MAI and Noise Constrained LMS Algorithm for MIMO CDMA Linear Equalizer

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***Abstract*—This paper presents a constrained least mean squared (LMS) algorithm for MIMO CDMA linear equalizer is presented, which is constrained on spreading sequence length, number of subscribers, variances of the Gaussian noise and the multiple access interference (MAI) plus the additive noise (introduced as a new constraint). The novelty of the proposed algorithm is that MAI and MAI plus noise variance has never been used as a constraint in MIMO CDMA systems. Convergence analysis is performed for the proposed algorithm in case when statistics of MAI and MAI plus noise are available. Simulation results are presented to compare the performance of the proposed constrained algorithm with other constrained algorithms and it is proved that the new algorithm has outperformed the existing constrained algorithms.**

***Index Terms*—Least mean squared (LMS), multiple input, multiple output (MIMO), linear equalizer, multiple access interference (MAI), Variance, AWGN, adaptive algorithm**

I. INTRODUCTION

It is shown in the literature that performance of an adaptive algorithm may be enhanced if partial knowledge of a particular channel is blended in the algorithm design[1], [2]. Based on this idea, [1] presented an algorithm (Noise-constrained LMS) for identification and tracking of finite impulse response (FIR) channels using the variance of the receiver noise. An advantage of the noise constrained least mean squared (NCLMS) is that it outperforms the LMS algorithm while keeping the same computational complexity. A complementary pair LMS (CP-LMS) [3] was initiated by using constrained optimization technique named augmented Lagrangian (AL) which can be utilized to solve the problem of selecting an appropriate update step-size in LMS algorithm. This technique was utilized in [4], in which the knowledge of the variance of MAI plus noise was incorporated to develop what is called the constrained LMS algorithm (MNCLMS) for CDMA systems.

Since MAI and the additive white Gaussian noise (AWGN) effect performance of CDMA multi user, multi-antenna environment, it is imperative to design a receiver architecture which will negate the effect of MAI and additive noise. This requires a MIMO implementation of the MNCLMS algorithm presented in [4]. The proposed constrained algorithm is developed by incorporating MIMO MAI and noise variances thus resulting in a generalized MIMO MAI plus noise constrained LMS (MIMO-MNCLMS) adaptive algorithm. As it is generalized, we can deduce MAI constrained algorithm, noise constrained algorithm and zero constrained noise algorithm as special cases.

This paper is organized as follows. After introductory remarks, section 2 presents the motivation for the algorithm development. Algorithm development is presented in section 3 whereas section 4 deals with the convergence analysis. Computational complexity of the algorithm is given in section 6. In order to find the theoretical findings, simulation results are presented in Section 7 . Concluding remarks are shown in section 8.

II. MOTIVATION

Adaptive algorithms such as LMS and RLS do not use models for channel coefficients and/or noise, whereas model based algorithms utilize various types of models such as random walk, auto-regressive etc. for coefficients and AWGN. Model parameters are either known or jointly estimated with a channel. Adaptive algorithms can be inferred to as model based algorithms with model parameters' choice dependent on data [5]. It has been reported in the literature that practically it is possible to enhance the performance of an adaptive algorithm if partial knowledge of the channel is available provided that the computational cost of an algorithm is not increased tremendously. According to the noise constrained LMS algorithm [6]

$$\mathbf{w}_{n+1} = \mathbf{w}_n + \mu_n^l e_n \mathbf{X}_n \quad \textbf{(1)}$$

$$\mu_{n+1} = 2\mu_n^l(1 + \gamma\lambda_n) \quad (2)$$

$$\lambda_{n+1} = \lambda_n + \beta\left[(\frac{1}{2}e_n^2 - \sigma_{v_m^l}^2) - \lambda_n\right] \quad (3)$$

Where λ, α and β are positive constants. This is a variable step size (LMS) algorithm because step size rule is applicable due to the constraint on the noise variance. The computational cost of the aforementioned algorithm is the same as of LMS but the convergence rate of the noise constrained LMS algorithm is much faster than the LMS due to its three independent parameters.

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