1:n+L-1}) p(\mathbf{d}_n) \propto \\ &\prod_{l=0}^{L-1} \beta\_l_{n,j}^{(i)} \end{aligned} \tag{33}$$

- Update the weights:

$$w_n^{(i)} \propto w_{n-1}^{(i)} \prod_{l=0}^{L-1} \beta\_l_{n,j}^{(i)} \tag{34}$$

- Normalize the weights such that $\sum_{i=1}^{N_s} w_n^{(i)} = 1$:
- Update the a posteriori mean and covariance of the channel:$\mathbf{h}_n^{(i)}$ and $\mathbf{\Sigma}_{n,j}^{(i)}$ for the particular drawn symbol. Update the mean and covariance of the received signal vector: $\mu_{n:n+L-1,j}^{(i)}$and $\mathbf{P}_{n:n+L-1,j}^{(i)}$ using equations (28-29).

$$\mathbf{h}_n^{(i)} = \mathbf{h}_{n-1}^{(i)} + \mathbf{K}_n^{(i)} (\mathbf{r}_n - \mu_{n,j}^{(i)}) \tag{35}$$

$$\mathbf{\Sigma}_{n,j}^{(i)} = (\mathbf{I} - \mathbf{K}_n^{(i)}) \mathbf{S}_{n,j}^{(i)} \mathbf{\Sigma}_{n-1,j}^{(i)}, \tag{36}$$

  where the Kalman gain is:

$$\mathbf{K}_n^{(i)} = \mathbf{\Sigma}_{n-1,j}^{(i)} \mathbf{S}_{n,j}^{(i)\,H} (\mathbf{P}_{n,j}^{(i)})^{-1} \tag{37}$$

- Compute the a posteriori probability for the drawn symbols:

$$P(\mathbf{c}_n = \mathbf{sym}_n) = \sum_{i=1}^{N_s} w^{(i)}((\mathbf{d}_n \odot \mathbf{c}_{n-1}) == \mathbf{sym}_n^{(i)}) \tag{38}$$

- Re-sample to increase particle efficiency.

Notice that the latter algorithm uses sufficient statistics to estimate the current symbol. The space from which the symbols are drawn, however, has L times fewer dimensions. If the symbol constellation has cardinality N_{symb}, the complexity is reduced from $\exp(KL\log(N_{symb}))$ to $L\exp(K\log(N_{symb}))$ without any sacrifice in performance.

One may argue that any error in the "sub-symbol" draws may propagate and lead to incorrect symbol estimate and, consequently, incorrect channel estimate. Such is not the case, because the received signal vectors are conditionally independent. Also note that, $p(\mathbf{r}_{n:n+L-1}|\mathbf{d}_{n+L-1}) = p(\mathbf{r}_{n+L-1}|\mathbf{d}_{n+L-1})$. Similar expressions could be written for the rest of the "sub-symbols". Therefore, the probability of incorrectly drawing a "sub-symbol" in the temporally partitioned case is the same as if we had considered the entire received signal vector and the entire symbol space. Our temporal partitioning of the space does not affect the performance of the algorithm other than reducing the computation significantly.

6. SIMULATION RESULTS

For our simulations, the channel encoder uses a rate $1/2$ convolutional code with generators $23, 35$ in octal form. The channel was a flat, block static, slow ($f_mT = 1e-3$) Rayleigh fading channel. We utilized $M = 4$ transmit antennas per user. The mutually orthogonal sequences were of length $L = 4$. We had 4 sequences per mate set and $K = 2$ mate sets – one for each user. All interferers had equal transmit power. In our simulations we utilized a space-time block code for 4 Tx antennas [8].

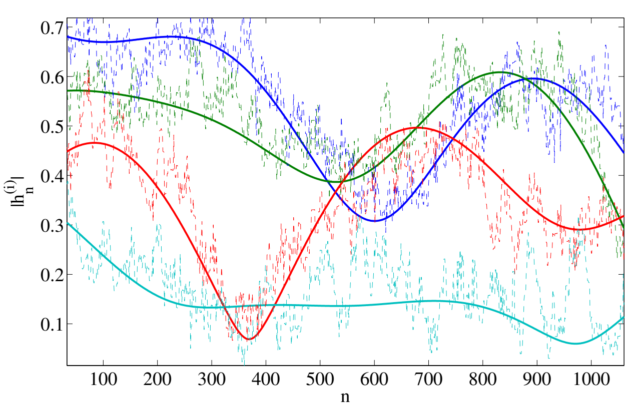

Fig. 3. Channel estimated by TPPF method. $K = 2$ users, 4 Tx antennas per user, SNR=6dB. One user's channel shown.

7. CONCLUSION

In this paper, we have utilized the properties of MO complementary sets to achieve near single user performance. The complexity is significantly reduced by implementing a smart partitioning of the symbol space without any reduction in performance. Additionally, the diversity order of the system is preserved, as is seen from the results.

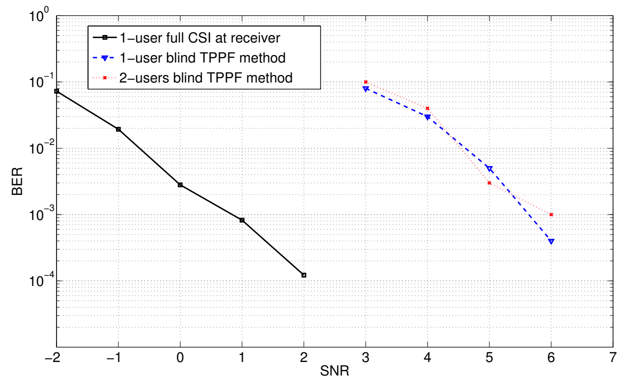

Fig. 4. Performance of TPPF compared to the case of full channel state information (CSI) at receiver. $K = 1, 2$ equal power users, 4 Tx antennas per user.

8. REFERENCES

[1] J. S. Liu and R. Chen, "Sequential monte carlo methods for dynamic systems," *Journal of the American Statistical Association*, vol. 93, no. 443, Sep. 1998.

[2] V. Cevher and J. H. McClellan, "General direction-of-arrival tracking with acoustic nodes," To appear in *IEEE Trans. on Signal Processing*.

[3] R. Chen, X. Wang, and J. S. Liu, "Adaptive joint detection and decoding in flat-fading channels via kalman filtering," *IEEE Transsactions on Information Theory*, vol. 46, Sep. 2000.

[4] S. Ozgur and D. B. Williams, "An iterative multi-user detector for coded mutually orthogonal complementary sets with space-time coding," *Proceedings of DSP Workshop*, Aug. 2004.

[5] J. MacCormick and M. Isard, "Partitioned sampling, articulated objects, and interface-quality hand tracking," in *Proceedings of the Europen Conference on Computer Vision*, 2000.

[6] M. Orton and W. Fitzgerald, "A Bayesian approach to tracking multiple targets using sensor arrays and particle filters," *IEEE Trans. on Signal Processing*, vol. 50, no. 2, pp. 216–223, February 2002.

[7] C. C. Tseng, "Complementary sets of sequences," *IEEE Transactions on Information Theory*, Sep. 1972.

[8] V. Tarokh, H. Jafarkhani, and A. R. Calderbank, "Space-time block coding for wireless communications: performance results," *IEEE Journal on Selected Areas in Communications*, vol. 17, no. 5, pp. 451–460, Mar. 1999.