Signal Acquisition and Tracking with Adaptive Arrays in Wireless Systems

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Abstract--**This paper considers the dynamic performance of adaptive arrays in wireless communication systems. With an adaptive array, the signals received by multiple antennas are weighted and combined to suppress interference and combat desired signal fading. In these systems, the weight adaptation algorithm must acquire and track the weights even with rapid fading. Here, we consider the performance of the Least-Mean-Square (LMS) and Direct Matrix Inversion (DMI) algorithms in the digital mobile radio system IS-54. Results for 2 base station antennas with flat Rayleigh fading show that the LMS algorithm has large tracking loss for vehicle speeds above 20 mph, but the DMI algorithm can acquire and track the weights to combat desired signal fading and suppress interference with close to ideal tracking performance at vehicle speeds up to 60 mph.**

I. INTRODUCTION

Antenna arrays with optimum combining reduce multipath fading of the desired signal and suppress interfering signals, thereby increasing both the performance and capacity of wireless systems. To be practical, though, the implemented combining algorithms must be able to rapidly acquire and track the desired and interfering signals.

Most previous theoretical and computer simulation studies of the increase in performance and capacity with optimum combining, e.g., [1-5], assumed ideal tracking of the desired and interfering signals. In the computer simulation study where tracking was considered [6], the data rate was at least 5 orders of magnitude greater than the fading rate, which is much greater than in many wireless systems. For example, in the North American digital mobile radio system standard IS-54 [7] with a data rate of 24.3 ksymbols/sec, at 60 mph the data-to-fading-rate ratio is only 300, while in GSM [7] it is around 2000. In a previous experiment that demonstrated the feasibility of optimum combining with a 3-fold increase in capacity (suppression of 2 equal-power interferers with 8 antennas), the Least-Mean-Square (LMS) algorithm tracked these signals with data-to-fading-rate ratios as low as 25. However, the tracking error loss could not be measured because of A/D quantization noise. Furthermore, this experimental system had many more antennas than interferers, which is not typical of most wireless systems.

Here we consider the dynamic performance of adaptive arrays in wireless communication systems. Specifically, we consider the performance of the LMS and Direct Matrix Inversion (DMI) algorithms in tracking the desired and interfering signals in the digital mobile radio system IS-54.

II. ADAPTIVE ARRAY DESCRIPTION

In the digital mobile radio system IS-54, the frequency reuse factor (number of channel frequency sets) is 7. However, as shown in [4], it may be possible to reduce the frequency reuse factor to 4 (nearly doubling the system capacity) through the use of optimum combining of the signals from the two existing receive base station antennas. However, for this result in [4], we assumed 1) ideal optimum combining, i.e, perfect tracking of the desired and interfering signals by the combining algorithm at the base station, 2) flat Rayleigh fading, 3) similar performance for the reverse link (base station to mobile), even though the mobile may have only one antenna, and 4) independent fading of the desired signal and all interfering signals at each antenna.

With respect to the fourth assumption, in most cases nearly independent fading can be achieved by spacing the antennas at the base station far enough apart. The effect of antenna spacing and correlation of fading between antennas is studied in [8].

With respect to the third assumption, transmit diversity techniques can be used to at least partially achieve the performance of optimum combining at the mobile, which may only have one antenna. One such technique is described in [9].

With respect to the second assumption, we showed in [5] that the performance of ideal optimum combining improves when optimum equalization is also used and the fading is frequency selective. Thus, flat Rayleigh fading may be considered as a worst case. In practice though, signal acquisition and tracking may be more difficult with joint equalization and optimum combining. The performance of signal acquisition and tracking algorithms depend on the equalization technique, however. Thus, to study the dynamic performance of optimum combining only, we will not consider frequency selective fading and equalization. This will be studied in a later paper.

In the remainder of this paper we will consider the first assumption, i.e., the dynamic performance of optimum combining in IS-54.

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Figure 1 shows a block diagram of an M antenna element adaptive array. The complex baseband signal received by the ith element in the kth symbol interval $x_i(k)$ is multiplied by a controllable complex weight $w_i(k)$ The weighted signals are then summed to form the array output $s_o(k)$. The output signal is subtracted from a reference signal $r(k)$ (described below) to form an error signal $\epsilon(k)$. Weight generation circuitry determines the weights from the received signals and the error signal. In this paper we are interested in determining the weights that minimize the mean-square error, i.e., $|\epsilon^2(k)|$. Note that the weights that minimize the mean-square error also maximize the output signal-to-interference-plus-noise ratio (SINR).

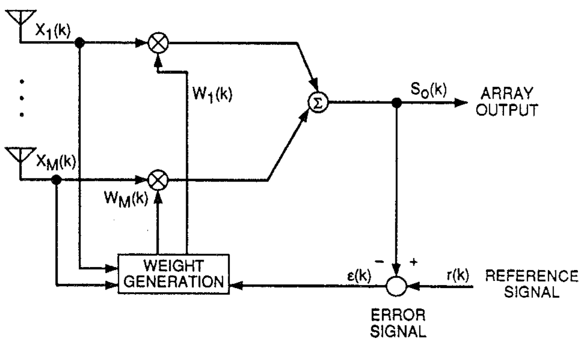

Figure 1 Block diagram of an M element adaptive array.

The weights can be calculated by a number of techniques. Here, we consider two techniques, the LMS algorithm and DMI [10]. For digital implementation of the LMS algorithm, the weight update equation is given by

$$\mathbf{w}(k+1) = \mathbf{w}(k) + \mu \mathbf{x}^*(k)\epsilon(k) \tag{1}$$

where

$$\mathbf{w}(k) = \left[w_1(k)\, w_2(k) \cdots w_M(k)\right]^T , \tag{2}$$

$$\mathbf{x}(k) = \left[x_1(k)\, x_2(k) \cdots x_M(k)\right]^T , \tag{3}$$

the superscripts $*$ and T denote complex conjugate and transpose, respectively, μ is a constant adjustment factor, and the error is given by

$$\epsilon(k) = r(k) - s_o(k) . \tag{4}$$

With DMI, the weights are given by [10]

$$\mathbf{w} = \hat{\mathbf{R}}_{xx}^{-1} \hat{\mathbf{r}}_{xd} \tag{5}$$

where the estimated receive signal correlation matrix is given by

$$\hat{\mathbf{R}}_{xx} = 1/K \sum_{j=1}^{K} \mathbf{x}^*(j)\mathbf{x}^T(j) \tag{6}$$

where K is the number of samples used, the superscript -1 denotes inverse, and the estimated reference signal correlation vector is given by

$$\hat{\mathbf{r}}_{xd} = 1/K \sum_{j=1}^{K} \mathbf{x}^*(j) r(j) . \tag{7}$$

Note that we have assumed that $\hat{\mathbf{R}}_{xx}$ is nonsingular. If it is not, pseudoinverse techniques can be used [11].

The LMS algorithm is the least computationally-complex weight adaptation algorithm. However, the rate of convergence to the optimum weights depends on the eigenvalues of $\mathbf{R}_{xx}$, i.e., on the power of the desired and interfering signals. Thus, weaker interference will be acquired and tracked at a slower rate than the desired signal, and the desired signal will be tracked at a slower rate during a fade (when accurate tracking is most important).

The DMI algorithm is the most computationally-complex algorithm because it involves matrix inversion. However, DMI has the fastest convergence, and the rate of convergence is independent of the eigenvalues of $\mathbf{R}_{xx}$, i.e., signal power levels. One issue with the DMI algorithm is its modification for tracking time-varying signals. Here we consider calculating the weights at each symbol interval using a sliding window (fixed K in (6) and (7)).

For $M = 2$, the DMI algorithm has about the same computational complexity as the LMS algorithm. For larger M, since the complexity of matrix inversion grows with M^3 (versus M for LMS), DMI becomes very computation intensive. However, the matrix inversion can be avoided by using recursive techniques based on least-square estimation or Kalman filtering methods [10], which greatly reduce complexity (to the order of M^2) but have performance that is similar to DMI [10]. Similarly, pseudoinverse techniques [11] can be used if $\hat{\mathbf{R}}_{xx}^{-1}$ does not exist. Therefore, our performance results for DMI should also apply to these recursive techniques.

Next, consider reference signal generation. Since this signal is used by the adaptive array to distinguish between the desired and interfering signals, it must be correlated with the desired signal and uncorrelated with any interference. Now, the digital mobile radio system IS-54 [7] uses time division multiple access (TDMA), with three user signals in each channel and each user transmitting two blocks of 162 symbols in each frame. For mobile to base transmission, each block includes a 14 symbol synchronization sequence starting at the 15th symbol. Thus, as proposed in [4], for weight acquisition we will use the known 14 symbol synchronization sequence as the reference signal. DMI is used to determine the initial weights using this sequence, since accurate initial weights are required. Note that the weights must be reacquired for each block, because with a 24.3 ksymbols/sec data rate and fading rates as high as 81 Hz, the fading may change completely between blocks received from a given user. After weight acquisition, the output signal consists mainly of the desired signal, and (during proper operation) the data is detected with a bit error rate that is not more than 10^{-2} to 10^{-1}. Thus, we can use the detected data as the reference signal, using either the LMS or DMI algorithm for tracking (starting from the synchronization sequence in the forward direction for symbols 29 to 162, and in the reverse direction for symbols 14 to 1). In our simulation results shown below, we did not consider the effect of data errors on the reference signal, i.e., the reference signal symbols were the same as the transmitted symbols.

III. RESULTS

To determine the performance of the acquisition and tracking algorithms in IS-54, we used IS-54 computer simulation programs written by S. R. Huszar and N. Seshadri. We modified the transmitter, fading simulator, and receiver programs for flat Rayleigh fading with one interferer and added our optimum combining algorithms with both coherent and differential detection.

Let us first consider the performance with DMI for acquisition and LMS for tracking with differential detection without interference. Figure 2 shows the bit error rate (BER) versus SINR for vehicle speeds of 0, 20, and 60 mph at 900 MHz, corresponding to fading rates of 0, 27, and 81 Hz. Computer simulation results are shown for the BER over 178 blocks ($\approx$ 28,000 symbols), along with theoretical results for optimum combining with perfect tracking.

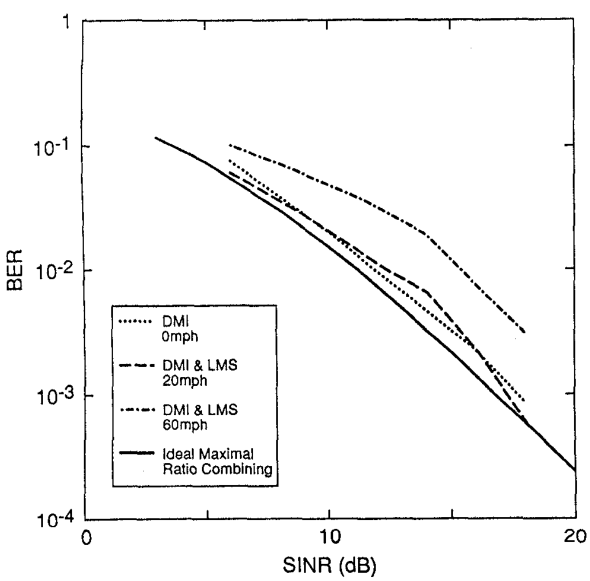

Figure 2 BER versus SINR for vehicle speeds of 0, 20, and 60 mph with DMI for acquisition and LMS for tracking.

At 0 mph, the fading channel was constant over each block, but independent between blocks. Also, LMS tracking was not used at 0 mph, and thus the results show the accuracy of weight acquisition by DMI. DMI is seen to have less than a 1 dB implementation loss for BER's between 10^{-3} and 10^{-1}. At 20 and 60 mph, the tracking performance of the LMS algorithm is poor. For SINR below 15 dB, the LMS algorithm tracks so poorly that the best BER is obtained with μ=0, i.e., if LMS tracking is not used. This lack of tracking causes little degradation at 20 mph, but a several dB loss in performance at 60 mph. For SINR above 15 dB, the LMS algorithm improves performance, with the best μ equal to 0.14. At 20 mph, the performance with the LMS algorithm is about the same as at 0 mph. However, at 60 mph there is a 4.2 dB implementation loss at a 10^{-2} BER. Thus, the LMS algorithm is not satisfactory for optimum combining in IS-54.

Next, consider DMI for both acquisition and tracking with differential detection without interference. As discussed above and shown in Figure 2, DMI has less than a 1 dB implementation loss at 0 mph. Our results showed that there is no increase in this loss even at 60 mph, for a 10^{-2} BER when a 14 symbol sliding window ($K = 14$ in (6) and (7)) is used.

Although differential detection is typically used in mobile radio because of phase tracking problems, we can also use coherent detection with optimum combining. This is because optimum combining requires coherent combining of the received signals, which means that the weights must track the received signal phase and the array output signal phase should match the phase of the coherent reference signal. Thus, coherent detection of the array output is possible, which can be shown to decrease the required SINR for a 10^{-2} BER by 1.0 dB with ideal phase tracking (almost half of the 2.5 dB gain needed for a frequency reuse factor of 3 rather than 4). With the LMS algorithm, however, tracking is so poor that coherent detection is worse than differential detection. On the other hand, with the DMI algorithm, our results showed that coherent detection decreases the required SINR for a 10^{-2} BER by 1 dB, resulting in performance that is 0.3 dB better than the theoretical performance of differential detection (but 0.7 dB worse than ideal coherent detection). At 60 mph, the performance degrades by an additional 0.5 dB, i.e., the performance is 0.2 dB worse than ideal differential detection (and 1.2 dB worse than ideal coherent detection). Thus, the use of coherent rather than differential detection cancels most of the implementation loss of DMI at 60 mph.

Finally, consider the dynamic performance of optimum combining for interference suppression. For the interferers, we used a synchronization sequence that was orthogonal to that of the desired signal. Independent random data was used for both the desired and interfering signals. Also, for the results shown below, the symbol timing for the desired and interfering signals was the same. Our results showed that this was the worst case since there was a slight improvement in performance with timing offset between the two signals.

With the LMS algorithm, even at 20 mph the performance does not improve with the interference-to-noise ratio (INR), showing that the algorithm is not accurately tracking the interferer.

However, with DMI, the performance improvement with INR agrees with predicted (from [1]) ideal tracking results. Figure 3 shows the average BER versus SINR at 0 mph with one interferer with INR $= -\infty$, 0, 3, 6, and 10 dB. DMI with a 14 symbol sliding window and coherent detection was used as before. The required SINR for a 10^{-2} BER is 10.7, 10.0, 9.1, and 7.0 dB for INR = 0, 3, 6, and 10 dB, respectively, which is within 0.5 dB of the predicted gain (from [1]). Note that the implementation loss increases with SINR, resulting in poor performance at a 10^{-3} BER. However, the performance can be greatly improved by decreasing the memory of DMI. In particular, with appropriate weighting, the improvement at a 10^{-3} BER can be made similar to that shown at a 10^{-2} BER in Figure 3.

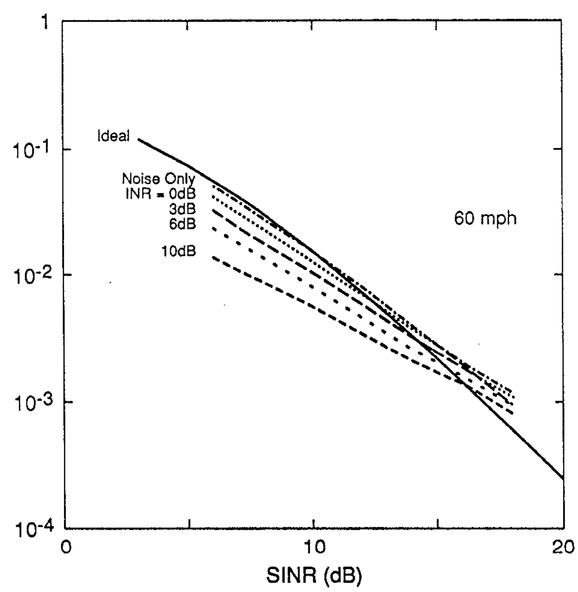

Figure 3 BER versus SINR with one interferer for a vehicle speed of 60 mph with DMI for acquisition and tracking.

IV. SUMMARY AND CONCLUSIONS

In this paper we have studied the dynamic performance of adaptive arrays in wireless communication systems. Specifically, we studied the performance of the LMS and DMI weight adaptation algorithms in IS-54 with data to fading rates as low as 300. We showed that implementation of optimum combining allows the use of coherent detection, which improves performance by over 1 dB as compared to differential detection. Although the performance of the LMS algorithm was not satisfactory, results showed that the DMI algorithm acquired the weights in the synchronization sequence interval and tracked the desired signal for vehicle speeds up to 60 mph with less than 0.2 dB degradation from the ideal performance with differential detection at a 10^{-2} BER. Similarly, an interfering signal was also suppressed with performance gains over maximal ratio combining within 0.5 dB of that predicted with perfect tracking. Thus, our results indicate that we can obtain close to the ideal performance improvement of optimum combining even in rapidly fading environments.

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