A Spatial Multiplexing Technique Based on Large-scale Fading for Distributed Antenna Systems

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Abstract - **A spatial multiplexing technique for distributed antenna systems is proposed, where the mobile co-located with multiple antennas is capable of receiving distinct sub-streams from multiple widely separated antennas. Modulation and power are adapted based on the knowledge of large-scale fading, which varies much slower than instantaneous channel state information. Three modulation and power adaptation criteria are presented, which minimize the error probability, minimize the power consumption and maximize data throughput, respectively. Simulations based on minimum error probability criterion illustrate the performance improvement compared with original V-BLAST. Based on minimum power consumption criterion and maximum data throughput criterion, numerical results also indicate that DAS is more power efficient, spectral efficient and uniform in quality of service than co-located antenna systems (CAS), which validates the previous theoretic analysis results.**

I. INTRODUCTION

As the demands for high quality and capacity grow in future wireless communication systems, distributed antenna systems (DAS) draw considerable attention since it can counteract large-scale fading, improve coverage, link quality and system capacity by exploiting its inherent macroscopic diversity and shortened access distance [1-3].

Recently, DAS that employs multiple co-located antennas at one end of the communication link and widely spaced antennas at the other has received new research attention due to its capacity advantages. Information theoretical research in [4] and [5] shows the MIMO channel capacity improvement in DAS compared with co-located antenna system (CAS) thanks to the independent large-scale fading in addition to the small-scale fading, However, in the downlink of conventional "simulcasting" DAS [1-3], the same signals are transmitted from multiple distributed antennas simultaneously. Though macroscopic diversity gain can be obtained, the channel capacity is not fully exploited. In order to realize very high spectral efficiency, spatial multiplexing schemes must be used, such as Vertical Bell-labs Layered Space-Time (V-BLAST). Therefore, in this paper, we are motivated to investigate the feasibility of employing spatial multiplexing BLAST-like scheme to the downlink DAS to exploit the information-theoretic capacity.

One major distinction between DAS and CAS is that DAS suffers different degree of large-scale fading (e.g. shadowing and path loss) from each distributed antenna, which significantly degrades the performance of open-loop V-BLAST. To alleviate this detrimental effect, link adaptation techniques should be used in conjunction with MIMO techniques. In [6], an extended V-BLAST with per-antenna rate and power control is proposed to achieve very high spectral efficiency. However it requires the knowledge of instantaneous channel realization and high computational intensity, which is too demanding for DAS. The large-scale fading, on the other hand, is locally stationary and thus varies on a much slower time scale. It is easy to be measured by local averaging. Therefore, we propose a spatial multiplexing technique (referred as adaptive V-BLAST), by which the rate and power of each distributed antenna are subject to large-scale fading only, offering a reasonable tradeoff between complexity and performance.

We describe our system model in the next section. The modulation and power adaptation criteria are derived in Section III. Based on these criteria, some numerical comparisons between adaptive V-BLAST and the original one, and between DAS and CAS are made in Section IV. Finally, Section V contains our concluding remarks.

II. SYSTEM MODEL

A. Channel Model

We consider a mobile equipped with m co-located receive antennas, around which the distributed antennas (DA) are spatially scattered (see Fig. 1). There is no specific signal processing at the distributed antennas except for RF amplification, frequency translation and possibly optic-electric conversion. Through separate optical fibres or coaxial cables these antennas are connected to a central processor where all complex signal processing is done. By measuring the local mean receive power of each distributed antenna in the uplink, the central processor selects the strongest n distributed antennas for downlink transmission simultaneously and on the same frequency. This is basically an (n, m) MIMO system. We assume that the channel is flat

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fading and quasi-static. The following downlink channel model is then applied.

$$\mathbf{y} = \mathbf{H}_w \mathbf{F}^{1/2} \mathbf{x} + \mathbf{n} \tag{1}$$

where $\mathbf{x}$ and $\mathbf{y}$ are the transmit and receive vectors respectively, and $\mathbf{n}$ is the complex additive white Gaussian noise vector. The small-scale fast fading is modeled as Rayleigh, denoted by an $m \times n$ matrix $\mathbf{H}_w$ with i.i.d. $\tilde{N}(0,1)$ entries. The large-scale fading is denoted by a local stationary $n \times n$ diagonal matrix $\mathbf{F} = diag(\alpha_1^2, \alpha_2^2, ..., \alpha_n^2)$. Both shadowing and path loss are modeled in the diagonal entries of $\mathbf{F}$, i.e. $\alpha_k^2 = C s_k / d_k^r$, where the shadowing is represented by an independent log-normal random variable s_k with unit mean and standard deviation σ, d_k is the access distance between the mobile and the k-th nearest distributed antenna, and r is the path loss exponent, typically between 3.0 and 5.0. Finally C is a scaling constant, which is trivial in our analysis and thus is set to 1.

B. Adaptive V-BLAST

Fig. 2 shows the transmitter structure of our proposed adaptive V-BLAST. A single user's data stream is demultiplexed among the n selected distributed antennas, each of which conveys a distinct sub-stream. Each sub-stream is separately encoded into symbols drawn from a modulation set $\mathcal{M}$ consisting of different QAM modulations. These sub-streams are then transmitted by different distributed antennas simultaneously and on the same frequency. Note that the QAM constellation size and average transmit power may differ from one sub-stream from another and is chosen via the modulation and power adaptation criteria described later. At the receiver, we assume that the channel is perfectly estimated and zero-forcing (ZF) is used for symbol detection.

Before proceeding further, we first describe some notations. Let $M_k (M_k \in \mathcal{M})$ denote the modulation of the k-th sub-stream. The corresponding rate is denoted as $R(M_k)$ equal to *log2(constellation size of* M_k *)*. In particular, $R(M_k) = 0$ means that the k-th antenna is not used for transmission. Define the *active antenna set* as $\mathcal{A} = \{k \mid R(M_k) > 0, \forall k\}$. For the effectiveness of our scheme, the number of active antennas $|\mathcal{A}|$ should not exceed the number of receive antennas. Define the *mode vector* as $\mathbf{M} = [M_1, M_2, ..., M_n]$. The total data throughput $R_t = \sum_{k=1}^{n} R(M_k)$ (bit/symbol vector). Likewise, define the *power allocation vector* as $\mathbf{\Gamma} = [\gamma_1, \gamma_2, ..., \gamma_n]$, where γ_k denotes the transmit signal to noise ratio (SNR) from the k-th distributed antenna. The total transmit SNR $\gamma_t = \sum_{k=1}^{n} \gamma_k$.

III. Modulation And Power Adaptation Criteria

In what follows, we will derive the modulation and power adaptation criteria solely based on the knowledge of large scale fading $\mathbf{F}$, which is much easier to be measured than instantaneous channel realization. Knowledge of $\mathbf{F}$ at the transmitter is a reasonable assumption due to the mechanism of antenna selection in DAS. We will start from the derivation of minimum error probability criterion. The derivations of minimum power consumption criterion and maximum data throughput criterion are then straightforward.

With ZF detection, the post-processing SNR on the k-th sub-stream ρ_k is a weighted Chi-squared distribution with $2(m - |\mathcal{A}| + 1)$ degree of freedom, distributed as [7]

$$f_{\rho_k}(x) = \frac{e^{-x/(\alpha_k^2 \gamma_k)}}{\alpha_k^2 \gamma_k (m - |\mathcal{A}|)!} \left(\frac{x}{\alpha_k^2 \gamma_k} \right)^{m - |\mathcal{A}|}, x \geq 0, k \in \mathcal{A} \tag{2}$$

where α_k^2 is the k-th diagonal entry of $\mathbf{F}$. Assuming independent maximum likelihood decoding per sub-stream, the symbol error probability on the k-th sub-stream is then bounded by

$$\begin{aligned} P_{s,k} &\leq N(M_k) \cdot E\left\{ e^{-d_{\min}^2(M_k)\rho_k/4} \right\} \\ &= N(M_k) \cdot \int_0^\infty e^{-d_{\min}^2(M_k)x/4} f_{\rho_k}(x) dx \end{aligned} \tag{3}$$

where $N(M_k)$ and $d_{\min}(M_k)$ are the average number of nearest neighbors and the minimum distance of separation of the unit energy constellation on the k-th sub-stream, respectively. The inequality follows from the Chernoff bound.

Performance specifications are typically more concerned with the bit error probability. If we assume Gray encoding and mapping between data bits and data symbols, then at relatively high SNRs, we can make the approximation [8]

$$P_{b,k} \approx \frac{P_{s,k}}{R(M_k)} \tag{4}$$

From (2), (3) and (4), we have the following upper bound after some algebra

$$P_{b,k} \leq \frac{K}{\left(1 + \frac{1}{4}\alpha_2^2 d_{\min}^2(M_k)\gamma_k\right)^{m - |\mathcal{A}| + 1}} \tag{5}$$

where $m - |\mathcal{A}| + 1$ is referred as the diversity order of ZF detection and K is a constant. An obvious upper bound of K is $\max_{M \in \mathcal{M}} \{N(M)/R(M)\}$. However, this is a rather loose bound. Through numerical methods, a much tighter bound which we find to be a good approximation for $2 \leq R(M_k) \leq 8$ and $10^{-5} \leq P_{b,k} \leq 10^{-2}$ is $K = 0.1$.

Based on the approximation in (5), we consider the optimization problem to minimize the bit error probability as

the total transmit SNR γ_t and total data throughput R_t are fixed over time. Since the sub-stream with the worst error rate limits the system performance, minimizing the bit error probability on the worst sub-stream is a reasonable approximate solution for minimizing the overall bit error probability. The optimal $\widehat{\mathbf{M}}$ and $\hat{\Gamma}$ are then given by

$$\widehat{\mathbf{M}},\hat{\Gamma} = \arg\max_{\mathbf{M},\Gamma}\left\{\min_{k\in\mathcal{A}}\left(1+\frac{1}{4}\alpha_k^2 d_{\min}^2(M_k)\gamma_k\right)^{m-|\mathcal{A}|+1}\right\} \quad (6)$$

There are two variables for optimization. But it is not difficult to prove that when $\mathbf{M}$ is given, the optimal Γ should satisfy

$$\gamma_k = \frac{\left(\alpha_k^2 d_{\min}^2(M_k)\right)^{-1}}{\sum_{i\in\mathcal{A}}\left(\alpha_i^2 d_{\min}^2(M_i)\right)^{-1}}\gamma_t \quad ,k\in\mathcal{A} \quad (7)$$

The consequence of this power allocation strategy equalizes the bit error probability of all sub-streams. Therefore, the overall bit error probability P_b should equals the bit error probability of any sub-stream, i.e. $P_b = P_{b,k}$, for $\forall k\in\mathcal{A}$.

By substituting (7) into (5) and replacing $P_{b,k}$ with P_b, we arrive at the expression of a simple relation among total transmit SNR γ_t, bit error probability P_b and transmit mode vector $\mathbf{M}$, given by

$$metric(\mathbf{M},\gamma_t)\cdot P_b \le K \quad (8)$$

where

$$metric(\mathbf{M},\gamma_t) = \left[1+\left(\gamma_t\Big/4\sum_{k\in\mathcal{A}}\left(\alpha_k^2 d_{\min}^2(M_k)\right)^{-1}\right)\right]^{m-|\mathcal{A}|+1} \quad (9)$$

The following criterion is then derived

Criterion 1: Minimum error probability

Given the total transmit SNR γ_t and the required data throughput R_t, the optimal $\widehat{\mathbf{M}}$ that minimizes the bit error probability on the worst sub-stream is given as

$$\widehat{\mathbf{M}} = \arg\max_{\mathbf{M}}\{metric(\mathbf{M},\gamma_t)\} \quad (10)$$

subject to $R_t = \sum_{k=1}^{n} R(M_k)$.

Note that though reducing $|\mathcal{A}|$ results in fewer sub-streams with higher modulation level and thus may decrease the base-number in (9), it increases the diversity order (i.e. the exponential in (9)), which may enlarge $metric(\mathbf{M},\gamma_t)$ to improve BER performance.

By alternating the constraints and the variable for optimizing, the other two criteria can be written out as follows

Criterion 2: Minimum power consumption

Given the required data throughput R_t and the target bit error probability P_b, the optimal $\widehat{\mathbf{M}}$ that minimizes the total transmit power is given as

$$\widehat{\mathbf{M}} = \arg\min_{\mathbf{M}}\gamma_t \quad (11)$$

subject to $R_t = \sum_{k=1}^{n} R(M_k)$ and $metric(\mathbf{M},\gamma_t)\cdot P_b \le K$.

Criterion 3: Maximum data throughput

Given the total transmit SNR γ_t and the target bit error probability P_b, the optimal $\widehat{\mathbf{M}}$ that maximizes the total data throughput is given as

$$\widehat{\mathbf{M}} = \arg\max_{\mathbf{M}}\sum R(M_k) \quad (12)$$

subject to $metric(\mathbf{M},\gamma_t)\cdot P_b \le K$.

In all three criteria, the corresponding optimal $\hat{\Gamma}$ follows from (7).

IV. Numerical Results

Based on the criteria, we will provide some numerical results through Monte Carlo simulations, where we consider an uncoded system with 4 transmit antennas and the modulation set is given as $\mathcal{M}=\{QPSK,16QAM,64QAM,256QAM\}$.

A. BER performance based on minimum error probability criterion

Fig. 3 shows the BER performance comparison of a (4, 6) system based on the minimum error probability criterion, where the total data rate R_t is constrained to be 16 bit/symbol vector. We assume that the path loss from each distributed antenna is 0 dB and the shadowing is modeled as log-normal with the standard deviation $\sigma = 10dB$. For comparison purpose, we also plot the performance of V-BLAST without shadowing, where adaptive V-BLAST selects the same transmission policy (four 16QAM with uniform power allocation) as original V-BLAST at SNRs of interest and thus they have the same performance. We note that the performance of both schemes degrades due to the independent shadowing of each transmit antenna. However the degradation of adaptive V-BLAST is slighter than that of the original one thanks to the utilization of the knowledge of large-scale fading. More than 2dB gain over original V-BLAST is found at a BER of 10^{-3} and the gain is more evident at higher SNRs.

Fig. 4 shows the BER performance comparison of a (4, 4) system with other parameters same as that in Fig. 3. We note that the performance of adaptive V-BLAST in environments with shadowing is almost as good as that in environments without shadowing while original V-BLAST suffers 2dB performance loss due to shadowing. It is also worth noting

that unlike the (4, 6) system, in the (4, 4) system, even in environments without shadowing, adaptive V-BLAST still shows significant performance gain (8dB at a BER of 10^{-3}) compared with the original one. This is because ZF detection behaves poorly due to lack of degree of freedom as there is merely equal number of transmit antennas and receive antennas. Adaptive V-BLAST, however, judiciously use fewer antennas with higher modulation level to provide diversity gain which may greatly improve the BER performance (see (8)-(10)).

Fig. 3 and Fig. 4 don't dealing with path loss variation. A more realistic performance simulation is shown in Fig. 5, which takes both shadowing and path loss into consideration. The statistical model of access distance with random antenna layout proposed in [5] is adopted with antenna density $1/\pi$. The path loss exponent r is 4 and $\sigma = 10dB$. We observe that, in this scenario, adaptive V-BLAST shows much more performance gain over original V-BLAST.

In the rest two subsections, we will consider the power consumption and data throughput in DAS under the same channel model and statistical model of access distance as Fig. 5, and compare them with those in CAS that has the same antenna density. Adaptive V-BLAST is adopted in both systems.

B. Power distribution based on minimum power consumption criterion

Fig. 6 shows the probability density of the power consumption in CAS and DAS based on minimum power consumption criterion, where the total data rate R_t is constrained to be 16 bit/symbol vector and the target uncoded BER is 10^{-3}. We note that the average power consumption in DAS is smaller than that in CAS, showing that DAS is more power efficient than CAS. Moreover, the standard deviation of power consumption in DAS is also smaller, which is desirable in multiuser systems to reduce variations in interference power. These observations are coincident with the theoretic analysis in [5].

C. Data throughput distribution based on maximum data throughput criterion

Fig. 7 shows the distribution of data throughput in CAS and DAS based on maximum data throughput criterion, where the total transmit SNR γ_t is constrained to be 26 dB and the target uncoded BER is 10^{-3}. We note that DAS obtains higher mean rate and rate with maximum probability than CAS, indicating that DAS is more spectral efficient. The smaller deviation of data throughput in DAS shows that DAS is less sensitive to user's location and thus offers a more uniform quality of service. Also the cut-off probability (corresponding to the probability of zero rate) in DAS is much smaller than that in CAS. These advantages of DAS are also well predicted by the information-theoretic study in [5].

V. CONCLUSION

We have proposed a technique for distributed antenna systems that support spatial multiplexing. The modulation level and power allocation of each sub-stream are adapted based on the local stationary large-scale fading, which is very practical for implementation. Simulation results showed that adaptive V-BLAST significantly outperforms original V-BLAST in environments with independent large-scale fading. Our proposed technique also exploits DAS's inherent advantages in power consumption and data throughput. Therefore, it is an excellent technique candidate for further DAS.

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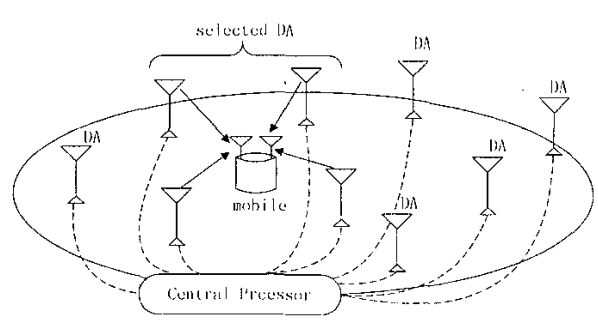

Fig. 1. Concept of distributed antenna systems

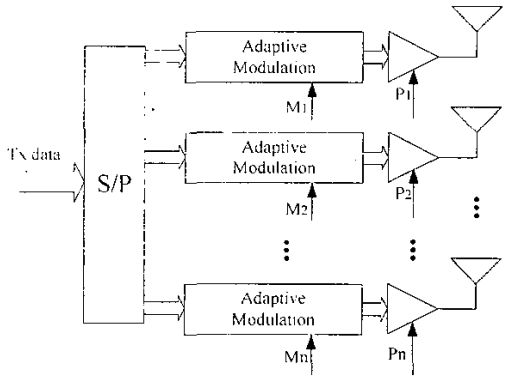

Fig. 2. Block diagram of adaptive V-BLAST transmitter

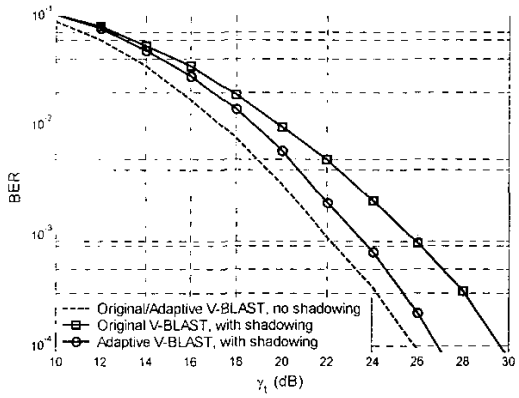

Fig. 3. BER performance comparison of original V-BLAST and adaptive V-BLAST in environments with shadowing, (4, 6) system

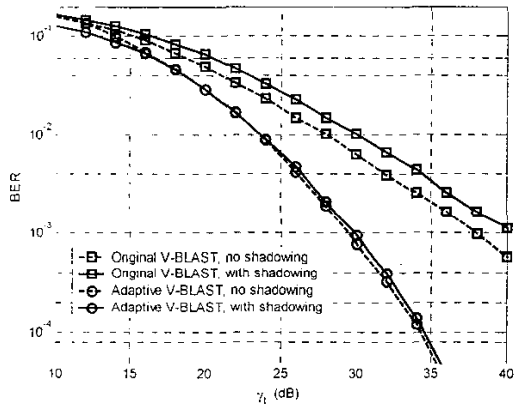

Fig. 4. BER performance comparison of original V-BLAST and adaptive V-BLAST in environments with shadowing, (4, 4) system

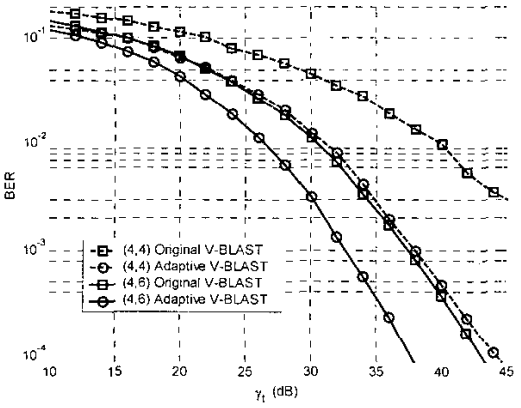

Fig. 5. BER performance comparison of original V-BLAST and adaptive V-BLAST in environments with path loss and shadowing

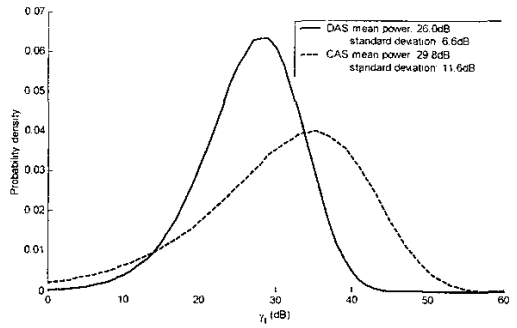

Fig. 6. Distribution of the total transmit SNR based on minimum power consumption criterion in environments with path loss and shadowing

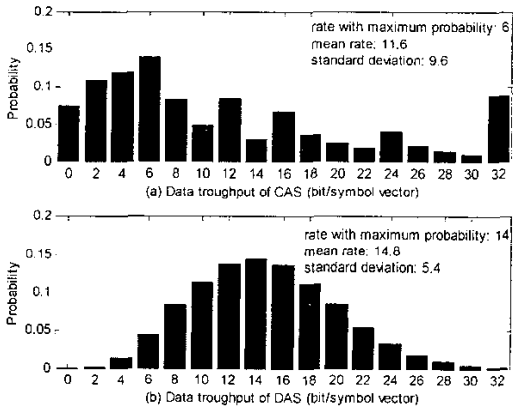

Fig. 7. Distribution of the data throughput based on maximum data throughput criterion in environments with path loss and shadowing