ADAPTIVE ANTENNAS FOR DIGITAL MOBILE RADIO

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Abstract: In this paper, we consider adaptive antenna arrays for digital cellular mobile radio. In mobile radio, the main limitation on performance and capacity is interference from other users. This interference can be suppressed by adaptive antenna techniques using the multiple base station antennas. We first present theoretical results that show that, with $L+N$ antennas, we can null $N-1$ interferers and achieve an $L+1$-fold antenna diversity gain against multipath fading of the desired signal. Experimental results demonstrate this interference nulling capability. We then present computer simulation results for the digital mobile radio system IS-54 that show that, with ideal tracking of the desired and interfering signals, an adaptive array with 2 antennas can nearly double the system capacity and with 5 antennas a 7-fold capacity increase (frequency reuse in every cell) can be achieved. Finally, our computer simulation results show that using the Direct Matrix Inversion algorithm we can acquire and track the antenna weights to combat desired signal fading and suppress interference with close to ideal performance for vehicle speeds up to 60 mph.

Introduction

The performance of digital mobile radio communication systems is limited by signal fading and interference from other users [1-5]. Both these effects can be reduced by the use of multiple antennas, with the appropriate signal combining of the received signals. Specifically, by optimum combining of the received signals to minimize the mean-square error in the output signal [2-5], adaptive antennas can provide path diversity against multipath fading and permit the use of the spatial dimension so that multiple users can coexist in the same channel.

In cellular mobile radio, a geographic area is divided into cells. In each cell, mobiles communicate with a central base station, using a different set of frequencies in each cell. These channel sets are reused in the cells in such a way that cells with the same channel set have the maximum separation to reduce cochannel interference. For example, in IS-54, 7 channel sets are used, resulting in up to 6 cochannel interferers that are 2 cells away. Thus, the capacity of mobile radio is limited by interference from other users. If this interference can be reduced, then a smaller number of channel sets could be used with a corresponding increase in system capacity.

Mobile radio systems are also affected by multipath fading. To compensate for this fading, current mobile radio systems use two antennas for reception at the base station (some vehicles also use two antennas). The receiver then selects the antenna with the stronger signal or combines the two signals to maximize signal-to-noise ratio. However, as discussed above and shown in [3-5], since interference, not noise, usually determines system performance, we can achieve better performance and higher capacity by using adaptive antenna techniques with the receive antennas to suppress interference as well as compensate for desired signal fading.

In this paper, we consider mobile radio systems with independent flat-Rayleigh fading at each antenna. For these systems, we prove theoretically that with $L+N$ antennas, $N-1$ interferers can be nulled out and $L+1$ path diversity improvement can be achieved. Experimental results demonstrate this interference nulling capability, and computer simulation results show an example of the improvement possible in the digital mobile radio system IS-54.

Theory

Figure 1 shows a wireless system with N users, each with one antenna, communicating with a base station with M antennas.

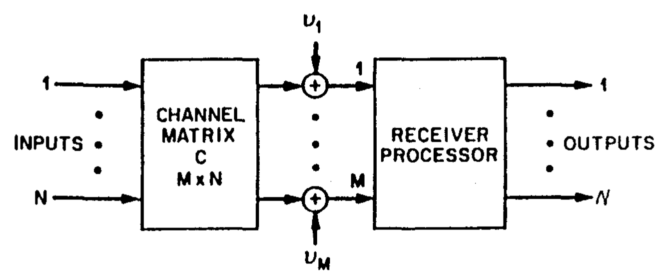

Figure 1 Multiuser communication block diagram.

The channel transmission characteristics matrix $C(\omega)$ can be expressed as

$$C(\omega) = \left[C_1(\omega),\ C_2(\omega)\ ,...,\ C_N(\omega)\right] \tag{1}$$

where the N M-column vectors $C_1(\omega)$, $C_2(\omega)$,...,$C_N(\omega)$ denote the transfer characteristics from the i^{th} user, $i = 1,2,...,N$ to the j^{th}, $j = 1,2,...,M$ receiver or antenna. Now consider the Hermitian matrix $C^\dagger(\omega)C(\omega)$, where the dagger sign stands for "conjugate transpose." If the vectors in (1) are linearly independent, for each ω, then the $N\times N$ matrix inverse, $(C^\dagger C)^{-1}$ exists. This is a mild mathematical requirement and will most often be satisfied in practice since it is assumed that users will be spatially separated.

At the receiver, the M receive signals are linearly combined to generate the output signals. We are interested in the performance of this system with the optimum linear combiner, which combines the received signals to minimize the mean-square error (MSE) in the output. An explicit expression was provided for the least obtainable MSE in [6]. The formula for user "1" without loss of generality is given by

$$(MSE)_{011} = \sigma_a^2 \frac{T}{2\pi} \int_{-\pi/T}^{\pi/T} \left[I + \frac{C^\dagger(\omega) C(\omega)}{N_0} \sigma_a^2 \right]_{11}^{-1} d\omega \quad (2)$$

where $\sigma_a^2 = E|a_n^{(1)}|^2$, $[\quad]_{11}^{-1}$ stands for the "1 1" component of the inverse of a matrix, T is the symbol duration, N_0 is the noise density, and $a_n^{(1)}$ are the 1^{st} user's complex data symbols.

With flat Rayleigh fading, the channel matrix $C(\omega)$ is independent of frequency and all the elements of C can be regarded as independent, zero-mean, complex Gaussian random variables with variance σ_i^2 for the i^{th} user, provided the antenna elements are separated by at least half a wavelength. Let us consider the high signal-to-noise case (which also results in the zero forcing optimum combiner solution). Under these assumptions (2) reduces to

$$(MSE)_{011} = (C^\dagger C)_{11}^{-1} N_0 \ . \quad (3)$$

It can be shown that the MSE for any signal-to-noise ratio is upper bounded by (3) and therefore the zero-forcing solution serves as an upper bound on the MSE solution. For these reasons and the fact that it is easier to analyze the zero-forcing structure, we proceed in this paper with this approach. Using (3), we find that an exponentially tight upper bound on the conditional probability of error is given by

$$P_{e1}(C) \le \exp\left\{ -\frac{\rho}{\sigma_a^2} \frac{1}{(C^\dagger C)_{11}^{-1}} \right\} , \quad (4)$$

where ρ is the signal-to-noise ratio for user "1", i.e., $\rho = \frac{\sigma_a^2 \sigma_1^2}{N_0}$.

In order to analyze the performance of the general set-up, we must be able to determine the statistical properties of the random variable $\alpha = 1/(C^\dagger C)_{11}^{-1}$. From the definition of the inverse of a matrix we express this quantity as follows,

$$\alpha = \frac{\det\,(C^\dagger C)}{A_{11}} = \frac{\Delta_N(C_1,...,C_N)}{\Delta_{N-1}(C_2,...,C_N)} \quad (5)$$

where $\det(\cdot)$ stands for determinant, A_{11} is the "11" cofactor, $\Delta_N(C_1,...,C_N) = \det\,(C^\dagger C)$, and $\Delta_{N-1}(C_2,...,C_N)$ is the determinant resulting from striking out the first row and first column of $C^\dagger C$. From the definition of the determinant

$$\Delta_N(C_1,C_2,...,C_N) = \sum \pm\, C_1^\dagger C_{i_1} C_2^\dagger C_{i_2} \cdots C_N^\dagger C_{i_N} \quad (6)$$

where the sum is extended over all $N!$ permutations of 1, 2,..., N, the "+" sign is assigned for an even permutation and "-" for an odd permutation, it can be seen that it is possible to factor out $C_1^\dagger$ on the left and C_1 on the right in each term. This factorization makes it possible to express Δ_N in the following form

$$\Delta_N(C_1,C_2,...,C_N) = C_1^\dagger F(C_2,C_3,...,C_N) C_1 \quad (7)$$

where F is an $M\times M$ matrix independent of C_1. By normalizing F by $\Delta_{N-1}(C_2...C_N)$ so that $F/\Delta_{N-1} = \tilde{M}$, we can express the quantity of interest as a positive quadratic form

$$\alpha = C_1^\dagger \tilde{M} C_1 \quad (8)$$

where $\tilde{M}$ is Hermitian and non-negative. Diagonalizing $\tilde{M}$ by a unitary transformation ϕ, we write for α

$$\alpha = C_1^\dagger \phi^\dagger \Lambda \phi C_1 = z^\dagger \Lambda z = \sum_{i=1}^{M} \lambda_i |z_i|^2 \quad (9)$$

where Λ is $diag(\lambda_1 \cdots \lambda_M)$, λ_i's being the eigenvalues of $\tilde{M}$, $z = \phi C_1$, and $z_i = (\phi C_1)_i$, $i = 1$,..., M.

Since C_1 is a complex Gaussian vector, so is z conditioned on ϕ. Also, the vectors C_1 and z possess identical statistics since ϕ is unitary. Therefore, conditioned on the eigenvalues, the random variable α is a sum-of-squares of Gaussian random variables and therefore has a known probability distribution.

One would expect the actual distribution of α to be rather complicated since for example the characteristic function of α, conditioned on the eigenvalues, is readily evaluated in the form

$$E\left\{ e^{i\alpha\omega} \middle| \lambda_i,\ i=1,...,M \right\} = \prod_{i=1}^{M} (1 - 2\omega\lambda_i)^{-1} \ . \quad (10)$$

But since the eigenvalues are complicated nonlinear functions of the remaining $N-1$ vectors, $(C_2,C_3,...,C_N)$, the actual characteristic function of α, the average of (10) with respect to the eigenvalues, appears to be intractable. A remarkable discovery, totally unexpected, revealed that the eigenvalues of $\tilde{M}$ are equal to either 1 or zero, with $M-N+1$ eigenvalues equal to 1. This astonishing fact makes it possible to claim that α is Chi-square distributed.

Applying this result in (4), we evaluate explicitly the average probability of error (a more detailed derivation of the results in this section is presented in [7]), i.e.,

$$P_e = E_C\, P_e(C) \le E_C \exp\left\{ -\frac{\rho}{\sigma_a^2} \frac{1}{(C^\dagger C)_{11}^{-1}} \right\}$$

$$= E_\alpha e^{-\frac{\rho}{\sigma_a^2}\alpha} = E_z \exp\left\{ -\frac{\rho}{\sigma_a^2} \sum_{i=1}^{M-N+1} |z_i|^2 \right\}$$

$$= \left[1 + \frac{\rho}{\sigma_a^2}\right]^{-(M-N+1)} \quad . \tag{11}$$

Thus, the average probability of error with optimum combining, M antennas, and N interferers is the same as maximal ratio combining with $M-N+1$ antennas and no interferers [8].

Experiment

To demonstrate and test the interference nulling ability of optimum combining in a fading environment, an experimental system was built. Figure 2 shows a block diagram of the experiment, which consisted of 3 users, a 24 channel Rayleigh fading simulator, 8 receive antennas, and a DSP32C processor at the receiver.

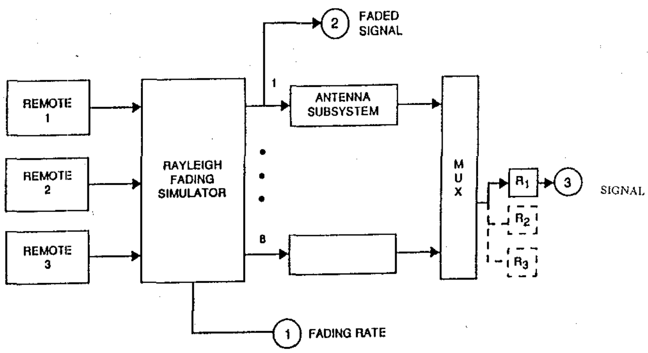

Figure 2 Experimental system.

The three remotes' signals used QPSK modulation, at a common 50 MHz IF frequency, consisting of a biphase data signal and a quadrature biphase signal with a pseudorandom code that was unique to each user. This pseudorandom code was used to generate a reference signal at the receiver that was used to distinguish the desired signal. The fading simulator generated the 8 output signals for the antennas by combining the three remotes' signals with independent flat, Rayleigh fading between each input and antenna output. The fading rate of the simulator was adjustable up to 81 Hz. The outputs of the simulator were demodulated by the 8 antenna subsystems, A/D converted, multiplexed, and input to a DSP32C. This DSP32C used the LMS algorithm [9] to acquire and track one of the remote's signals. With our program in the DSP32C, the maximum weight update rate was 2 kHz, and the data rate was set to 2 kbps for convenience (although any data rate greater than 2 kbps could have been used). The experiment successfully demonstrated the suppression of 2 interferers for a 3-fold capacity increase even with a fading rate of 81 Hz. Note that this corresponds to a data rate to fading rate ratio of 25. In all cases the bit error rate did not exceed 10^{-2}. Noise on the circuitry backplane limited the accuracy of the A/D to 6 bits, which did not allow verification of the 6-fold diversity improvement predicted by (11).

IS-54 Example

To illustrate the application of adaptive antennas to digital mobile radio systems, in this section we consider the proposed TDMA system for mobile radio, IS-54. In this cellular system, 3 remotes communicate with the base station in each 30 kHz channel, at a data rate of 13 kbps per user using DQPSK modulation. Each user's slot contains 324 bits, including a 28 bit synchronization sequence, 12 bit user identification sequence, plus 260 data bits, resulting in a data rate for each channel of 48.6 kbps (24.3 kbaud)[1].

Figure 3 shows a block diagram of the system to be considered.

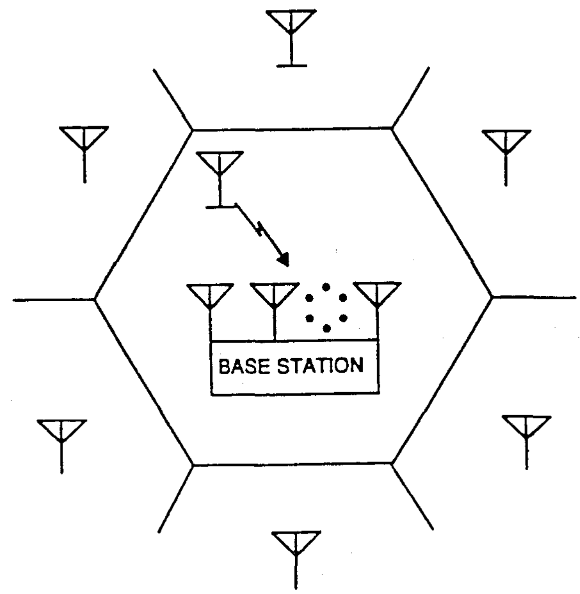

Figure 3 Cellular mobile radio system.

At the base station there are multiple antennas, but only one antenna at each mobile (transmit diversity can be used for the base-to-mobile link [10]). The antennas are positioned such that the fading of each signal at each antenna is independent, which can usually be obtained by spacing the antennas several wavelengths apart at the base station (because in many cases there is a line of sight from the base station to the vicinity of the mobile). At the base station, the received signals are linearly combined to reduce the effects of multipath fading and eliminate interference from other users.

Figure 4 shows a block diagram of the M element adaptive array.

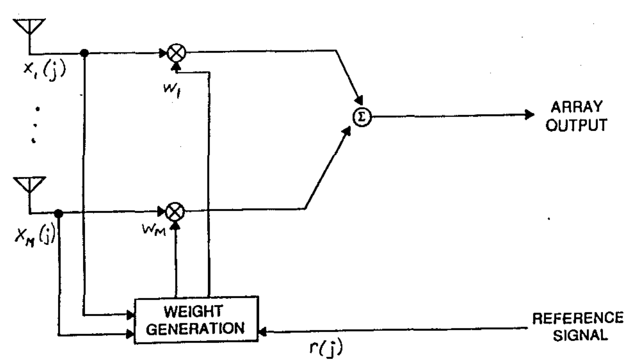

Figure 4 Block diagram of an M element adaptive array.

The signal received by the ith antenna element in the jth symbol interval, $x_i(j)$ is multiplied by the weight w_i, and the weighted signals are then summed to form the array output.

Here, we consider the Direct Matrix Inversion (DMI) algorithm for weight generation. With DMI, the weights are given by

$$\mathbf{w} = \hat{\mathbf{R}}_{xx}^{-1} \hat{\mathbf{r}}_{xd} \tag{12}$$

where

$$\mathbf{w} = [w_1 \cdots w_M]^T \tag{13}$$

where T denotes transpose,

$$\hat{\mathbf{R}}_{xx} = 1/K \sum_{j=1}^{K} \mathbf{x}(j)\mathbf{x}^{\dagger}(j) \tag{14}$$

where K is the number of samples used, and

$$\mathbf{x}(j) = [x_1(j)x_2(j) \cdots x_M(j)]^T \tag{15}$$

and

$$\hat{\mathbf{r}}_{xd} = 1/K \sum_{j=1}^{K} \mathbf{x}(j)r^*(j) \quad , \tag{16}$$

where $r(j)$ is the reference signal in the jth symbol interval.

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 [9], which greatly reduce complexity (to the order of M^2) but have performance that is similar to DMI [9]. 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 the reference signal generation. For weight acquisition, we will use the known 28 bit synchronization sequence as the reference signal, using DMI to determine the initial weights. 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.

With the ideal optimum combining weights, the performance improvement with optimum combining can be calculated directly from our results [summarized in (11)] and from previous papers. Consider the use of differential detection of the DQPSK signal, followed by postdetection combining of the signals from the two antennas. Theoretically, such a system requires a 17.2 dB average signal-to-interference-plus-noise ratio (SINR) to operate at an average bit error rate of 10^{-3}, although slightly higher error rates (and lower SINR) may be acceptable. Maximum ratio combining (which maximizes the signal-to-noise ratio) decreases this by 1.6 dB [8], while optimum combining decreases the average SINR by 3.6 dB [3]. Note that optimum combining reduces the signal-to-noise ratio as compared to maximum ratio combining in order to reduce the interference power and achieve a lower SINR. Three antennas with optimum combining permit a 9.2 dB reduction, which increases to 12.4 dB with 4 antennas and 15 dB with 5 antennas.

In terms of frequency reuse, the average SINR is 18.7 dB with a frequency reuse factor of 7, while the worst case SINR (which occurs when the desired mobile is at the edge of the cell and the interfering mobiles are all as close as possible to the desired mobile's base station) is 14.4 dB [12]. A frequency reuse factor of 4 lowers the SINR to 13.8 (average) and 7.9 dB (worst case), which decreases to 11.3 and 4.3 dB with a frequency reuse factor of 3 and 1.8 and -7.8 dB with frequency reuse in every cell. Thus, with optimum combining at the base station with two antennas, a frequency reuse factor of 4 may be possible except in some worse cases. However, we can avoid the worst cases by using dynamic channel assignment, whereby, the channel of a user is changed if the interference is too strong, i.e., if the adaptive array cannot adequately suppress the interference. Note that the range between the average and worst cases increases as the frequency reuse factor decreases, and thus dynamic channel assignment becomes more useful. Dynamic channel assignment may also permit a frequency reuse factor of 3, which more than doubles the capacity of the mobile to base link, while 4 or 5 antennas may be required for frequency reuse in every cell. Alternatively, we may wish to increase the capacity of only a few congested cells, keeping the frequency reuse factor of 7. In this case we can achieve an M-fold capacity increase for the mobile to base station link by adding M antennas with optimum combining to the base station.

Finally, consider the dynamic performance of optimum combining for interference suppression. To determine the performance of DMI for weight acquisition and tracking 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. 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.

Figure 5 shows the average bit error rate (BER) versus SINR at 0 mph with one interferer with (interference-to-noise ratio) INR = $-\infty$, 0, 3, 6, and 10 dB. DMI with $K=14$ and coherent detection was used. The required SINR for a 10^{-2} BER is 10.2, 9.5, 8.6, and 6.5 dB for INR = 0, 3, 6, and 10 dB, respectively, which is within 0.5 dB of the predicted gain (from [3]).

Figure 6 shows the average BER versus SINR at 60 mph (81 Hz fading rate at 900 MHz) with one interferer. Again, $K=14$ was used since this gave the best results at a 10^{-2} BER. At a 10^{-2} BER these results show a gain with INR that is within 0.5 dB of the predicted gain. 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, i.e., by decreasing K.

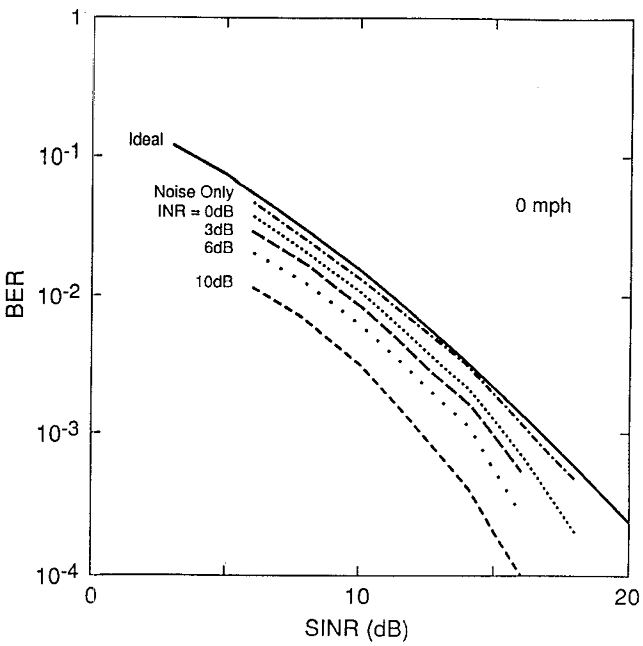

Figure 5 The average BER versus SINR at 0 mph with one interferer.

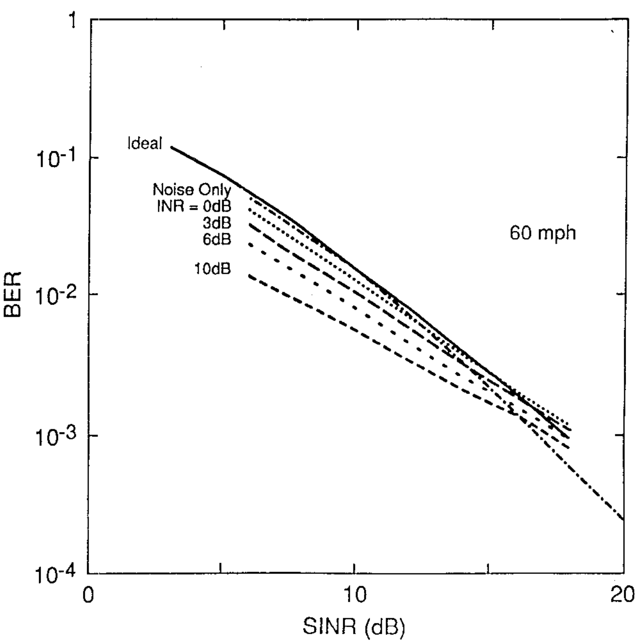

Figure 6 The average BER versus SINR at 60 mph with one interferer.

Conclusions

In this paper, we studied adaptive antenna arrays for digital cellular mobile radio. We first presented theoretical results that show that, with $L+N$ antennas, we can null $N-1$ interferers and achieve an $L+1$-fold antenna diversity gain against multipath fading of the desired signal. Experimental results demonstrated this interference nulling capability. We then presented computer simulation results for the digital mobile radio system IS-54 that show that, with ideal tracking of the desired and interfering signals, an adaptive array with 2 antennas can nearly double the system capacity and with 5 antennas a 7-fold capacity increase can be achieved. Finally, our computer simulation results show that using DMI we can acquire and track the antenna weights to combat desired signal fading and suppress interference with close to ideal performance for vehicle speeds up to 60 mph.

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Biography for Jack H. Winters

Jack H. Winters received his B.S.E.E. degree from the University of Cincinnati, Cincinnati, OH, in 1977 and M.S. and Ph.D. degrees in Electrical Engineering from The Ohio State University, Columbus, in 1978 and 1981, respectively. Since 1981 he has been with AT&T Bell Laboratories, where he is in the Network Systems Research Department. He has studied adaptive signal processing techniques for increasing the capacity and reducing signal distortion in fiber optic, mobile radio, and indoor radio systems and is currently studying adaptive arrays and equalization for mobile radio.