Digital Signal Processing 56 (2016) 43–52

Contents lists available at ScienceDirect

Digital Signal Processing

www.elsevier.com/locate/dsp

Joint beamforming and power control using continuous updates of transmission power

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ARTICLE INFO

Article history:
Available online 27 May 2016

Keywords:
Adaptive array algorithm
Beamforming
Mobile communication
Power control

ABSTRACT

The goal of algorithms for joint beamforming and power control in communication systems with antenna arrays is to minimize the transmission power while keeping the signal-to-interference-plus-noise ratio (SINR) above a minimum acceptable level. To meet this goal, one appealing approach is to first use a training sequence to adaptively obtain the beamforming coefficients and then, in a second step, to update the transmission power. However, such a power update often changes the beamforming scenario abruptly, leading to a nonstationary behavior that may greatly impair the performance of the adaptive beamforming algorithm. To overcome this problem, a novel approach for joint beamforming and power control is proposed here. Such an approach is based on a continuous iterative update of the transmission power that allows controlling the undesirable nonstationary behavior of the beamforming scenario, thereby significantly improving the performance of the joint beamforming and power control. Simulation results are shown aiming to confirm the effectiveness of the proposed approach.

1. Introduction

In mobile communication systems, the control of the transmission power is of fundamental importance to reduce interference levels as well as increase the battery lifetime of mobile terminals [1–3]. Such control can greatly benefit from the use of adaptive antenna arrays, since their beamforming capability allows the reduction of the transmission power without compromising the link quality. In this context, considerable research effort has been devoted to develop algorithms for jointly performing power control and beamforming in mobile communication systems [4–13].

The optimization problem that has given rise to most of the joint beamforming and power control algorithms found in the literature was originally formulated in [5] and [6]. This problem corresponds to the minimization of the total system transmission power subject to constraints of minimum signal-to-interference-plus-noise ratio (SINR) [12,14–20]. The challenge in many practical applications is to solve such a minimization problem in real time. One interesting approach to meet this challenge is based on exploiting training sequences available in some communication systems, thus avoiding the need to estimate the channel state information. This approach forms the foundation of one of the algorithms proposed in [6], in which the power control is based on the minimum mean-square error (MMSE) between the training sequence and the antenna array output. The first stage of such an MMSE-based algorithm is devoted to obtaining the beamforming coefficients that minimize the mean-square error (MSE) between the training sequence and the antenna array output. This process takes a certain period of time since it depends either on the convergence of an adaptive algorithm (that iteratively seeks to find the optimal beamforming coefficients) or on the estimation of the correlation data required for the direct evaluation of the optimal coefficients (by using the Wiener solution). After this period, the MMSE-based algorithm proceeds to a second stage in which the achieved MMSE is exploited to update the uplink transmission power aiming to attain a minimum acceptable SINR. The main problem of such an approach arises from the fact that the second stage (transmission power update) often produces abrupt changes in the system characteristics. As a result, the beamforming coefficients obtained in the first stage are no longer optimal and the SINR actually falls below its minimum acceptable level. Then, the MSE minimization (first stage) has to be repeated again before carrying out a new update of the transmission power. This cycle is repeated after each new power update, leading to a highly nonstationary environment that threatens the beamforming convergence process and makes the power control slow and ineffective.

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http://dx.doi.org/10.1016/j.dsp.2016.05.009
1051-2004/

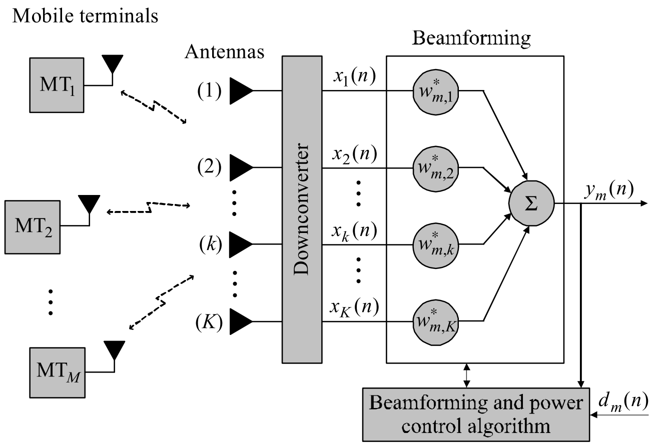

Fig. 1. Uplink communication scenario.

In this paper, a novel algorithm for updating the beamforming and the transmission power in the uplink channel of mobile communication systems is proposed. Such an algorithm is developed with the aim of providing control over the nonstationary behavior arising from the transmission power update, which is particularly valuable for preserving the tracking capability of the adaptive beamforming algorithm used in a joint beamforming and power control scheme. In this context, the proposed algorithm performs a simultaneous update of both the transmission power and the beamforming coefficients at each iteration, leading to a very effective joint beamforming and power control with high robustness against system changes.

This paper is organized as follows. Section 2 lays the groundwork for joint beamforming and power control based on training sequences, including a description of the aforementioned MMSE-based algorithm and its practical implementation. In Section 3, the proposed algorithm and the optimality of the obtained solution are discussed. Section 4 shows numerical simulation results aiming to assess the performance of the proposed algorithm. Finally, concluding remarks are presented in Section 5.

2. System model and problem statement

In this section, the system model considered to derive the proposed algorithm is first presented. Then, the MMSE-based algorithm is described followed by a discussion regarding its implementation in real-world applications.

2.1. System model

In the scenario considered in this paper (see Fig. 1), each of the M mobile terminals (MTs) from co-channel users transmits its own signal using a single antenna, whereas the reception at the base station is carried out through an array of K antennas. In this context, considering that the signal coming from the mth user is composed of L_m predominant multipath components, the corresponding signal vector received by the antenna array can be modeled as

$$\mathbf{s}_m(n) = \sqrt{P_m(n)}\mathbf{H}_m(n)\boldsymbol{\nu}_m(n) \tag{1}$$

where $P_m(n)$ denotes the transmission power, $\boldsymbol{\nu}_m(n) = [\nu_{m,1}(n)\ \nu_{m,2}(n)\ \cdots\ \nu_{m,L_m}(n)]^{\mathrm{T}}$, the L_m-dimensional complex vector containing the data symbols arriving from each multipath component, and $\mathbf{H}_m(n) = [\mathbf{h}_{m,1}(n)\ \mathbf{h}_{m,2}(n)\ \cdots\ \mathbf{h}_{m,L_m}(n)]$, the $K \times L_m$ spatial-response matrix of the mth user whose column $\mathbf{h}_{m,l}(n)$ represents the K-dimensional complex steering vector [21] of the lth multipath signal. It is worth mentioning that (1) can also be used for modeling multiple-input multiple-output (MIMO) systems with a single data stream, no multipath, and an array with L_m antennas available in the MTs. However, for the scenario with single-antenna users and multipath channels illustrated in Fig. 1, we can assume that the channels have independent fading. Thus, the elements of $\boldsymbol{\nu}_m(n)$ are modeled as complex Gaussian random variables whose magnitude and phase have, respectively, Rayleigh and uniform probability density functions. Now, summing the signals coming from all users and also considering a K-dimensional complex vector $\mathbf{z}(n)$ to represent the additive white Gaussian noise (AWGN) of each antenna, one can model the complex baseband input vector $\mathbf{x}(n) = [x_1(n)\ x_2(n)\ \cdots\ x_K(n)]^{\mathrm{T}}$ of the antenna array as

$$\mathbf{x}(n) = \sum_{m=1}^{M} \mathbf{s}_m(n) + \mathbf{z}(n) = \sum_{m=1}^{M} \sqrt{P_m(n)}\mathbf{H}_m(n)\boldsymbol{\nu}_m(n) + \mathbf{z}(n). \tag{2}$$

Such a vector is then processed by using beamforming coefficients that are specific for each user in the system. Thus, the array output [21] for the mth user can be written as

$$y_m(n) = \mathbf{w}_m^{\mathrm{H}}(n)\mathbf{x}(n) \tag{3}$$

with $\mathbf{w}_m(n) = [w_{m,1}(n)\ w_{m,2}(n)\ \cdots\ w_{m,K}(n)]^{\mathrm{T}}$ denoting the corresponding complex beamforming vector. Considering equal mean powers for the multipaths and assuming that the fading is normalized and independent [22], one has

$$\mathrm{E}\big[\boldsymbol{\nu}_m(n)\boldsymbol{\nu}_m^{\mathrm{H}}(n)\big] = \frac{1}{L_m}\mathbf{I}_{L_m} \tag{4}$$

with $\mathbf{I}_{L_m}$ denoting an $L_m \times L_m$ identity matrix. Then, substituting (2) into (3) and considering (4), the mean power of $y_m(n)$ can be expressed as

$$\mathrm{E}\big[|y_m(n)|^2\big] = \sum_{i=1}^{M} P_i(n)\mathbf{w}_m^{\mathrm{H}}(n)\mathbf{R}_i(n)\mathbf{w}_m(n) + \sigma_z^2\|\mathbf{w}_m(n)\|^2 \tag{5}$$

with

$$\mathbf{R}_i(n) = \frac{1}{L_i}\mathbf{H}_i(n)\mathbf{H}_i^{\mathrm{H}}(n) \tag{6}$$

representing the spatial covariance matrix for the ith user and σ_z^2 denoting the variance of the noise.

The SINR for the mth user (which is a measure of link quality) is defined as the ratio between the term of (5) related to such a user [the one that depends on $\mathbf{R}_m(n)$] and the (remaining) terms related to other users and to the noise [23,24]. Thus,

$$\Gamma_m(n) = \frac{P_m(n)\mathbf{w}_m^{\mathrm{H}}(n)\mathbf{R}_m(n)\mathbf{w}_m(n)}{\sum_{i\neq m}^{M} P_i(n)\mathbf{w}_m^{\mathrm{H}}(n)\mathbf{R}_i(n)\mathbf{w}_m(n) + \sigma_z^2\|\mathbf{w}_m(n)\|^2}. \tag{7}$$

As depicted in Fig. 1, the beamforming and power control algorithm for the mth user uses a reference (training) signal $d_m(n)$ that is available at the base station. In this context, the mth-user error signal is defined as

$$e_m(n) = d_m(n) - y_m(n). \tag{8}$$

Now, using (8) along with (3)–(6), the MSE for the mth user can be written as

$$\mathrm{E}\big[|e_m(n)|^2\big] = \sigma_{d_m}^2 - 2\,\mathrm{Re}\big[\mathbf{w}_m^{\mathrm{H}}(n)\mathbf{r}_m(n)\big] + \mathbf{w}_m^{\mathrm{H}}(n)\mathbf{R}_{\mathbf{x}}(n)\mathbf{w}_m(n) \tag{9}$$

where $\sigma_{d_m}^2$ denotes the variance of $d_m(n)$,

$$\mathbf{R}_{\mathbf{x}}(n) = \mathrm{E}\big[\mathbf{x}(n)\mathbf{x}^{\mathrm{H}}(n)\big] = \sum_{m=1}^{M} P_m(n)\mathbf{R}_m(n) + \sigma_z^2\mathbf{I}_K \tag{10}$$