Cooperative Particle Swarm Optimization Based Receiver for Large-Dimension MIMO-ZPSC Systems

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***Abstract*—In this paper, we propose a cooperative particle swarm optimization (CPSO) based channel estimation/equalization scheme for multiple-input multiple-output zero-padded single-carrier (MIMO-ZPSC) systems with large dimensions in frequency selective channels. We estimate the channel state information at the receiver in time domain using a PSO based algorithm during training phase. Using the estimated channel, we perform information symbol detection in the frequency domain using FFT based processing. For this detection, we use a low complexity OLA (OverLap Add) likelihood ascent search equalizer which uses minimum mean square (MMSE) equalizer solution as the initial solution. Multiple iterations between channel estimation and data detection are carried out which significantly improves the mean square error and bit error rate performance of the receiver.**

Keywords – *MIMO, ISI channels, zero padding, single-carrier systems, channel estimation/equalization, particle swarm optimization, frequency domain processing.*

I. INTRODUCTION

In wireless communications, signaling in large dimensions can offer attractive benefits. For example, signaling in large spatial dimensions using increased number of antennas can offer increased spectral efficiencies [1]. Likewise, increased processing gains (large dimensions in time) in code division multiple access can increase the number of simultaneous users in the system [2]. Also, severely delay-spread inter-symbol interference (ISI) channels with large number of multipaths (e.g., ultrawideband channels [3], underwater acoustic channels [4]) can offer rich diversity opportunities. In such channels, multipath diversity can be achieved by transmitting data in frames where each frame consists of K channel uses (i.e., K dimensions in time, $K > L$ where L is the number of multipaths), and carrying out equalization jointly over the entire frame of data. Our interest in this paper is on receiver techniques (channel estimation/equalization) suited for MIMO-ISI channels with large dimensions (i.e., large Kn_t, where n_t is the number of transmit antennas).

Single carrier (SC) block transmission schemes are considered as good alternatives to address the peak-to-average power ratio (PAPR) issue that arises in multicarrier systems [5]- [12]. Two types of single carrier schemes, namely, zero padded SC (ZPSC) and cyclic prefixed SC (CPSC) schemes, are common. ZPSC scheme is shown to perform better than CPSC scheme under linear equalization like zero forcing (ZF) and minimum mean square error (MMSE) equalization [9]. Zero padding has other advantages of power efficiency and guaranteed symbol recovery in the presence of channel nulls and hence improved performance [13], [7]. In [14], the optimal training sequence that minimizes the channel estimation mean square error (MSE) of the linear channel estimator is shown to be of length n_tL per transmit antenna. Blind/semi-blind channel estimation methods can be considered, but they require long data samples and the complexity is high [15], [16]. In this paper, we propose an iterative channel estimation/equalization scheme for MIMO-ZPSC systems that scales well for large dimensions while achieving better performance than linear equalizers.

We adopt a new approach for channel estimation based on particle swarm optimization (PSO) [17], [18]. For equalization/detection in frequency domain, we adopt a low complexity local neighborhood search method, termed as likelihood ascent search (LAS) [19], which gives near-optimal performance in large dimensions. PSO is a population based stochastic optimization technique, originally used to model the sociological behavior of animals like fish schooling, bird flocking, etc. [17]. It has been applied in many areas of optimization problems because of its easy implementation and quick convergence behavior. PSO has found good application in communication problems as well, reported mainly for flat fading channels [20]- [24]. Here, we propose a PSO based channel estimation scheme for MIMO-ZPSC in frequency selective fading channels. In the proposed receiver, we use a modified version of the PSO called cooperative PSO (CPSO) [25], which achieves improved performance compared to the conventional PSO algorithm, by using multiple swarms to optimize different components of the solution vector in a cooperative manner.

Notation: Vectors and matrices are denoted by bold face lowercase and bold face uppercase letters, respectively. $[.]^T$, $(.)^H$, $\odot$, $\otimes$ denote transpose, Hermitian, element-by-element product, and Kronecker product operators, respectively. $\mathbf{I}_K$, $\mathbf{F}_K$ and $\mathbf{0}_{m\times n}$ denote $K \times K$ identity matrix, $K \times K$ normalized DFT matrix, and $m \times n$ matrix of zeros, respectively.

II. MIMO-ZPSC SYSTEM MODEL

Consider a MIMO-ZPSC system with n_t transmit antennas and n_r receive antennas. The channel between each pair of transmit and receive antennas is assumed to be frequency selective with L multipaths. Let $h^{(j,k)}(l)$ denote the channel gain between kth transmit antenna and jth receive antenna on the lth path, which is modeled as $\mathcal{CN}(0, \sigma_l^2)$. Transmission is carried out in frames, where each frame consists of several

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blocks as shown in Fig. 1. The channel is assumed to be constant over one frame duration. Each frame consists of a pilot block (PB) for the purpose of initial channel estimation, followed by M data blocks (DB). The pilot block consists of n_tL channel uses, where a n_t-sized pilot symbol vector is transmitted in each channel use using n_t antennas. Each data block consists of $K+L$ channel uses, where K information symbol vectors followed by L zero vectors (zero padding) each of size n_t are sent using n_t antennas. With M data blocks in a frame, the number of channel uses in the data part of the frame is $M(K+L)$. Taking both pilot and data channel uses into account, the total number of channel uses per frame is $n_tL+M(K+L)$. Initial channel estimation is done during the pilot phase using CPSO. Data blocks are detected using a low-complexity likelihood ascent search algorithm. The detected data blocks are iteratively used to refine the channel estimates using CPSO during data phase.

III. CPSO Based Channel Estimation in Pilot Phase

Let $\mathbf{b}^k = [b^k(0), b^k(1), \cdots, b^k(n_tL-1)]$ denote the pilot symbol vector transmitted from antenna k in n_tL channel uses in a frame (Fig. 1). We use the optimal training sequence in [14] that minimizes the mean square error of the linear channel estimator in MIMO-ZPSC, which is given by

$$\mathbf{b}^k = [\mathbf{0}_{(k-1)L\times 1} \quad b \quad \mathbf{0}_{((n_t-(k-1))L-1)\times 1}]. \tag{1}$$

Because of the zeros in the end, this training sequence decouples the pilot and data phases. The signal received at the jth receive antenna during pilot phase at the nth channel use is given by

$$y_{\rm P}^j(n) = \sum_{k=1}^{n_t}\sum_{l=0}^{L-1} h^{(j,k)}(l) b^k(n-l) + q_{\rm P}^j(n), \tag{2}$$

$j=1,2\cdots,n_r$, $n=0,1,\cdots,n_tL-1$, where the subscript P in $y_{\rm P}^j(n)$ and $q_{\rm P}^j(n)$ denotes pilot phase. $\{q_{\rm P}^j(n)\}$ are noise samples modeled as i.i.d. $\mathcal{CN}(0,\sigma^2)$. Writing (2) in matrix notation after substituting (1), we get

$$\mathbf{y}_{\rm P}^j = \mathbf{B}_{\rm P}\mathbf{h}^j + \mathbf{q}_{\rm P}^j, \quad j=1,2,\cdots,n_r, \tag{3}$$

where

$$\mathbf{y}_{\rm P}^j = [y_{\rm P}^j(0), y_{\rm P}^j(1), \cdots, y_{\rm P}^j(n_tL-1)]^T,$$

$$\mathbf{h}^j = [(\mathbf{h}^{(j,1)})^T, \cdots, (\mathbf{h}^{(j,k)})^T, \cdots, (\mathbf{h}^{(j,n_t)})^T]^T,$$

$$\mathbf{h}^{(j,k)} = [h^{(j,k)}(0), h^{(j,k)}(1), \cdots, h^{(j,k)}(L-1)]^T,$$

$$\mathbf{q}_{\rm P}^j = [q_{\rm P}^j(0), q_{\rm P}^j(1), \cdots, q_{\rm P}^j(n_tL-1)]^T,$$

$$\mathbf{B}_{\rm P} = [\mathbf{B}_{{\rm P}_1}\mathbf{B}_{{\rm P}_2}\cdots\mathbf{B}_{{\rm P}_{n_t}}],$$

$$\mathbf{B}_{{\rm P}_k} = [\mathbf{0}_{L\times(k-1)L} \quad b\mathbf{I}_L \quad \mathbf{0}_{L\times(n_t-k)L}]^T.$$

From the signal observed at receive antenna j from time 0 to n_tL-1 during pilot phase, we estimate the channel $\mathbf{h}^j$ using CPSO technique.

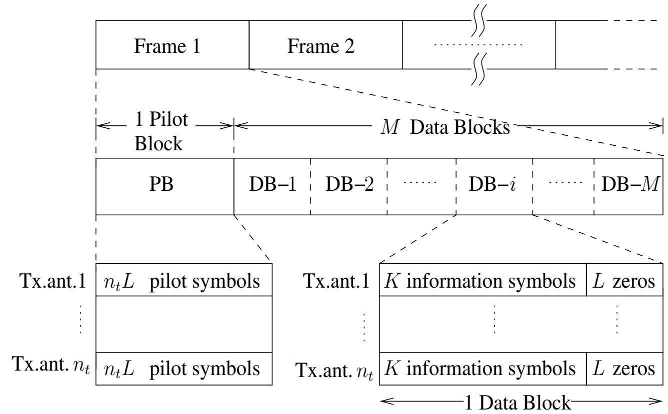

Fig. 1. Frame structure for MIMO-ZPSC system.

A. CPSO Based Channel Estimation

PSO [17] involves a swarm of particles, where each particle is associated with a position, velocity and cost. The algorithm declares the position of the particle with the least cost observed over a certain number of iterations as the solution to the optimization problem. In our channel estimation problem, the particles are randomly initialized in the search space of dimension $\mathbb{C}^{n_tL}$. During each iteration, the particles will move with a velocity in the direction influenced by its own best position (cognitive component) and global best position (social component). Let

$$\mathbf{p}_t^m = [p_t^m(1), p_t^m(2), \cdots, p_t^m(n_tL)]^T,$$

$$\mathbf{v}_t^m = [v_t^m(1), v_t^m(2), \cdots, v_t^m(n_tL)]^T, \quad \text{and}$$

$$\mathbf{u}_t^m = [u_t^m(1), u_t^m(2), \cdots, u_t^m(n_tL)]^T$$

denote be the position, velocity and individual best position of the tth particle after mth iteration, respectively. Let $\mathbf{g}^m$ be the global best position of the entire swarm after mth iteration. The position and velocity of a particle are updated according to the following equations after every iteration:

$$\mathbf{v}_t^{m+1} = c_0\left(\mathbf{v}_t^m + c_1\mathbf{r}_1 \odot (\mathbf{u}_t^m - \mathbf{p}_t^m) + c_2\mathbf{r}_2 \odot (\mathbf{g}^m - \mathbf{p}_t^m)\right), \tag{4}$$

$$\mathbf{p}_t^{m+1} = \mathbf{p}_t^m + \mathbf{v}_t^{m+1}, \tag{5}$$

where c_0 is the constriction factor, c_1, c_2 are acceleration coefficients, and $\mathbf{r}_1, \mathbf{r}_2$ are random vectors whose entries are uniformly distributed from $(0,1)$. The individual best position of each particle and global best position of the entire swarm are updated after each iteration as follows:

for each particle in the swarm
  if $(f(\mathbf{p}_t^{m+1}) < f(\mathbf{u}_t^m))$ then $\mathbf{u}_t^{m+1} = \mathbf{p}_t^{m+1}$
  if $(f(\mathbf{p}_t^{m+1}) < f(\mathbf{g}^m))$ then $\mathbf{g}^{m+1} = \mathbf{p}_t^{m+1}$
end for

The cost function $f(.)$ for our channel estimation problem is as defined in (6).

We divide the n_tL-sized search space dimension into a number of smaller (d-sized) sub-dimensions, such that there are $N = \frac{n_t L}{d}$ sub-dimensions (swarms). For each swarm, we apply the PSO algorithm cooperatively [25]. For our channel estimation problem, the cost function for a given position vector $\mathbf{p}$ is given by

$$f(\mathbf{p}) = \|\mathbf{y}_{\rm P} - \mathbf{B}_{\rm P}\mathbf{p}\|_2^2. \quad (6)$$

To calculate the cost for all the particles in a swarm, the other components in the possible solution vector are kept constant, with their values set to the global best position from the other swarms. That is, to calculate the cost of tth particle from ith swarm during $(m+1)$th iteration, we put

$$\mathbf{p} = [(\mathbf{g}_1^m)^T, \cdots, (\mathbf{g}_{i-1}^m)^T, (\mathbf{p}_{i,t}^m)^T, (\mathbf{g}_{i+1}^m)^T, \cdots, (\mathbf{g}_N^m)^T]^T$$

in (6), where $\mathbf{g}_i^m$ is the global best position for the ith swarm after mth iteration, and $\mathbf{p}_{i,t}^m$ is the position of the tth particle from ith swarm after mth iteration. For each swarm, we obtain the global best position and update the position and velocity of the particles of that swarm using (4) and (5). This is repeated for all swarms for certain MAX number of iterations. The global best position at the end of MAX iterations, $\mathbf{g}^{MAX}$, is declared as the estimated channel vector. The above procedure is run n_r times to obtain the channel estimates $\hat{\mathbf{h}}^j$, j=$1, 2, \cdots, n_r$, which are used in the detection of information symbols in the data phase.

IV. Iterative Equalization/Channel Estimation

In the data phase, let $\mathbf{a}_i^k = [a_i^k(0), a_i^k(1), \cdots, a_i^k(K+L-1)]^T$ denote the data vector of size $(K+L)\times 1$ with K information symbols and L zeros (to avoid inter-block interference) transmitted from kth antenna during ith data block, $i = 1, \cdots, M$. The signal received at jth receive antenna at nth channel use of ith data block is given by

$$y_i^j(n) = \sum_{k=1}^{n_t}\sum_{l=0}^{L-1} h^{(j,k)}(l) a_i^k(n-l) + q_i^j(n), \quad (7)$$

$j = 1, 2\cdots, n_r$, $n = 0, 1, \cdots, K+L-1$, where $q_i^j(n)$ is the noise sample modeled as i.i.d. $\mathcal{CN}(0, \sigma^2)$.

Now define the following vectors and matrices: $\mathbf{y}_i^j \triangleq [y_i^j(0), y_i^j(1), \cdots, y_i^j(K+L-1)]^T$, $\mathbf{q}_i^j \triangleq [q_i^j(0), q_i^j(1), \cdots, q_i^j(K+L-1)]^T$, $\mathbf{x}_i^k \triangleq [a_i^k(0), a_i^k(1), \cdots, a_i^k(K-1)]^T$, and $\mathbf{H}^{j,k}$ as a $(K+L)\times K$ Toeplitz matrix with $[h^{(j,k)}(0), 0, \cdots, 0]$ as the first row and $[h^{(j,k)}(0), h^{(j,k)}(1), \cdots, h^{(j,k)}(L-1), 0, \cdots, 0]^T$ as the first column. With these definitions, (7) can be written in the form

$$\mathbf{y}_i^j = \sum_{k=1}^{n_t} \mathbf{H}^{j,k}\mathbf{x}_i^k + \mathbf{q}_i^j, \quad j = 1, 2, \cdots, n_r. \quad (8)$$

We can write (8) as

$$\mathbf{y}_i = \mathbf{H}\mathbf{x}_i + \mathbf{q}_i, \quad i = 1, 2, \cdots, M, \quad (9)$$

where $\mathbf{y}_i = [(\mathbf{y}_i^1)^T, (\mathbf{y}_i^2)^T, \cdots, (\mathbf{y}_i^{n_r})^T]^T$, $\mathbf{x}_i = [(\mathbf{x}_i^1)^T, (\mathbf{x}_i^2)^T, \cdots, (\mathbf{x}_i^{n_t})^T]^T$, $\mathbf{q}_i = [(\mathbf{q}_i^1)^T, (\mathbf{q}_i^2)^T, \cdots, (\mathbf{q}_i^{n_r})^T]^T$, and

$$\mathbf{H} = \begin{bmatrix} \mathbf{H}^{1,1} & \mathbf{H}^{1,2}\cdots & \mathbf{H}^{1,n_t} \\ \mathbf{H}^{2,1} & \mathbf{H}^{2,2}\cdots & \mathbf{H}^{2,n_t} \\ \vdots & \vdots & \vdots \\ \mathbf{H}^{n_r,1} & \mathbf{H}^{n_r,2}\cdots & \mathbf{H}^{n_r,n_t} \end{bmatrix}.$$

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A. Equalization Using OLA Based LAS Method

We can recover the information symbols directly from (9), using ZF equalizer or MMSE equalizer. But the complexity will be high due to large matrix inversion. Here, we will use a low-complexity equalizer using overlap-add (OLA) signal model [13]. The main idea behind OLA method is to convert the Toeplitz matrix into a circulant matrix so that we can block diagonalize $\mathbf{H}$ and do FFT based processing, which will reduce complexity.

Define a matrix $\mathbf{G} \triangleq [\mathbf{I}_K \quad \tilde{\mathbf{I}}_{K\times L}]$, where $\tilde{\mathbf{I}}_{K\times L}$ is the matrix with the first L columns of $\mathbf{I}_K$. Now multiplying (8) by $\mathbf{G}$, we get

$$\begin{aligned}\tilde{\mathbf{y}}_i^j = \mathbf{G}\mathbf{y}_i^j &= \sum_{k=1}^{n_t} \mathbf{G}\mathbf{H}^{j,k}\mathbf{x}_i^k + \mathbf{G}\mathbf{q}_i^j \\ &= \sum_{k=1}^{n_t} \tilde{\mathbf{H}}^{j,k}\mathbf{x}_i^k + \tilde{\mathbf{q}}_i^j, \quad j = 1, 2, \cdots, n_r, \quad (10)\end{aligned}$$

where $\tilde{\mathbf{H}}^{j,k} \triangleq \mathbf{G}\mathbf{H}^{j,k}$ is a circulant matrix with $[h^{(j,k)}(0), h^{(j,k)}(1), \cdots, h^{(j,k)}(L-1), 0, \cdots, 0]^T$ as the first column, and $\tilde{\mathbf{q}}_i^j \triangleq \mathbf{G}\mathbf{q}_i^j$. The circulant matrix $\tilde{\mathbf{H}}^{j,k}$ can be decomposed as

$$\tilde{\mathbf{H}}^{j,k} = \mathbf{F}_K^H \mathbf{D}^{j,k}\mathbf{F}_K, \quad (11)$$

where $\mathbf{F}_K$ is $K\times K$ DFT matrix, and $\mathbf{D}^{j,k}$ is a diagonal matrix with its diagonal elements to be the DFT of the vector $[h^{(j,k)}(0), h^{(j,k)}(1), \cdots, h^{(j,k)}(L-1), 0, \cdots, 0]^T$. Now taking the DFT of $\tilde{\mathbf{y}}_i^j$ in (10), we get

$$\mathbf{z}_i^j = \mathbf{F}_K\tilde{\mathbf{y}}_i^j = \sum_{k=1}^{n_t}\mathbf{D}^{j,k}\mathbf{b}_i^k + \mathbf{w}_i^j, \quad j = 1, 2, \cdots, n_r, \quad (12)$$

where $\mathbf{z}_i^j = [z_i^j(0), z_i^j(1), \cdots, z_i^j(K-1)]^T$, $\mathbf{b}_i^k \triangleq \mathbf{F}_K\mathbf{x}_i^k = [b_i^k(0), b_i^k(1), \cdots, b_i^k(K-1)]^T$, and $\mathbf{w}_i^j \triangleq \mathbf{F}_K\tilde{\mathbf{q}}_i^j = [w_i^j(0), w_i^j(1), \cdots, w_i^j(K-1)]^T$. $\mathbf{w}_i^j$ is colored noise distributed as $\mathcal{CN}(\mathbf{0}, \mathbf{K}_{cov})$, where $\mathbf{K}_{cov} = \sigma^2(\mathbf{F}_K\mathbf{G})(\mathbf{F}_K\mathbf{G})^H$. Now writing (12) in matrix form, we get

$$\mathbf{z}_i = \mathbf{D}\mathbf{b}_i + \mathbf{w}_i, \quad i = 1, 2, \cdots, M, \quad (13)$$

where $\mathbf{z}_i = [(\mathbf{z}_i^1)^T, (\mathbf{z}_i^2)^T, \cdots, (\mathbf{z}_i^{n_r})^T]^T$, $\mathbf{b}_i = [(\mathbf{b}_i^1)^T, (\mathbf{b}_i^2)^T, \cdots, (\mathbf{b}_i^{n_t})^T]^T$, $\mathbf{w}_i = [(\mathbf{w}_i^1)^T, (\mathbf{w}_i^2)^T, \cdots, (\mathbf{w}_i^{n_r})^T]^T$, and

$$\mathbf{D} = \begin{bmatrix} \mathbf{D}^{1,1} & \mathbf{D}^{1,2}\cdots & \mathbf{D}^{1,n_t} \\ \mathbf{D}^{2,1} & \mathbf{D}^{2,2}\cdots & \mathbf{D}^{2,n_t} \\ \vdots & \vdots & \vdots \\ \mathbf{D}^{n_r,1} & \mathbf{D}^{n_r,2}\cdots & \mathbf{D}^{n_r,n_t} \end{bmatrix}.$$

Rearranging the terms, we can also write (13) as

$$\bar{\mathbf{z}}_i = \bar{\mathbf{D}}\bar{\mathbf{b}}_i + \bar{\mathbf{w}}_i, \quad i = 1, 2, \cdots, M, \tag{14}$$

where

$$\bar{\mathbf{z}}_i = \begin{bmatrix} \bar{\mathbf{z}}_i(0) \\ \vdots \\ \bar{\mathbf{z}}_i(m) \\ \vdots \\ \bar{\mathbf{z}}_i(K-1) \end{bmatrix}, \quad \bar{\mathbf{b}}_i = \begin{bmatrix} \bar{\mathbf{b}}_i(0) \\ \vdots \\ \bar{\mathbf{b}}_i(m) \\ \vdots \\ \bar{\mathbf{b}}_i(K-1) \end{bmatrix},$$

$$\bar{\mathbf{D}} = \begin{bmatrix} \bar{\mathbf{D}}(0) & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \bar{\mathbf{D}}(K-1) \end{bmatrix}, \bar{\mathbf{w}}_i = \begin{bmatrix} \bar{\mathbf{w}}_i(0) \\ \vdots \\ \bar{\mathbf{w}}_i(m) \\ \vdots \\ \bar{\mathbf{w}}_i(K-1) \end{bmatrix},$$

$\bar{\mathbf{z}}_i(m) = [z_i^1(m), z_i^2(m), \cdots, z_i^{n_r}(m)]^T$, $\bar{\mathbf{b}}_i(m) = [b_i^1(m), b_i^2(m), \cdots, b_i^{n_r}(m)]^T$, $\bar{\mathbf{w}}_i(m) = [w_i^1(m), w_i^2(m), \cdots, w_i^{n_r}(m)]^T$,

$$\bar{\mathbf{D}}(m) = \begin{bmatrix} \mathbf{D}^{1,1}(m) & \mathbf{D}^{1,2}(m)\cdots & \mathbf{D}^{1,n_t}(m) \\ \mathbf{D}^{2,1}(m) & \mathbf{D}^{2,2}(m)\cdots & \mathbf{D}^{2,n_t}(m) \\ \vdots & \vdots & \vdots \\ \mathbf{D}^{n_r,1}(m) & \mathbf{D}^{n_r,2}(m)\cdots & \mathbf{D}^{n_r,n_t}(m) \end{bmatrix}.$$

where $\mathbf{D}^{j,k}(m)$ is the mth diagonal element of the matrix $\mathbf{D}^{j,k}$. Also, $\bar{\mathbf{b}}_i = \bar{\mathbf{F}}\bar{\mathbf{x}}_i$, where $\bar{\mathbf{F}} \stackrel{\triangle}{=} \mathbf{F}_K \otimes \mathbf{I}_{n_t}$, $\bar{\mathbf{x}}_i = [a_i^1(0)\cdots a_i^{n_t}(0), \cdots, a_i^1(m)\cdots a_i^{n_t}(m), \cdots, a_i^1(K-1)\cdots a_i^{n_t}(K-1)]^T$. Now, we have

$$\begin{aligned} \bar{\mathbf{z}}_i &= \bar{\mathbf{D}}\bar{\mathbf{F}}\bar{\mathbf{x}}_i + \bar{\mathbf{w}}_i \\ &= \bar{\mathbf{H}}\bar{\mathbf{x}}_i + \bar{\mathbf{w}}_i, \quad i = 1, 2, \cdots, M, \end{aligned} \tag{15}$$

where $\bar{\mathbf{H}} \stackrel{\triangle}{=} \bar{\mathbf{D}}\bar{\mathbf{F}}$.

For each i in (15), we can obtain a ZF or MMSE equalized solution for the information symbols of the ith block, whose performance can be far from optimal. So, in order to improve the performance beyond ZF/MMSE performance, we run a low-complexity local neighborhood search using the likelihood ascent search (LAS) method in [19], by starting the search with ZF or MMSE equalizer output vector as the initial vector. The LAS method improves over the ZF/MMSE equalizer performance by reaching the local minima in the neighborhood of the initial ZF/MMSE vector. When the problem dimension is large, LAS method is shown to achieve near-maximum likelihood (ML) performance. The output information symbol vectors from the ZF/MMSE-initialized LAS equalizer are denoted by $\hat{\mathbf{x}}_i^k$, $k = 1, \cdots, n_t$, $\quad i = 1, \cdots, M$. These output vectors are used to improve the channel estimates through iterations between equalization and channel estimation as follows.

B. CPSO Aided Iterative Equalization/Channel Estimation in Data Phase

Consider (12), which can be rewritten as

$$\mathbf{z}_i^j = \sum_{k=1}^{n_t} \mathbf{B}_i^k \mathbf{d}^{j,k} + \mathbf{w}_i^j, \quad j = 1, 2, \cdots, n_r, \tag{16}$$

where $\mathbf{B}_i^k = diag(\mathbf{b}_i^k)$, $\mathbf{d}^{j,k}$ is a vector consisting of diagonal elements of matrix $\mathbf{D}^{j,k}$, which is the K-point DFT of $\mathbf{h}^{(j,k)}$ (zero padded to length K), i.e., $\mathbf{d}^{j,k} = \tilde{\mathbf{F}}_{K\times L}\mathbf{h}^{(j,k)}$, where $\tilde{\mathbf{F}}_{K\times L}$ is the matrix with the first L columns of $\mathbf{F}_K$. Now, (16) can be written as

$$\mathbf{z}_i^j = \sum_{k=1}^{n_t} \mathbf{B}_i^k \tilde{\mathbf{F}}_{K\times L}\mathbf{h}^{(j,k)} + \mathbf{w}_i^j. \tag{17}$$

Defining $\mathbf{A}_i^k \stackrel{\triangle}{=} \mathbf{B}_i^k \mathbf{F}_{K\times L}$, we can write (17) as

$$\mathbf{z}_i^j = \mathbf{A}_i \mathbf{h}^j + \mathbf{w}_i^j, \quad i = 1, \cdots, M \tag{18}$$

where $\mathbf{A}_i = [\mathbf{A}_i^1\ \mathbf{A}_i^2\ \cdots\ \mathbf{A}_i^{n_t}]$. We can write (18) as

$$\mathbf{z}^j = \mathbf{A}\mathbf{h}^j + \mathbf{w}^j \tag{19}$$

where

$$\mathbf{z}^j = \begin{bmatrix} \mathbf{z}_1^j \\ \vdots \\ \mathbf{z}_2^j \\ \vdots \\ \mathbf{z}_M^j \end{bmatrix}, \ \mathbf{A} = \begin{bmatrix} \mathbf{A}_1 \\ \vdots \\ \mathbf{A}_2 \\ \vdots \\ \mathbf{A}_M \end{bmatrix}, \ \mathbf{w}^j = \begin{bmatrix} \mathbf{w}_1^j \\ \vdots \\ \mathbf{w}_2^j \\ \vdots \\ \mathbf{w}_M^j \end{bmatrix}.$$

Using the signal received at antenna j from blocks 1 to M in a frame (i.e., using $\mathbf{z}^j$) and the matrix $\hat{\mathbf{A}}$ which is formed by replacing the information symbols $\{\mathbf{x}_i^k\}$ in $\mathbf{A}$ by the detected information symbols $\{\hat{\mathbf{x}}_i^k\}$, the channel coefficients $\{\mathbf{h}^j\}$ are estimated again using CPSO technique explained in Section III. The cost function for this data-aided CPSO is $f(\mathbf{p}) = \|\mathbf{z}^j - \hat{\mathbf{A}}\mathbf{p}\|_2^2$. This sequence of channel estimation and equalization is carried out for a certain number of iterations.

V. Results and Discussions

In this section, we present the MSE and BER performance of the proposed receiver scheme obtained through simulations. We also compare the MSE and BER performance of CPSO based receiver with conventional PSO based receiver. The power delay profile of channel is assumed to follow an exponential model, i.e., $\mathbb{E}[|h^{(j,k)}(l)|^2] = \exp(-\beta l)$, $l = 0, 1, \cdots, L-1$ and $\beta \geq 0$. BPSK and 4-QAM are used for training symbols and information symbols, respectively. For channel estimation during pilot phase, the parameters used in the CPSO algorithm are: size of sub-dimension $d = 4$, number of particles per swarm is 10, constriction factor $c_0 = 0.73$, acceleration coefficients $c_1 = 2.8$, $c_2 = 1.3$ [25], [18], and maximum number of iterations $MAX = 100$. The CPSO parameters for data aided channel estimation during data phase are the same as above except that the maximum number of iterations MAX is 50. For PSO, we use the same parameters as that of CPSO except that $N = 1$ always. For data equalization, the LAS algorithm [19] applied in frequency domain as described in Sec. III is used. MMSE solution vector is used as the initial vector in the LAS algorithm.

In Fig. 2, we compare MSE of PSO and CPSO channel estimation in a MIMO-ZPSC system with $n_t = 16$, $n_r = 16$, $L = 6$, $\beta = 0$, $K = 64$, and $M = 16$. The error is averaged over 100 channel realizations for each SNR. The 'Initial Channel Estimation' plot corresponds to the estimation during pilot phase. MSE plots for data-aided channel estimation with different number of iterations between channel estimation and equalization are also plotted (for number of iterations = 1, 2). It can be seen that iterations between estimation and equalization significantly reduces MSE with CPSO channel estimation. Even one iteration brings in significant improvement. However, such improvement does not happen with PSO. Also, as expected, the improved MSE performance using CPSO translates into improved BER performance of the receiver. This is illustrated in Fig. 3, where we have plotted the BER performance as a function of SNR for the same set of system parameters in Fig. 2. Two equalizers are considered for detection in the data phase: $i)$ MMSE equalizer without LAS search (designated as 'MMSE detection'), and $ii)$ LAS search based equalizer using MMSE output vector as the initial vector (designated to as 'MMSE-LAS equalizer'). From Fig. 3, we see that the data aided channel CPSO channel estimation significantly improves the MMSE-LAS detection BER performance compared to channel estimation using pilot phase alone. We also observe that BER performance with CPSO channel estimation is close to the performance with perfect CSI at the receiver. We can see that with PSO based channel estimation there is no improvement in MSE and BER performance even after iterating between detection and estimation. This is due to the fact that PSO suffers from dimensionality problem, whereas CPSO gains through cooperation among multiple swarms.

In Fig. 4 and 5 we have plotted the MSE and BER performance as a function of swarm size (N) at a fixed SNR of 12 dB. Swarm size $N = 1$ corresponds to PSO. We can see that the performance of receiver improves significantly upto certain swarm size and there after the return diminishes.

VI. Conclusions

We proposed a CPSO based receiver for MIMO-ZPSC systems. Both channel estimation and equalization in frequency selective fading were carried out using heuristic based algorithms. Iterations between channel estimation and equalization helped in improving the mean square error and bit error performance of the receiver as shown in the simulations. Simulation results also showed that the BER performance of the receiver with estimated CSI is close to that with perfect CSI.

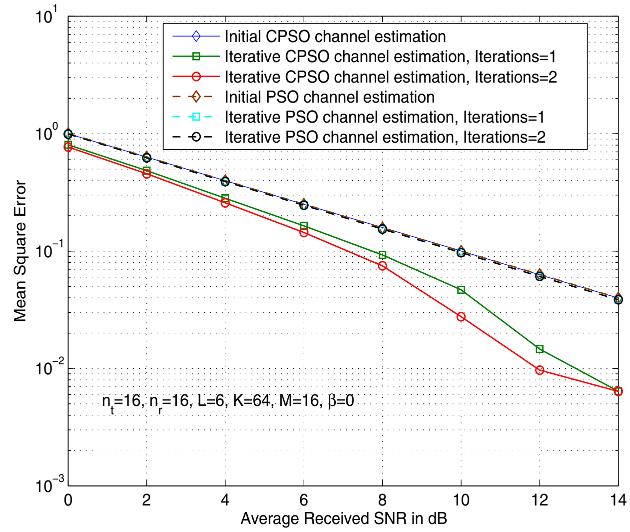

Fig. 2. MSE performance of CPSO/PSO channel estimation for different number of iterations between channel estimation and detection for $n_t = 16, n_r = 16, \beta = 0, L = 6, K = 64, M = 16$.

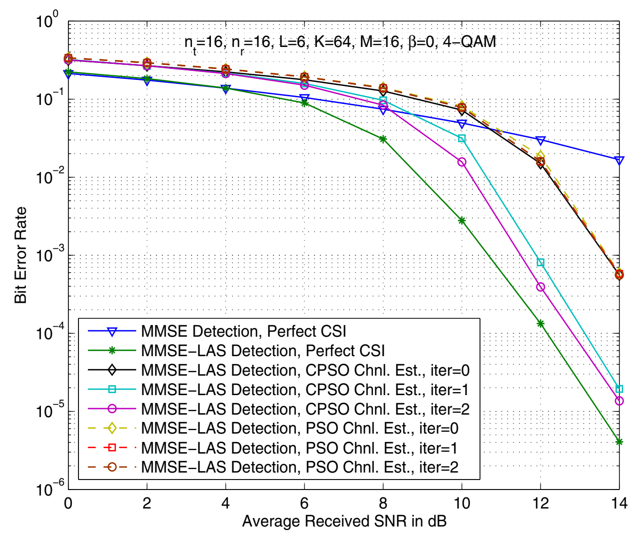

Fig. 3. BER performance of the receiver for different number of iterations between CPSO/PSO channel estimation and LAS detection for $n_t = 16, n_r = 16, L = 6, \beta = 0, K = 64, M = 16$, 4-QAM.

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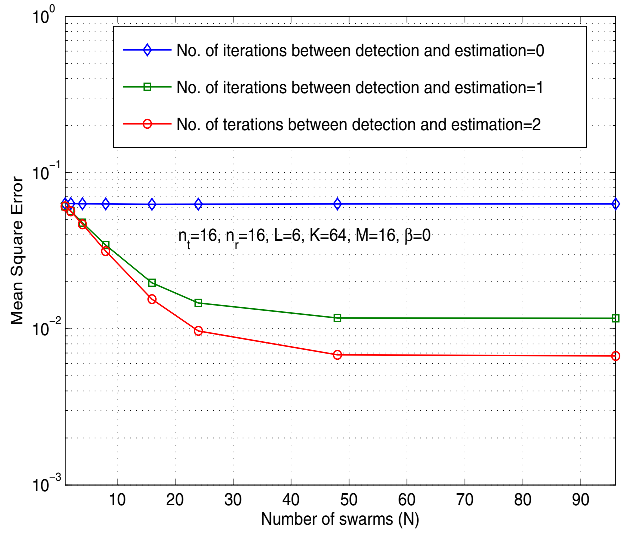

Fig. 4. Mean square error of iterative CPSO channel estimation as a function of number of swarms N for $n_t = 16, n_r = 16, L = 6, \beta = 0, K = 64, M = 16$ and SNR = 12 dB.

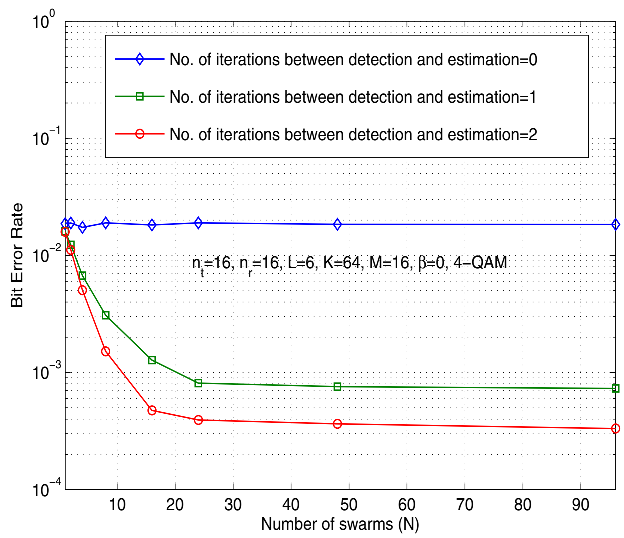

Fig. 5. Bit error rate of receiver as a function of number of swarms N for $n_t = 16, n_r = 16, L = 6, \beta = 0, K = 64, M = 16$, 4-QAM and SNR = 12 dB.

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