Chip-level LMMSE Equalization for Downlink MIMO CDMA in Fast Fading Environments

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Abstract—In this paper¹, we consider linear MMSE equalization for wireless downlink transmission with multiple transmit and receive antennas in fast fading environments. We propose a new algorithm based on the conjugate-gradient algorithm with enhanced channel estimation. In order to be robust to the channel variations, the channel coefficients are estimated by using a weighted sliding window. Two methods to determine optimal weights with respect to the Doppler frequency are proposed. The algorithm has been simulated in a fast fading environment (Vehicular A with a velocity for the mobile station of 120 km/h). We show by simulations that good performance is obtained in a correlated fast fading environment with reasonable complexity. Moreover, this approach outperforms methods based on basic sliding window or forgetting factor and the LMS algorithm.

Index terms—Signal Processing in Communications, Channel Estimation, CDMA, Equalization, MIMO Systems.

I. INTRODUCTION

We consider a wireless downlink transmission with multiple transmit and receive antennas as shown in Fig. 1. Motivation for such a system comes from high data-rate 3rd generation (3G) wireless standards. Data for all users are simultaneously transmitted from the base station in the same frequency band, and orthogonality between all users is assumed. For such data rate, multipath delay spread may span several symbol periods, so that the transmission channel is frequency-selective. As a result, the orthogonality of the Walsh spreading codes is lost at the receiver and there is a significant multiple access interference (MAI). Furthermore, the environment is subject to changes when the mobile subscriber moves. Time-varying channel dispersion dramatically deteriorates the performance of the transmission. To mitigate this interference, powerful equalization able to track the channel variations is necessary at the mobile handset.

The common chip-level linear equalizer for Code Division Multiple Access (CDMA) systems is the RAKE receiver ([1], [2]). Performance of the RAKE receiver significantly deteriorates for high system loads/spectral efficiency in high scattering environments [3]. Linear chip-level minimum mean-square error (LMMSE) receivers based on the conjugate-gradient (CG) algorithm have been proposed in [3], [4] for

Fig. 1. Downlink transmission scheme (from the base station to the mobile receiver).

slow fading environments and have been shown to significantly outperform both Zero-Forcing and RAKE receivers. Furthermore, this method has low complexity and does not suffer from any instability problems [5] as in the Recursive Least Squares (RLS) algorithm. However, for fast fading channels, *i.e.* when the mobile velocity is over 30 km/h, performance remains poor. In order to improve performance of equalization in rapidly time-varying environments, Kalman filtering has been proposed in [6], [7]. It represents the optimal solution in the sense of minimum square error but the computational complexity becomes prohibitive in a multiple transmit and receive antennas environment.

In this paper, an efficient algorithm for training-based block chip-level LMMSE receiver for CDMA2000 downlink is developed for fast fading environments. Because the channels are rapidly changing, we propose to enhance channel estimation by using a weighted sliding window; optimal weights are derived with respect to the Doppler frequency. In order to reduce the computational complexity, the conjugate gradient technique is applied so that matrix inversion involved in computing equalizer coefficients is avoided entirely, leading to a low complexity implementation. Simulation results validate the superiority of this scheme at a computational cost comparable to the Least Mean Squares (LMS). The results are for a CDMA downlink with synchronous users, saturated loading, frequency selective fading, long code scrambling and employing multiple antennas at the base station and at the mobile receiver.

This document is organized as follows. In section II, a model for the received CDMA downlink signal in time varying environments is defined. In section III, a chip-level LMMSE equalizer is described for time invariant channels. The proposed algorithm for fast fading channel equalization is addressed in section IV. Finally, the performance of the

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receiver is studied in section V.

II. DATA MODEL

In a CDMA2000 downlink, the user of interest, denoted by k , is separated by means of orthogonal spreading waveforms among all users. On the transmitting (base station) side, user symbols are multiplexed in separate data streams and each data stream is transmitted from a different antenna. The transmitted signal from antenna $t = 1, \dots, T$ at time $Gl + g$, $l = 1, \dots, L$, $g = 1, \dots, G$ can be represented as $d^{(t)}[l, g] = c[Gl + g] \sum_{k=1}^K s_k[g] b_k^{(t)}[l]$ where $c[Gl + g]$ is the $(Gl + g)$ -th complex chip of the long scrambling code, G is the spreading code length, l denotes the symbol number (QPSK symbol), g is the chip index, $s_k[g]$ is the spreading sequence for the user k and $b_k^{(t)}[l]$ is the original user symbol that is transmitted from the antenna t . In order to achieve high spectral efficiency, the same spreading sequence is used for one user over all transmit antennas. The transmitted signal from the antenna t , $d^{(t)}[l, g]$, represents the multiuser signal (summation over all users). Training symbols are sent from each antenna together with data symbols. 90% of the total transmit power on each antenna is dedicated to the users' data and the remaining 10% to the training sequence. The discrete equivalent baseband received signal on antenna m can be represented as

$$r^{(m)}[i] = \sum_{t=1}^T d^{(t)}[i] * h_i^{(t,m)} + n^{(m)}[i], \quad \text{where } i = lG + g. \quad (1)$$

Operator $*$ denotes the convolution, $d^{(t)}[i]$ is the i -th transmitted chip from the antenna t and $h_i^{(t,m)}$ is the equivalent baseband channel impulse response of length L_h for the chip sample i between transmit antenna t and receive antenna m . $n^{(m)}[i]$ is the zero-mean white Gaussian noise component at the receive antenna m . We assume that the noise samples are spatially uncorrelated. The numbers of transmit and receive antennas in the system are T and M , respectively.

III. CHIP-LEVEL LINEAR MMSE EQUALIZER

Channel equalization is used to restore the orthogonality between users in the system and consequently to mitigate the MAI and co-channel interference. Fig. 2 shows the principle of the chip-level MIMO block equalization at the receiver for the downlink transmission. First, the channel impulse responses and the covariance matrix of the received data are estimated. From these estimates, a $M \times T$ equalizer is computed by using the CG algorithm (CGA). Then, the equalizer is used to filter the multiantenna received signal and to give as an output the estimated chips from the corresponding transmit antenna. Finally, the user detection is performed by mean of a correlator using the spreading sequence of the user of interest. Assuming that the scrambling sequence at the base-station is an i.i.d. sequence, the Chip-Level LMMSE equalizer at time i is of the form:

$$\mathbf{f}_i^{(t)} = C_r^{-1}[i] \mathcal{T}(\mathbf{h}_i^{(t)}) \boldsymbol{\delta}_{F+1} \quad (2)$$

Fig. 2. Receiver in mobile handset for a system with $T = 2$ transmit and $M = 2$ receive antennas. The $M \times T$ filter is fed with the M received data streams ($r^{(1)}[l, g]$ and $r^{(2)}[l, g]$) and generate T streams corresponding to the estimates of the transmit data ($\hat{d}^{(1)}[l, g]$ and $\hat{d}^{(2)}[l, g]$).

where $\mathbf{f}_i^{(t)} = [f_i^{(t)}[1] \dots f_i^{(t)}[MF]]^T$ is the filter coefficients of the chip-level equalizer that corresponds to the transmit antenna t , MF is the number of taps for each equalizer t , $t = 1, \dots, T$. $C_r[i]$ is the MF -by- MF covariance matrix of the received data and $\mathcal{T}(\mathbf{h}_i^{(t)})$ is the channel convolution matrix of size $MF \times (L_h + F - 1)$ for the t -th transmit antenna defined as follows, $\mathcal{T}(\mathbf{h}_i^{(t)}) = [\mathcal{T}(\mathbf{h}_i^{(t,1)}) : \mathcal{T}(\mathbf{h}_i^{(t,M)})]^T$ where $\mathcal{T}(\mathbf{h}_i^{(t,m)})$, $m = 1, \dots, M$ is a Toeplitz matrix of size $F \times (L_h + F - 1)$ with first row $[\mathbf{h}_i^{(t,m)}[1] \dots \mathbf{h}_i^{(t,m)}[L_h] \mathbf{0}_{1 \times (F-1)}]$ and first column $[\mathbf{h}_i^{(t,m)}[1] \mathbf{0}_{1 \times (F-1)}]^T$. $\boldsymbol{\delta}_{F+1}$ is a column vector of all zeros except one in the $(F + 1)$ -th position. $F + 1$ is the combined delay of the equalizer. Assuming that data are corrupted by additive zero-mean white Gaussian noise of variance σ^2 , we have:

$$C_r[i] = \sum_{t=1}^T \sigma_d^2 \mathcal{T}(\mathbf{h}_i^{(t)}) \mathcal{T}^H(\mathbf{h}_i^{(t)}) + \sigma^2 \mathcal{I}_{MF} \quad (3)$$

where $\mathcal{I}_{MF}$ denotes the identity matrix of size $MF \times MF$ and σ_d^2 is the variance of the transmitted signal supposed to be identical for each transmit antenna (no power control is used).

Given the orthogonality of the spreading codes, the estimated symbol of the user of interest k for the transmit antenna t , $\hat{b}_k^{(t)}[l]$ can be obtained by performing the inner product between the channel/scrambling code k and the corresponding output of the chip-level MMSE equalizer, once per symbol, $\hat{b}_k^{(t)}[l] = \sum_{g=1}^G \{\mathbf{f}_i^{(t)} \mathbf{r}^{(t)}[lG + g]\} s_k^*[g] c^*[Gl + g]$, where $(\cdot)^*$ and $(\cdot)^H$ denote the conjugate and the transpose conjugate operations, respectively.

IV. CHIP-LEVEL LMMSE EQUALIZER BASED ON THE CGA IN FAST FADING ENVIRONMENTS

In the case of slow fading channels, *i.e.* when the velocity of the mobile station is low, typically less than 10km/h, variations of the channel impulse responses $\mathbf{h}_i^{(t,m)}$, $t = 1, \dots, T$, $m = 1, \dots, M$, $i = 1, \dots, N$ can be neglected. In that case, Eq. 2 becomes $\mathbf{f}^{(t)} = C_r^{-1} \mathcal{T}(\mathbf{h}^{(t)}) \boldsymbol{\delta}_{F+1}$. The conjugate gradient algorithm, [8], is ideally suited for solving Eq. 2 where $C_r[i]$ is a positive-definite Hermitian matrix. Indeed, convergence

is guaranteed in a few steps and the CG method does not require computation of the inverse of the covariance matrix of the received data C_r .

In fast varying environments, time selectivity dramatically deteriorates the quality of the channel estimates leading to a large performance loss. To improve the performance, the CGA proposed in [3] based either on an exponentially decaying data window or block processing with forgetting factor, λ , can be used. This algorithm performs well for a mobile station at moderate velocity (less than 30km/h). For a velocity of 90 – 120 km/h for a mobile station, it is not able to track the channel variations. Moreover, the faster the channel variations, the more sensitive this approach is to the value chosen for the forgetting factor. Indeed, in the 3G standard, only 10% of the total transmitted power is dedicated to the training sequence meaning that a large amount of data is needed in order to obtain accurate channel estimation, typically at least 1000 chip samples. In that case, the forgetting factor should be chosen very carefully (close to 1) to keep a significant contribution from the previous samples. In the next section, we propose to use a weighted sliding window instead of a forgetting factor for very fast fading environments.

A. Chip-level LMMSE equalizer based on the CGA using weighted sliding window

As shown in Fig. 3, we apply the CGA for block processing using a sliding window. If the block size is L , then the updates for the channel estimates for the p -th block are (here, the index t is omitted in order to simplify the notation)

$$\begin{aligned} \tilde{\mathbf{h}}_p &= \frac{1}{1 + 2 \sum_{p=1}^P \lambda_p} \left(\lambda_P \tilde{\mathbf{h}}_{p-P} + \dots + \lambda_1 \tilde{\mathbf{h}}_{p-1} + \tilde{\mathbf{h}}_p \right. \\ &\quad \left. + \lambda_1 \tilde{\mathbf{h}}_{p+1} + \dots + \lambda_P \tilde{\mathbf{h}}_{p+P} \right) \end{aligned} \quad (4)$$

where $\tilde{\mathbf{h}}_{p'}$, $p' = p-P, \dots, p+P$ represents the partial channel impulse response estimate over the p -th data block computed as follows: $\tilde{\mathbf{h}}_{p'} = \frac{1}{L} \sum_{j=p'L}^{(p'+1)L-1} \mathbf{r}[j] d_{tr}^*[j]$. $d_{tr}[j]$ is the j -th chip of the training sequence. The channel estimates of the central block p are calculated by using a sliding window over the $2P+1$ blocks surrounding block p . Although it requires some extra storage for partial channel estimates $\tilde{\mathbf{h}}_{p'}$, $p' = p-P, \dots, p+P$, it dramatically improves the quality of the second order statistics if the weights are well chosen.

The steps of the proposed algorithm are listed in Table I for the p -th block, p denoting the current block of data to equalize. $\mathbf{v}[n]$ and $\mathbf{p}[n]$ are the residual vectors and the current gradient vector, respectively. The following algorithm is applied for each transmit antenna $t = 1, 2, \dots, T$ and it is repeated J iterations.

B. Weights optimization

The weights λ_l , $l = 1, \dots, L$ should be adapted to the velocity (or equivalently to the Doppler coefficient) of the mobile subscriber. Basically, they should be chosen in order to minimize the mean square error ε between the channel

TABLE I
CONJUGATE GRADIENT ALGORITHM WITH WEIGHTED SLIDING WINDOW

Channel estimation from Eq. 4
Covariance matrix computation calculated from Eq. 3
Initialization
$\mathbf{f}^{(t)}[0] = \mathbf{f}^{(t)}[J]$ from the previous block
$\mathbf{v}[0] = \mathbb{E} \left[\mathbf{r} d_{tr}^{(t)*} \right] - C_r \mathbf{f}^{(t)}[0]$
$\mathbf{p}[1] = \mathbf{v}[0]$, $\delta_0 = \ \mathbf{v}[0]\ ^2$, $\delta_1 = \delta_0$
For $n=1, 2, \dots, J$:
$\alpha[n] = \delta_1 / \mathbf{p}^H[n] C_r \mathbf{p}[n]$
$\mathbf{f}^{(t)}[n] = \mathbf{f}^{(t)}[n-1] + \alpha[n] \mathbf{p}[n]$
$\mathbf{v}[n] = \mathbf{v}[n-1] - \alpha[n] C_r \mathbf{p}[n]$
$\delta_0 = \delta_1$, $\delta_1 = \ \mathbf{v}[n]\ ^2$, $\beta[n] = \delta_1 / \delta_0$
$\mathbf{p}[n+1] = \mathbf{v}[n] + \beta[n] \mathbf{p}[n]$

estimate given by Eq. 4 and the average channel impulse response over the central block:

$$\varepsilon = \sum_p \|\hat{\mathbf{h}}_p(\lambda_1, \dots, \lambda_P) - \bar{\mathbf{h}}_p\|^2. \quad (5)$$

We present two methods in order to find the optimal weights subject to the velocity of the subscriber, the width of the blocks L and the number $2P+1$ of blocks considered in the sliding window. To simplify the notation, we do not show the indices m (receive antenna index) and t (transmit antenna index). Moreover, without loss of generality, we assume that the current block number p to process is 0.

Proposition 1: The optimal weights $\lambda_1, \dots, \lambda_P$ which minimize Eq. 5 are given by:

$$\boldsymbol{\lambda} = [\lambda_1 \ \lambda_2 \ \dots \ \lambda_P]^T = (\Re \{A^H A\})^{-1} \Re \{A^H \mathbf{w}\}, \quad (6)$$

where $\Re\{x\}$ denotes the real part of x , $\boldsymbol{\lambda} \in \mathbb{R}^P$, the matrix A of size $MF \times P$ and the vector $\mathbf{w}$ of length MF are defined as follows:

$$A = \left(\tilde{\mathbf{h}}_{-1} + \tilde{\mathbf{h}}_1 - 2\bar{\mathbf{h}}_0, \dots, \tilde{\mathbf{h}}_{-P} + \tilde{\mathbf{h}}_P - 2\bar{\mathbf{h}}_0 \right), \quad (7)$$

$$\mathbf{w} = \left(\bar{\mathbf{h}}_0 - \tilde{\mathbf{h}}_0 \right). \quad (8)$$

The partial channel impulse response $\tilde{\mathbf{h}}_{p'}$, $p' = -P, \dots, P$ corresponds to the channel estimate over the p' -th block. $\bar{\mathbf{h}}_0$ is the channel impulse response averaging over the central block ($p = 0$). It corresponds to the optimal estimate for the channel impulse response for the central block in the sense of the minimum mean square error. In a practical system, this quantity is unknown making estimation of the λ 's unrealizable. One suboptimal solution consists to evaluate the coefficients λ 's by Monte-Carlo simulations. It leads to an array of length $2P+1$ which in average minimizes Eq. 5. Although it is a suboptimal solution, this method performs very well for fast fading environments as shown in Sec. V.

Proof: By replacing the channel estimate $\hat{\mathbf{h}}_0(\lambda_1, \dots, \lambda_P)$ given by Eq. 4 in Eq. 5, we have to minimize the following quantity subject to the constraint $\lambda_p \in \mathbb{R}$, $p = 1, \dots, P$:

$$\left\| \frac{\tilde{\mathbf{h}}_0 + \lambda_1(\tilde{\mathbf{h}}_{-1} + \tilde{\mathbf{h}}_1) + \dots + \lambda_P(\tilde{\mathbf{h}}_{-P} + \tilde{\mathbf{h}}_P)}{1 + 2 \sum_{p=1}^P \lambda_p} - \bar{\mathbf{h}}_0 \right\|^2. \quad (9)$$

Fig. 3. Chip-level Block MMSE based on CG with Weighted Sliding Window Approach to improve accuracy of second order statistics estimation in fast-fading channels.

Let $\mathcal{F}(\lambda_1, \dots, \lambda_P)$ denote the last quantity given by Eq. 9. By gathering the contributions of each coefficient λ_p , we have:

$$\begin{aligned} \mathcal{F}(\lambda_1, \dots, \lambda_P) &= \left\| \lambda_P (\tilde{\mathbf{h}}_{-P} + \tilde{\mathbf{h}}_P - 2\tilde{\mathbf{h}}_0) + \dots + \right. \\ &\quad \left. \lambda_1 (\tilde{\mathbf{h}}_{-1} + \tilde{\mathbf{h}}_1 - 2\tilde{\mathbf{h}}_0) - (\tilde{\mathbf{h}}_0 - \tilde{\mathbf{h}}_0) \right\|^2 \\ &= \|A\lambda - \mathbf{w}\|^2, \end{aligned}$$

where matrix A and vector $\mathbf{w}$ are defined by Eqs. 7 and 8, respectively. The solution to this least square problem under the constraint that the solution should be real, is given by Eq. 6.

Computational complexity of the partial channel estimates could be important if the number of blocks is large (typically in very fast fading environments). Indeed, the proposed solution requires multiplication of all partial channel estimates by a new factor λ_p at each step according to Eq. 4, the number of steps being equal to the number of blocks. We propose a second method still based on the sliding window approach but which requires only one parameter, λ , similar to the forgetting factor approach. According to this, we assume that $\lambda_p = \lambda^p$, $p = 1, \dots, P$ with $0 < \lambda < 1$. In that case, the channel estimate for the p -th block is given by Eq. 10:

$$\begin{aligned} \hat{\mathbf{h}}_0 &= \frac{1 - \lambda}{1 + \lambda - 2\lambda^{P+1}} \cdot \left(\sum_{p=-P}^P \lambda^{|p|} \tilde{\mathbf{h}}_p \right) \\ &= \frac{1 - \lambda}{1 + \lambda - 2\lambda^{P+1}} \cdot \left(\underbrace{\sum_{p=-P}^{-1} \lambda^{-p} \tilde{\mathbf{h}}_p}_{\tilde{\mathbf{h}}_{0-}} + \underbrace{\sum_{p=1}^P \lambda^p \tilde{\mathbf{h}}_p}_{\tilde{\mathbf{h}}_{0+}} \right). \end{aligned} \quad (10)$$

It is possible to derive a recursive solution for channel estimates for the next block, $\tilde{\mathbf{h}}_{1-}$ and $\tilde{\mathbf{h}}_{1+}$ directly from $\tilde{\mathbf{h}}_{0-}$ and

$\tilde{\mathbf{h}}_{0+}$. In that case, we have to update only three partial channel estimates: $\tilde{\mathbf{h}}_{0-}$, $\tilde{\mathbf{h}}_0$ and $\tilde{\mathbf{h}}_{0+}$.

$$\begin{cases} \tilde{\mathbf{h}}_{0-} &= \lambda (\tilde{\mathbf{h}}_{-1-} + \tilde{\mathbf{h}}_{-1}) - \lambda^{P-1} \tilde{\mathbf{h}}_{-P-1} \\ \tilde{\mathbf{h}}_0 &= \lambda \tilde{\mathbf{h}}_{-1} \\ \tilde{\mathbf{h}}_{0+} &= \frac{1}{\lambda} \tilde{\mathbf{h}}_{-1+} - \lambda \tilde{\mathbf{h}}_0 + \lambda^P \tilde{\mathbf{h}}_P \end{cases}$$

In the same manner as for the first method, we propose to find the coefficient λ which minimizes:

$$\varepsilon = \sum_p \|\hat{\mathbf{h}}_p(\lambda) - \bar{\mathbf{h}}_p\|^2. \quad (11)$$

Proposition 2: The coefficient λ which minimizes Eq. 11 is the solution of the equation of degree $2P+1$ $\sum_{p=0}^{2P+1} \alpha_p \lambda^p = 0$ where $\alpha_p = \sum_{q=\max(0, p+1-P)}^{\min(p, P)} \|\beta_{p+1-q} \beta_q\|^2$. The coefficients β_p , $p = 0, \dots, P$ are equal to:

$$\begin{cases} \beta_0 &= \tilde{\mathbf{h}}_{-1} + \tilde{\mathbf{h}}_1 - \tilde{\mathbf{h}}_0 - \bar{\mathbf{h}}_0 \\ \beta_q &= (q+1) \cdot (\tilde{\mathbf{h}}_{-q} + \tilde{\mathbf{h}}_q), \quad q = 2, \dots, P-1 \\ \beta_P &= 2(P+1) \tilde{\mathbf{h}}_0 \end{cases}$$

The proof is directly obtained by using the roots/coefficients relationships.

V. SIMULATIONS RESULTS

Table II shows optimal weights λ 's which are solutions of Eq. 6 for several Doppler velocities from 30 to 120 km/h. These coefficients are used to enhance the channel estimation in our approach based on a weighted sliding window. As expected, the faster are the channel variations, the faster vanish the weights from the central block. Optimization has been performed for a signal-to-noise ratio (SNR) of 10 dB. We noticed that optimal weights do not change significantly for other SNR's or for different antenna configurations. Bit Error

TABLE II

OPTIMAL WEIGHTS λ_p , $p = -7, \dots, 7$ CALCULATED FROM EQ. 6 FOR THE CHANNEL ESTIMATION WITH SLIDING WINDOW WITH RESPECT TO THE VELOCITY (30, 60, 90 AND 120 KM/H) FOR VEHICULAR A CHANNEL.

Speed	± 7	± 6	± 5	± 4	± 3	± 2	± 1	0
30km/h	0.68	0.71	0.75	0.78	0.81	0.86	0.91	1
60km/h	0.22	0.28	0.39	0.56	0.69	0.80	0.89	1
90km/h	0.02	0.04	0.06	0.08	0.11	0.23	0.41	1
120km/h	0.004	0.01	0.02	0.03	0.07	0.17	0.39	1

Rate (BER) performance of the proposed CG equalizer has been simulated as a function of Signal to Noise Ratio (SNR) of the transmission. All users have spreading factor 16 and there are 14 QPSK active users in the case of two transmit and two receive antennas which represents the highest load since two spreading sequences are dedicated to the training sequences. Spatially correlated, frequency-selective, time varying channels are used for testing MIMO equalization algorithms. The chip rate is 1.2288 Mc/sec, carrier frequency is 2.15 GHz and the correlation magnitude between antennas on the base station and mobile handset side is 50% and 44%, [9].

Performance results for a Vehicular A environment with the velocities of 30 km/h and 120 km/h in the case of two transmit antennas and two receive antennas are presented in Fig. 4. We compare both proposed methods based on the CGA with weighted sliding window with optimal weights from Eq. 6 and with simplified weights from Eq. 11 referred to as 'SW+WA CGA' and as 'Simplified SW+WA CGA', respectively. In order to show the importance of the choice of the weights, we show performance for basic sliding window (referred to as 'SW CGA') where all coefficients Λ_p are set to one. We present also the approach developed for moderate channel variations in [3] based on the CGA as well, but with a forgetting factor which is referred to as 'FF CGA'. We also compare with the LMS algorithm which has comparable complexity. The number of iterations for the Conjugate Gradient Algorithm for all methods is fixed to 3 which is sufficient to ensure convergence of the algorithm. All equalizers have 8 taps. We consider $2P + 1 = 15$ blocks in the sliding window approach and the width of each block L is equal to 256 chip periods. The proposed method outperforms the CGA with basic sliding window or with forgetting factor and the LMS algorithm for the 30 km/h and 120 km/h cases. It is due essentially to the benefit of the optimization of the weights. Moreover, a small number of blocks is sufficient in our case (15 blocks). This means that we need to update the filter coefficients 7 times more often than in the approach with basic block-CG. This is reasonable since the number of operations for filter update via the CGA is small in comparison with the number of operations required for channel estimation.

VI. CONCLUSION

In this paper, we considered equalization for wireless downlink transmission with multiple transmit and receive antennas in fast fading environments. We proposed a new algorithm

Fig. 4. Comparison of different methods described in Sec. IV for downlink equalization for fast fading Vehicular A channels, 30 and 120 km/h. Both proposed methods referred to as 'SW+WA CGA' and 'Simplified SW+WA CGA' are based on the CGA with weighted sliding window for channel estimation; Technique 'FF CGA' proposed in [3] is also based on the CGA but uses a forgetting factor approach for channel estimation; For 'SW CGA', basic sliding window is used. Two transmit and two receive antennas, Nb Users=14, Spreading Factor=16, Filter length=8, Nb Iterations=3.

based on the CGA with enhanced channel estimation. In order to be robust to the channel variations, we estimated the channel coefficients by using a weighted sliding window. Two methods to determine optimal weights have been proposed. We have shown by simulations that this approach gives good performance in a correlated fast fading environment, Vehicular A at a velocity of 120 km/h, with a computational complexity of the same order as the LMS algorithm.

REFERENCES

- [1] Z. Xu, P. Liu, and M. Zoltowski, "Diversity-Assisted Channel Estimation and Multiuser Detection for Downlink CDMA With Long Spreading Codes," *IEEE Transactions on Signal Processing*, pp. 190–201, January 2004.
- [2] G. E. Bottomley, T. Ottosson, and Y. Wang, "A generalized RAKE Receiver for Interference Suppression," *IEEE Journal on selected areas in Communications*, August 2000.
- [3] S. Chowdhury and M. Zoltowski, "Application of Conjugate Gradient Methods in MMSE Equalization for the Forward Link of DS-CDMA," in *Vehicular Technology Conference Fall*, Oct. 2001, pp. 2434–2438.
- [4] M. Heikkilä, K. Routsallainen, and J. Lilleberg, "Space-Time Equalization using Conjugate-Gradient Algorithm in WCDMA Downlink," in *IEEE Personal, Indoor and Mobile Radio Communications Conference*, Sept. 2002.
- [5] G. Boray, M. Srinath, and R. Iltis, "Conjugate Gradient Techniques for Adaptive Filtering," *IEEE Transactions on Circuits and Systems I: Fundamental Theory and Applications*, pp. 1–10, Jan. 1992.
- [6] R. Iltis, "A DS-CDMA Tracking Mode Receiver with Joint Channel/Delay Estimation and MMSE Detection," *IEEE Transactions on Communications*, pp. 1770–1779, October 2001.
- [7] M. Tsatsanis, G. Giannakis, and G. Zhou, "Estimation and Equalization of Fading Channels with Random Coefficients," in *IEEE International Conference on Acoustics, Speech, and Signal Processing*, May 1996, pp. 1093–1096.
- [8] G. Golub and C. Van Loan, *Matrix Computations*. The Johns Hopkins University Press, 1991.
- [9] J.R. Fonollosa et al., "The IST METRA Project," *IEEE Communications Magazine*, pp. 78–86, July 2002.