Semi-Blind Gradient-Newton CMA and SDD Algorithm for MIMO Space-Time Equalisation

S. Chen, L. Hanzo and H.-T. Cheng
School of Electronics and Computer Science, University of Southampton
Southampton SO17 1BJ, UK. E-mails: {sqc, lh, htc1e08}@ecs.soton.ac.uk

***Abstract*— Semi-blind space-time equalisation is considered for dispersive multiple-input multiple-output systems that employ high-throughput quadrature amplitude modulation signalling. A minimum number of training symbols, approximately equal to the dimension of the space-time equaliser (STE), are first utilised to provide a rough initial least squares estimate of the STE's weight vector. A gradient-Newton-type concurrent constant modulus algorithm and soft decision-directed scheme is then applied to adapt the STE. The proposed semi-blind adaptive STE is capable of converging fast and accurately to the optimal minimum mean square error STE solution.**

I. Introduction

With the aid of smart antenna arrays and by exploiting both the space and time dimensions, space-time processing is capable of effectively improving the achievable system capacity, coverage and quality of service by suppressing both inter-symbol interference and co-channel interference [1]–[7]. In this contribution, we consider space-division multiple-access (SDMA) induced frequency selective multiple-input multiple-output (MIMO) systems that employ quadrature amplitude modulation (QAM) signalling. A bank of space-time equalisers (STEs) [8]–[14] form the multiuser receiver. Adaptive implementation of STE can be realised using the training-based least mean square (LMS) or recursive least squares (RLS) algorithm [15]. However, a large number of training symbols is required to adapt a STE, which considerably reduces the achievable system throughput. Blind adaptive methods may be applied to adjust a STE, which does not require training symbols and, therefore, does not reduce the achievable system throughput. However, blind methods require high computational complexity and, moreover, they result in unavoidable estimation and decision ambiguities [16], [17], which can only be resolved with the aid of a few training symbols. At the cost of requiring a few training symbols, semi-blind schemes can avoid the estimation and decision ambiguity problem and are computationally simpler than their blind counterparts.

Many semi-blind methods have been proposed for narrowband MIMO systems [18]–[24]. In particular, the work of [24] has developed a semi-blind spatial equalisation scheme for narrowband MIMO systems that employ QAM signalling. In this semi-blind method, a few training symbols, approximately equal to the dimension of the spatial equaliser, are first used to provide a rough least squares (LS) estimate of the spatial equaliser's weight vector. The stochastic-gradient (SG) based constant modulus algorithm (CMA) and soft decision-directed (SDD) scheme, originally developed for blind equalisation of single-input single-output systems [25], [26], is then employed to adapt the spatial equaliser. This semi-blind SG spatial equalisation scheme converges fast to the minimum mean square error (MMSE) solution with a complexity in the order of the LMS algorithm. Direct adopting this semi-blind SG strategy to adapt the STE, however, suffers from slow convergence and excessive steady-state misadjustment because, under dispersive MIMO environment, the STE's input signal is highly correlated. The novelty of this contribution is that we propose a gradient-Newton (GN) based CMA and SDD algorithm to adapt the STE. GN-type algorithms [27] employ second-order statistics of input signal to "whiten" stochastic gradient, which results in much faster convergence than SG-type algorithms in highly correlated signal environments at the cost of an increased complexity. A GN-type algorithm has been adopted in a training-based multiuser receiver for dispersive MIMO systems [28]. Our proposed semi-blind GN-CMA+SDD algorithm is capable of converging fast and accurately to the optimal MMSE STE solution and it has a complexity in the order of the RLS algorithm. Simulation results show that the convergence speed of this semi-blind GN-CMA+SDD algorithm is close to that of the RLS algorithm.

II. System Model and STE Structure

The SDMA induced MIMO system is depicted in Fig. 1, where each of the Q users is equipped with a single transmit antenna and the receiver is assisted by a P-element antenna array. Denote the symbol-rate channel impulse response (CIR) connecting the qth transmit antenna to the pth receive antenna as $\mathbf{c}_{p,q} = [c_{0,p,q}\ c_{1,p,q} \cdots c_{n_C-1,p,q}]^T$, where for notational

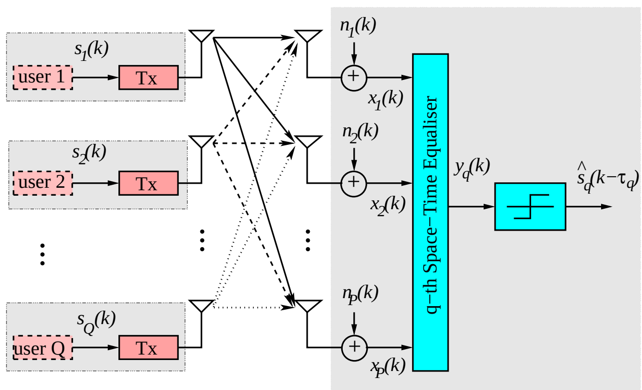

Fig. 1. SDMA induced MIMO system, where each of the Q users is equipped with a single transmit antenna and the receiver is assisted by a P-element antenna array.

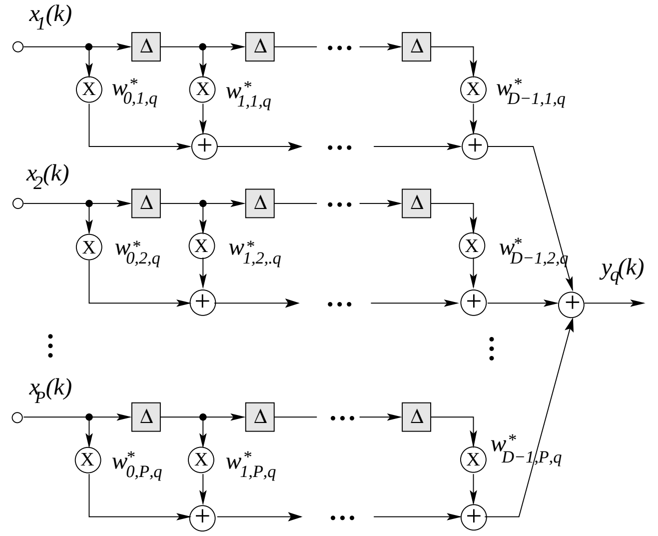

Fig. 2. Space-time equaliser for user q, where Δ denotes the symbol-spaced delay, P is the number of receive antennas, D denotes the length of temporal filter, and $1 \leq q \leq Q$ with Q being the number of users.

simplicity we have assumed that each of the $P \times Q$ CIRs has the same length of n_C. The symbol-rate received signal samples $x_p(k)$, $1 \leq p \leq P$, can be expressed as

$$x_p(k) = \sum_{q=1}^{Q} \sum_{i=0}^{n_C-1} c_{i,p,q} s_q(k-i) + n_p(k), \tag{1}$$

where $n_p(k)$ is a complex-valued Gaussian white noise process with $E[|n_p(k)|^2] = 2\sigma_n^2$, $s_q(k)$ is the kth transmitted symbol of user q with the symbol energy $E[|s_q(k)|^2] = \sigma_s^2$, and $s_q(k)$ takes the values from the M-QAM symbol set

$$\mathcal{S} \stackrel{\triangle}{=} \{s_{i,l} = u_i + j u_l,\ 1 \leq i,l \leq \sqrt{M}\} \tag{2}$$

with the real-part symbol $u_i = 2i - \sqrt{M} - 1$ and the imaginary-part symbol $u_l = 2l - \sqrt{M} - 1$. The overall system's receive signal-to-noise ratio (SNR) is defined as

$$\text{SNR} = \frac{\sum_{q=1}^{Q} \sum_{p=1}^{P} \mathbf{c}_{p,q}^H \mathbf{c}_{p,q} \sigma_s^2}{2QP\sigma_n^2}. \tag{3}$$

The STE for detecting the qth user's data is depicted in Fig. 2. The STE's output, given by

$$y_q(k) = \sum_{p=1}^{P} \sum_{i=0}^{D-1} w_{i,p,q}^* x_p(k-i), \tag{4}$$

is passed to the decision device to produce an estimate $\hat{s}_q(k-\tau_q)$ of the transmitted symbol $s_q(k-\tau_q)$, where D is the temporal filter's length, $w_{i,p,q}$ are the weights of the STE, and $0 \leq \tau_q \leq D + n_C - 2$ is the decision delay.

Define the overall received signal vector $\mathbf{x}(k) = [\mathbf{x}_1^T(k)\ \mathbf{x}_2^T(k) \cdots \mathbf{x}_P^T(k)]^T$, where

$$\mathbf{x}_p(k) = [x_p(k)\ x_p(k-1) \cdots x_p(k-D+1)]^T, \tag{5}$$

for $1 \leq p \leq P$. Then $\mathbf{x}(k)$ can be expressed by the well-known MIMO model

$$\mathbf{x}(k) = \mathbf{C}\ \mathbf{s}(k) + \mathbf{n}(k) \tag{6}$$

where $\mathbf{n}(k) = [\mathbf{n}_1^T(k)\ \mathbf{n}_2^T(k) \cdots \mathbf{n}_P^T(k)]^T$ with

$$\mathbf{n}_p(k) = [n_p(k)\ n_p(k-1) \cdots n_p(k-D+1)]^T \tag{7}$$

for $1 \leq p \leq P$, the tranmitted symbol vector of all the users $\mathbf{s}(k) = [\mathbf{s}_1^T(k)\ \mathbf{s}_2^T(k) \cdots \mathbf{s}_Q^T(k)]^T$ with

$$\mathbf{s}_q(k) = [s_q(k)\ s_q(k-1) \cdots s_q(k-D-n_C+2)]^T \tag{8}$$

for $1 \leq q \leq Q$, and the overall system's CIR matrix

$$\mathbf{C} = \begin{bmatrix} \mathbf{C}_{1,1} & \mathbf{C}_{1,2} & \cdots & \mathbf{C}_{1,Q} \\ \mathbf{C}_{2,1} & \mathbf{C}_{2,2} & \cdots & \mathbf{C}_{2,Q} \\ \vdots & \vdots & \cdots & \vdots \\ \mathbf{C}_{P,1} & \mathbf{C}_{P,2} & \cdots & \mathbf{C}_{P,Q} \end{bmatrix} \tag{9}$$

with the $D \times (D + n_C - 1)$ CIR matrix associated with the user q and the receive antenna p given by the Toeplitz form

$$\mathbf{C}_{p,q} = \begin{bmatrix} \mathbf{c}_{p,q}^T & 0 & \cdots & 0 \\ 0 & \mathbf{c}_{p,q}^T & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \mathbf{c}_{p,q}^T \end{bmatrix} \tag{10}$$

for $1 \leq p \leq P$ and $1 \leq q \leq Q$.

Similarly, the STE for detecting the qth user's data can be expressed in the vector form

$$y_q(k) = \mathbf{w}_q^H \mathbf{x}(k) \tag{11}$$

where the overall weight vector of the STE $\mathbf{w}_q = [\mathbf{w}_{1,q}^T\ \mathbf{w}_{2,q}^T \cdots \mathbf{w}_{P,q}^T]^T$ with

$$\mathbf{w}_{p,q} = [w_{0,p,q}\ w_{1,p,q} \cdots w_{D-1,p,q}]^T,\ 1 \leq p \leq P. \tag{12}$$

The dimension of the STE is thereofore $N_{\text{STE}} = P \cdot D$. The mean square error (MSE) value $J_{\text{MSE}}(\mathbf{w}_q) = E\left[|s_q(k-\tau_q) - y_q(k)|^2\right]$ of the STE (11) is given by

$$\begin{aligned} J_{\text{MSE}}(\mathbf{w}_q) \quad &= \quad \sigma_s^2 \left(1 - \mathbf{w}_q^H \mathbf{C}_{|q_\eta} - \mathbf{w}_q^T \mathbf{C}_{|q_\eta}^*\right) \\ &\quad + \sigma_s^2 \mathbf{w}_q^H \left(\mathbf{C}\mathbf{C}^H + \frac{2\sigma_n^2}{\sigma_s^2}\mathbf{I}\right)\mathbf{w}_q, \end{aligned} \tag{13}$$

where $\mathbf{I}$ denotes the $N_{\text{STE}} \times (Q \cdot (D + n_C - 1))$ dimensional identity matrix, $q_\eta = (q-1)(D+n_C-1) + (\tau_q + 1)$ and $\mathbf{C}_{|i}$ the ith column of $\mathbf{C}$. The average MSE is then defined as

$$J_{\text{AMSE}}(\mathbf{W}) = \frac{1}{Q} \sum_{q=1}^{Q} J_{\text{MSE}}(\mathbf{w}_q), \tag{14}$$

where $\mathbf{W} = \left[\mathbf{w}_1\ \mathbf{w}_2 \cdots \mathbf{w}_Q\right]$ denotes the weight matrix of all the Q STEs. Define the impulse response of the combined STE (11) and MIMO channel as

$$\mathbf{f}_q^T = [f_{0,q}\ f_{1,q} \cdots f_{\tau_{\max},q}] = \mathbf{w}_q^H \mathbf{C} \tag{15}$$

where $\tau_{\max} = (D + n_C - 1) \cdot Q - 1$, and let

$$i_{\max,q} = \arg \max_{0 \leq i \leq \tau_{\max}} |f_{i,q}|, \tag{16}$$

where, in fact, $i_{\max,q} = q_\eta$. The maximum distortion (MD) measure of the STE (11) is defined by

$$J_{\mathrm{MD}}(\mathbf{w}_q) = \left(\sum_{i=0}^{\tau_{\max}} |f_{i,q}| - |f_{i_{\max},q}| \right) / |f_{i_{\max},q}|, \tag{17}$$

and the average MD measure over all the Q STEs is given by

$$J_{\mathrm{AMD}}(\mathbf{W}) = \frac{1}{Q} \sum_{q=1}^{Q} J_{\mathrm{MD}}(\mathbf{w}_q). \tag{18}$$

Ultimately, the average symbol error rate (SER) over all the Q STEs can be simulated to assess the equalisation performance. With the perfect channel knowledge, the optimal MMSE solution for the STE (11) is

$$\mathbf{w}_{q(\mathrm{MMSE})} = \left(\mathbf{C}\mathbf{C}^H + \frac{2\sigma_n^2}{\sigma_s^2}\mathbf{I} \right)^{-1} \mathbf{C}_{|q_\eta}. \tag{19}$$

III. The Proposed Semi-Blind Algorithm

Let the number of available training symbols be K, and denote the available training data as $\{\mathbf{X}_K, \bar{\mathbf{s}}_{K,q}\}$, where $\mathbf{X}_K = [\mathbf{x}(1)\ \mathbf{x}(2) \cdots \mathbf{x}(K)]$ and $\bar{\mathbf{s}}_{K,q} = [s_q(1-\tau_q)\ s_q(2-\tau_q) \cdots s_q(K-\tau_q)]^T$. The LS estimate of the STE's weight vector is readily given as

$$\mathbf{w}_q(0) = \left(\mathbf{X}_K \mathbf{X}_K^H \right)^{-1} \mathbf{X}_K \bar{\mathbf{s}}_{K,q}^*. \tag{20}$$

In order to maintain throughput, the number of training pilots should be as small as possible. To ensure that $\mathbf{X}_K\mathbf{X}_K^H$ has a full rank, we will choose K slightly larger than N_{STE}, the dimension of $\mathbf{x}(k)$. Because the training data with $K \approx N_{\mathrm{STE}}$ are generally insufficient, the initial LS weight vector (20) may not be sufficiently accurate to open the eye. Therefore, decision direct adaptation is generally unsafe. Also directly apply the SG-CMA+SDD blind scheme of [25] to adapt the STE (11) with $\mathbf{w}_q(0)$ of (20) as the initial weight vector suffers from slow convergence and high steady-state MSE misadjustment, because $\mathbf{x}(k)$ is highly correlated. We propose a GN-CMA+SDD algorithm for adjusting the STE (11).

A GN algorithm [27] uses the inverse of the autocorrelation matrix of $\mathbf{x}(k)$ to modify the stochastic gradient. Just like in the RLS algorithm, this inverse matrix can be updated recursively according to [15]

$$\mathbf{P}(k) = \lambda^{-1}\mathbf{P}(k-1) - \lambda^{-1}\mathbf{g}(k)\mathbf{x}^H(k)\mathbf{P}(k-1) \tag{21}$$

with

$$\mathbf{g}(k) = \frac{\lambda^{-1}\mathbf{P}(k-1)\mathbf{x}(k)}{1 + \lambda^{-1}\mathbf{x}^H(k)\mathbf{P}(k-1)\mathbf{x}(k)}, \tag{22}$$

where $\lambda \leq 1$ is the forgetting factor [15]. For stationary channels, $\lambda = 1$ is appropriate. The initial $\mathbf{P}(0)$ can be set to $\mathbf{P}(0) = \left(\mathbf{X}_K\mathbf{X}_K^H\right)^{-1}$. Let the STE's weight vector be split into two parts, yielding $\mathbf{w}_q = \mathbf{w}_{q,c} + \mathbf{w}_{q,d}$. The initial $\mathbf{w}_{q,c}$ and $\mathbf{w}_{q,d}$ are simply set to $\mathbf{w}_{q,c}(0) = \mathbf{w}_{q,d}(0) = 0.5\mathbf{w}_q(0)$. Denote the STE's output at sample k as $y_q(k) = \mathbf{w}_q^H(k)\mathbf{x}(k)$.

The weight vector $\mathbf{w}_{q,c}$ is updated using the GN-CMA according to

$$\mathbf{w}_{q,c}(k+1) = \mathbf{w}_{q,c}(k) + \mu_{\mathrm{CMA}}\mathbf{P}(k)\varepsilon^*(k)\mathbf{x}(k) \tag{23}$$

with

$$\varepsilon(k) = y_q(k)\left(\Delta - |y_q(k)|^2\right), \tag{24}$$

where $\Delta = E\left[|s_q(k)|^4\right]/E\left[|s_q(k)|^2\right]$ and μ_{CMA} is the step size of the CMA. It is obvious that this GN-CMA algorithm reduces to the conventional SG-CMA [29], [30] if $\mathbf{P}(k)$ is replaced with an identity matrix. Note that the step size of the GN-CMA algorithm can be set to a value much larger than the step size of the SG-CMA counterpart.

The weight vector $\mathbf{w}_{q,d}$ is updated using the GN-SDD scheme, which is now described. The complex phasor plane is divided into the $M/4$ rectangular regions, as depicted in Fig. 3, and each region $\mathcal{S}_{i,l}$ contains four symbol points as defined in the following

$$\mathcal{S}_{i,l} = \{s_{r,m},\ r = 2i-1, 2i, m = 2l-1, 2l\}, \tag{25}$$

where $1 \leq i, l \leq \sqrt{M}/2$. If the STE's output $y_q(k) \in \mathcal{S}_{i,l}$, a local approximation of the marginal probability density function (PDF) of $y_q(k)$ is given by [25], [26]

$$\hat{p}(\mathbf{w}_q, y_q(k)) \approx \sum_{r=2i-1}^{2i} \sum_{m=2l-1}^{2l} \frac{1}{8\pi\rho} e^{-\frac{|y_q(k)-s_{r,m}|^2}{2\rho}}, \tag{26}$$

where ρ is the cluster width associated with the four clusters of each $\mathcal{S}_{i,l}$. The SG-SDD algorithm [25], [26] is designed to maximise the log of the local marginal PDF criterion $E[J_{\mathrm{LMAP}}(\mathbf{w}_q, k)]$, where $J_{\mathrm{LMAP}}(\mathbf{w}_q, k) = \rho \log\left(\hat{p}(\mathbf{w}_q, y_q(k))\right)$, via a stochastic gradient optimisation. By contrast, the proposed GN-SDD algorithm uses $\mathbf{P}(k)$ to modify the stochastic gradient and updates $\mathbf{w}_{q,d}$ according to

$$\mathbf{w}_{q,d}(k+1) = \mathbf{w}_{q,d}(k) + \mu_{\mathrm{SDD}}\mathbf{P}(k)\frac{\partial J_{\mathrm{LMAP}}(\mathbf{w}_q(k), k)}{\partial \mathbf{w}_{q,d}}, \tag{27}$$

where μ_{SDD} is the step size of the SDD, and

$$\frac{\partial J_{\mathrm{LMAP}}(\mathbf{w}_q, k)}{\partial \mathbf{w}_{q,d}} = \frac{1}{Z_N} \sum_{r=2i-1}^{2i} \sum_{m=2l-1}^{2l} e^{-\frac{|y_q(k)-s_{r,m}|^2}{2\rho}} \times (s_{r,m} - y_q(k))^* \mathbf{x}(k), \tag{28}$$

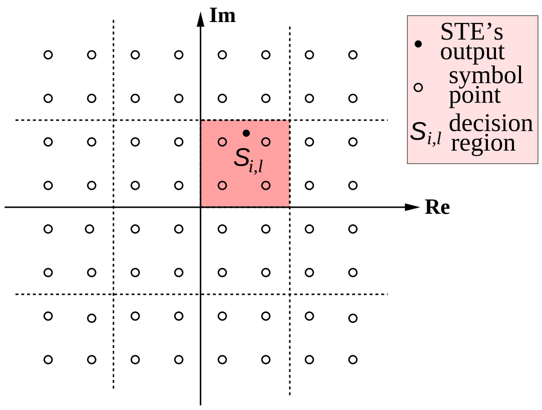

Fig. 3. Local decision region partition for soft decision-directed adaptation with 64-QAM constellation.

TABLE I

CIRs FOR THE 3-USER 4-ANTENNA 16-QAM MIMO SYSTEM.

$\mathbf{c}_{p,q}$	$q=1$	$q=2$	$q=3$
$p=1$	$-0.424+j0.339$	$-0.095-j0.191$	$-0.516+j0.664$
	$+0.594+j0.509$	$+0.667+j0.572$	$+0.442+j0.295$
	$+0.255-j0.170$	$+0.381+j0.191$	$-0.074+j0.074$
$p=2$	$+0.432-j0.346$	$-0.223+j0.372$	$-0.419+j0.559$
	$-0.691-j0.259$	$-0.520-j0.669$	$-0.419-j0.489$
	$+0.173+j0.346$	$+0.074+j0.297$	$-0.279-j0.140$
$p=3$	$+0.306-j0.306$	$-0.093-j0.186$	$+0.253-j0.421$
	$-0.535-j0.612$	$+0.650+j0.557$	$+0.758+j0.084$
	$+0.382+j0.077$	$+0.464+j0.093$	$+0.337-j0.253$
$p=4$	$+0.385+j0.385$	$-0.479-j0.319$	$-0.505-j0.505$
	$+0.462-j0.692$	$+0.718-j0.319$	$+0.674+j0.000$
	$-0.077-j0.077$	$+0.160+j0.160$	$+0.168+j0.084$

with

$$Z_N = \sum_{r=2i-1}^{2i} \sum_{m=2l-1}^{2l} e^{-\frac{|y_q(k)-s_{r,m}|^2}{2\rho}}. \quad (29)$$

This GN-SDD algorithm reduces to the SG-SDD algorithm of [25], [26] by replacing $\mathbf{P}(k)$ with an identity matrix. Note that μ_{SDD} of the GN-SDD can be set to a much larger value than the step size of the SG-SDD, and the performance of the GN-SDD algorithm is insensitive to the cluster width ρ, defined in the context of the local PDF (26). It is also clear that this GN-CMA+SDD algorithm has a complexity similar to that of the RLS algorithm, while the SG-CMA+SDD algorithm has a complexity similar to that of the LMS algorithm.

IV. Simulation Study

The system used in our simulation supported $Q=3$ users with $P=4$ receive antennas, and the modulation scheme was 16-QAM. The $P \cdot Q = 12$ CIRs $\mathbf{c}_{p,q}$, $1 \le p \le 4$ and $1 \le q \le 3$, are listed in Table I, each CIR having $n_C = 3$ taps. The STE's temporal filter order was chosen as $D=7$. The optimal decision delays were found to be $\tau_1 = 5$ for user one, $\tau_2 = 4$ for user two and $\tau_3 = 3$ for user three. These decision delays were used in our simulation. The average SER over

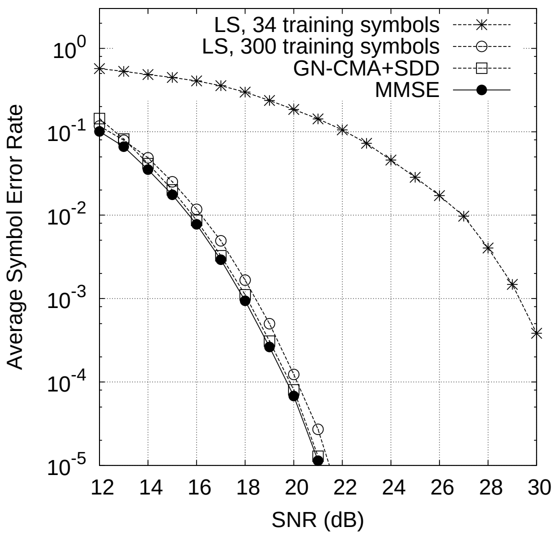

Fig. 4. Comparsion of the average symbol error rate performance for the training-based LS, semi-blind GN-CMA+SDD, and optimal MMSE STEs.

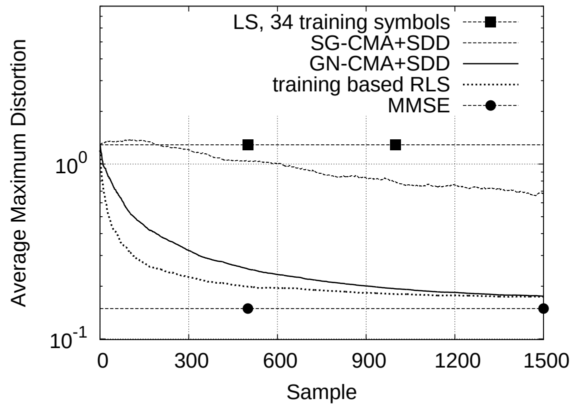

Fig. 5. Convergence performance of the SG-CMA+SDD, GN-CMA+SDD and training-based RLS STEs in terms of the average maximum distortion, given SNR of 19 dB and averaged over ten runs.

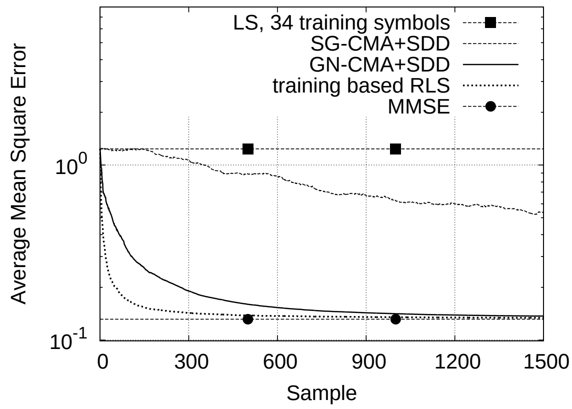

Fig. 6. Convergence performance of the SG-CMA+SDD, GN-CMA+SDD and training-based RLS STEs in terms of the average mean square error, given SNR of 19 dB and averaged over ten runs.

all the $Q=3$ optimal MMSE STEs, depicted in Fig. 4, was used as the benchmark performance. The LS training-based STEs were also tested. Given the training data $\{\mathbf{X}_K, \bar{\mathbf{s}}_{K,q}\}$, the LS estimate of the STE weight vector was provided by (20), and the average SER performance of the two LS training-based STEs were also depicted in Fig. 4, given $K=34$ and 300, respectively. It can be seen that $K=34$ was insufficient for the LS training based STEs to achieve an adequate SER performance and at least $K=300$ training symbols were required by the STEs to approximate the optimal MMSE STE solutions.

The proposed semi-blind STE was next investigated. Given a SNR value, $K=34$ training pilots were first used to provide the initial weight vector of the STE according to (20). The GN-CMA+SDD blind algorithm then adapted the STE. The convergence performance of the proposed GN-CMA+SDD algorithm was investigated, in comparison with the SG-CMA+SDD algorithm of [24]. For all the three blind SG-CMA+SDD STEs, $\mu_{\text{CMA}} = 0.00001$, $\mu_{\text{SDD}} = 0.0002$ and $\rho = 0.1$ were chosen, while $\mu_{\text{CMA}} = 0.01$, $\mu_{\text{SDD}} = 0.95$ and $\rho = 0.1$ were used for all the three blind GN-CMA+SDD STEs. These parameters were found empirically to yield the best performance in terms of convergence speed and steady-state misadjustment. Note that the step size values of the GN-CMA+SDD based semi-blind STEs were much larger than their counterparts for the SG-CMA+SDD based semi-blind STEs, and the GN-CMA+SDD adaptive algorithm was also seen to be insensitive to the value of ρ. Figs. 5 and 6 plot the learning curves of the GN-CMA+SDD adaptive algorithm for the three users obtained by averaging over ten different runs, in terms of the average MSE $J_{\mathrm{AMSE}}(\mathbf{W}(k))$ and the average MD meaure $J_{\mathrm{AMD}}(\mathbf{W}(k))$, respectively, in comparison with those obtained by the SG-CMA+SDD based STEs as well as the results obtained by the training-based RLS STEs. As expected, under a highly dispersive MIMO environment, the SG-CMA+SDD algorithm converged very slowly and was incapable of approaching the optimal MMSE STE solution due to an excessively high steady-state misadjustment. By contrast, the proposed GN-CMA+SDD algorithm was capable of converging fast and accurately to the optimal MMSE STE solution. Next, given a range of SNR values, the average SER performance of the three GN-CMA+SDD based semi-blind STEs after adaptation of 1000 samples, were plotted in Fig. 4, in comparion with those of the optimal MMSE STEs and the LS training-based STEs.

V. Conclusions

A semi-blind STE scheme has been proposed for frequency selective MIMO systems that employ high throughput QAM signalling. A minimum number of training symbols, approximately equal to the dimension of the STE, is used to provide a rough LS estimate of the STE's weight vector for the initialisation. A novel GN-CMA+SDD blind adaptive scheme then adjusts the STE. The proposed semi-blind STE scheme has a complexity similar to that of the training-based RLS algorithm, and it is capable of converging fast and accurately to the optimal MMSE STE solution calculated based on the perfect channel knowledge. Our simulation study has confirmed that this semi-blind GN-CMA+SDD algorithm has a convergence speed very close to the training-based RLS algorithm under the highly dispersive MIMO environment.

References

[1] G. J. Foschini, "Layered space-time architecture for wireless communication in a fading environment when using multiple antennas," *Bell Labs Tech. J.*, vol. 1, pp. 41–59, 1996.

[2] J. H. Winters, "Smart antennas for wireless systems," *IEEE Personal Communications*, vol. 5, pp. 23–27, February 1998.

[3] P. Vandenameele, L. van Der Perre and M. Engels, *Space Division Multiple Access for Wireless Local Area Networks*. Boston, MA: Kluwer Academic Publishers, 2001.

[4] J. S. Blogh and L. Hanzo, *Third Generation Systems and Intelligent Wireless Networking – Smart Antennas and Adaptive Modulation*. Chichester, UK: Wiley, 2002.

[5] A. Paulraj, R. Nabar and D. Gore, *Introduction to Space-Time Wireless Communications*. Cambridge, UK: Cambridge University Press, 2003.

[6] A. J. Paulraj, D. A. Gore, R. U. Nabar and H. Bölcskei, "An overview of MIMO communications - A key to gigabit wireless," *Proc. IEEE*, vol. 92, pp. 198–218, February 2004.

[7] D. Tse, and P. Viswanath, *Fundamentals of Wireless Communication*. Cambridge, UK: Cambridge University Press, 2005.

[8] U. Trautwein, G. Sommerkorn and R. S. Thomä, "A simulation study on space-time equalization for mobile broadband communication in an industrial indoor environment," in *Proc. VTC 1999-Spring*, vol. 1, (Houston, TX), pp. 511–515, May 16-20, 1999.

[9] U. Trautwein, D. Hampicke, G. Sommerkorn and R. S. Thomä, "Performance of space-time processing for ISI- and CCI-suppression in industrial scenarios," in *Proc. VTC 2000-Spring*, vol. 3, (Tokyo, Japan), pp. 1894–1898, May 15-18, 2000.

[10] A. Lozano and C. Papadias, "Layered space-time receivers for frequency-selective wireless channels," *IEEE Trans. Communications*, vol. 50, pp. 65–73, January 2002.

[11] X. Zhu and R. D. Murch, "Layered space-time equalization for wireless MIMO systems," *IEEE Trans. Wireless Communications*, vol. 2, pp. 1189–1203, November 2003.

[12] S. Chen, A. Livingstone and L. Hanzo, "Minimum bite-error rate design for space-time equalization-based multiuser detection," *IEEE Trans. Communications*, vol. 54, pp. 824–832, May 2006.

[13] S. Chen, L. Hanzo and A. Livingstone, "MBER space-time decision feedback equalization assisted multiuser detection for multiple antenna aided SDMA systems," *IEEE Trans. Signal Processing*, vol. 54, pp. 3090–3098, August 2006.

[14] Y. Lee and W.-R. Wu, "Adaptive decision feedback space-time equalization with generalized sidelobe cancellation," *IEEE Trans. Vehicular Technology*, vol. 57, pp. 2894–2906, September 2008.

[15] S. Haykin, *Adaptive Filter Theory*. Upper Saddle Rever, NJ: Prentice Hall, 3rd ed., 1996.

[16] L. Tang, R. W. Liu, V. C. Soon and Y. F. Huang, "Indeterminacy and identifiability of blind identification," *IEEE Trans. Circuits and Systems*, vol. 38, pp. 499–509, May 1991.

[17] Y. Inouye and R. W. Liu, "A system-theoretic foundation for blind equalization of an FIR MIMO channel system," *IEEE Trans. Circuits and Systems Part I: Fundamental Theory and Applications*, vol. 49, pp. 425–436, April 2002.

[18] A. Medles and D. T. M. Slock, "Semiblind channel estimation for MIMO spatial multiplexing systems," in *Proc. VTC2001-Fall*, vol. 2, (Atlantic City, NJ), pp. 1240–1244, October 7-11, 2001.

[19] C. Cozzo and B. L. Hughes, "Joint channel estimation and data detection in space-time communications," *IEEE Trans. Communications*, vol. 51, pp. 1266–1270, August 2003.

[20] T. Wo, P. A. Hoeher, A. Scherb and K. D. Kammeyer, "Performance analysis of maximum-likelihood semiblind estimation of MIMO channels," in *Proc. VTC2006-Spring*, vol. 4, (Melbourne, Australia), pp. 1738–1742, May 7-10, 2006.

[21] A. K. Jagannatham and B. D. Rao, "Whitening-rotation-based semi-blind MIMO channel estimation," *IEEE Trans. Signal Processing*, vol. 54, pp. 861–869, March 2006.

[22] Z. Ding, T. Ratnarajah and C. F. N. Cowan, "HOS-based semi-blind spatial equalization for MIMO Rayleigh fading channels," *IEEE Trans. Signal Processing*, vol. 56, pp. 248–255, January 2008.

[23] M. Abuthinien, S. Chen and L. Hanzo, "Semi-blind joint maximum likelihood channel estimation and data detection for MIMO systems," *IEEE Signal Processing Letters*, vol. 15, pp. 202–205, 2008.

[24] S. Chen, W. Yao and L. Hanzo, "Semi-blind adaptive spatial equalisation for MIMO systems with high-order QAM signalling," *IEEE Trans. Wireless Communications*, vol. 7, pp. 4486–4491, November 2008.

[25] S. Chen and E. S. Chng, "Concurrent constant modulus algorithm and soft decision directed scheme for fractionally-spaced blind equalization," in *Proc. ICC 2004*, vol. 4, (Paris, France), pp. 2342–2346, June 20-24, 2004.

[26] S. Chen, T. B. Cook and L. C. Anderson, "A comparative study of two blind FIR equalizers," *Digital Signal Processing*, vol. 14, pp. 18–36, January 2004.

[27] P. S. R. Diniz, *Adaptive Filtering: Algorithms and Practical Implementation*. Boston, MA: Kluwer Academic Publishers, 2nd ed., 2003.

[28] R. C. de Lamare and R. Sampaio-Neto, "Adaptive MBER decision feedback multiuser receivers in frequency selective fading channels," *IEEE Communications Letters*, vol. 7, pp. 73–75, February 2003.

[29] D. Godard, "Self-recovering equalization and carrier tracking in two-dimensional data communication systems," *IEEE Trans. Communications*, vol. COM-28, pp. 1867–1875, November 1980.

[30] J. R. Treichler and B. G. Agee, "A new approach to multipath correction of constant modulus signals," *IEEE Trans. Acoustics, Speech and Signal Processing*, vol. ASSP-31, pp. 459–472, April 1983.