Robust Wireless Location Over Fading Channels

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***Abstract*—This paper develops an estimation algorithm for the time and amplitude of arrival of a known transmitted sequence over a single-path fading channel. The algorithm is optimized to enhance robustness to fast channel fading and low signal-to-noise ratio (SNR) conditions, which are common in wireless location applications. The paper also presents a noise and fading bias correction technique for amplitude of arrival estimation that improves the estimation accuracy significantly. The proposed algorithm is then applied to the case of code-division multiple-access (CDMA) wireless location finding for which the paper gives simulation results that demonstrate significant estimation accuracy improvement over known algorithms.**

***Index Terms*—Amplitude estimation, bias estimation, code-division multiple-access (CDMA), channels, multipath fading, searcher, time-delay estimation, wireless location.**

I. Introduction

WIRELESS location finding has emerged as an essential public safety feature of future cellular systems. This has been emphasized by a recent federal order issued by the federal communications commission (FCC), which mandates all wireless service providers to provide public safety answering points with information to locate an emergency 911 caller with an accuracy of 100 meters for 67% of the cases [1]. It is also expected that the FCC will tighten its requirements in the near future [2]. This has boosted research in the field of wireless location finding (see, e.g., [3]–[10]), which has many other potential applications in areas such as location sensitive billing, fraud protection, mobile yellow pages, and fleet management (see, e.g., [11]–[15]).

Wireless location requires accurate estimates of the time and/or amplitude of arrival of the mobile station (MS) signal when received at various base stations (BSs). As we will see in the next section, obtaining such estimates is usually difficult due to the low signal-to-noise ratios (SNRs)and fast channel fading conditions encountered in wireless propagation environments [2].

Although several estimation procedures already exist in the literature (see, e.g., [10], [16], [17]), these algorithms have originally been designed for signal acquisition or tracking purposes, where coarse estimates for the channel time delays and amplitudes are sufficient for online signal decoding. Using the same algorithms for wireless location applications is not adequate for the following reasons.

1) Channel fading is mainly considered constant during the relatively short estimation period of these algorithms, thus totally ignored. This assumption cannot be made for wireless location applications where the estimation period could be much longer.
2) The low precision of the coarse estimates provided by these algorithms generally does not satisfy the precision levels needed in wireless location applications, especially the FCC requirements.

In this paper, we first develop an efficient algorithm for estimating unknown parameters of a measured transmitted signal over a single-path Rayleigh-fading channel in the presence of additive white Gaussian noise. The algorithm uses a maximum-likelihood interpretation and it combats the effects of high noise levels and fast channel fading conditions. This is achieved by exploiting the fading channel autocorrelation model and an estimate of the maximum Doppler frequency of the channel. The proposed algorithm is then applied to estimate the time and amplitude of arrival of a known CDMA sequence transmitted over a single-path fading channel.

The paper is organized as follows. In the next section, we describe the signal parameter estimates that are needed for several wireless location techniques and the challenges facing the estimation process in each case. In Section III, we formulate the signal parameter estimation problem over a fading channel as a maximum-likelihood estimation problem, and explain why the optimal solution is computationally not feasible in this case. Under some realistic assumptions on the data, the full-blown optimization problem can be reduced to a simpler (sub-optimal) problem that we develop in Section IV. In Section V, we optimize the algorithm parameters and propose a bias correction technique for amplitude estimation. The proposed algorithm is then applied to the case of CDMA location finding in Section VI. Several simulation results are discussed showing remarkable robustness of the proposed algorithm in this case. Section VII studies the sensitivity of the algorithm to errors in the maximum Doppler frequency of the fading channel, which is needed in the estimation process. Conclusions of the paper are given in Section VIII.

II. Parameter Estimation for Wireless Location

Several wireless location techniques have been introduced during the past few years, most of which are based on combining estimates of the time and/or amplitude of arrival of the

Manuscript received December 21, 1999; revised August 2, 2000 and December 21, 2001. The work of N. R. Yousef and A. H. Sayed was supported in part by the National Science Foundation under Awards CCR-9732376, ECS-9820765, and CCR-0208573.

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Digital Object Identifier 10.1109/TVT.2002.807153

mobile station (MS) signal when received at various base stations (BS's). We now briefly review some of these existing techniques and indicate the challenges facing accurate signal parameter estimation in each case.

Time of arrival (TOA) estimates from three or more BSs can be used to obtain a location estimate as follows. First, knowing that wireless signals travel at the speed of light, each TOA estimate can directly be converted to an estimate of the distance between the MS and the corresponding BS forming a circular locus on which the MS may lie and with the BS at its center. The intersection of three of these loci forms a MS location estimate [3]. Such a method requires accurate synchronization between the BS's and MS clocks. Many of the current wireless system standards only mandate tight timing synchronization among BS's (see, e.g., [18]). Another widely-used technique that avoids the need for MS clock synchronization is based on time difference of arrival (TDOA) of the MS signal at two BS's. Each TDOA measurement forms a hyperbolic locus for the MS. Combining two or more TDOA measurements results in a MS location estimate that avoids MS clock synchronization errors, which are cancelled when obtaining TDOA measurements (see, e.g., [19]–[22]).

In both TOA and TDOA methods for wireless location in cellular environments, three or more BSs are involved in the MS location process. In situations where the MS is much closer to one BS (serving site) than the other BSs, the accuracy of these methods is significantly degraded due to the relatively low signal-to-noise ratio (SNR) of the received MS signal at one or more BSs. Such accuracy is further reduced due to the use of power control, which requires the MS to further reduce its transmitted power when it approaches a BS, causing what is known as the *hearability* problem [23]. In these cases, an alternate location procedure is to obtain an angle of arrival estimate (AOA) from the serving site and combine it with either a TOA estimate of the serving site or another AOA estimate from another site (if only two BS's have reasonable received SNR) (see, e.g., [9]).

AOA estimates can be obtained using multibeam antennas, which already exist in current cellular systems, using the technique described in [24].[1] In this technique an estimate of the AOA is obtained based on the difference between the measured signal amplitude of arrival (AmpOA) at the main beam (beam 1) and the corresponding AmpOA measured at the adjacent beam (beam 2).[2] This difference is denoted by $A_1 - A_2$ in Fig. 1, where A_1 and A_2 are the measured amplitude levels in dB). The measured AmpOA at the third beam may be used to resolve any ambiguity that might result from antenna side lobes. One main challenge facing this technique is the relatively low SNR of the received MS signal at the adjacent beam, especially in cases where the AOA is close to a null in the adjacent beam field pattern (e.g., θ close to 0 degrees in Fig. 1). This significantly limits the AmpOA estimation accuracy at the adjacent beam.

[1]Although other methods for estimating the AOA using antenna arrays exist in the literature (see, e.g., [25]), we do not discuss them here as we focus only on wireless location methods that rely only on the current cellular infrastructure.

[2]Here, the main beam denotes the beam with the highest received signal level and the adjacent beam refers to the beam that receives the second highest signal level.

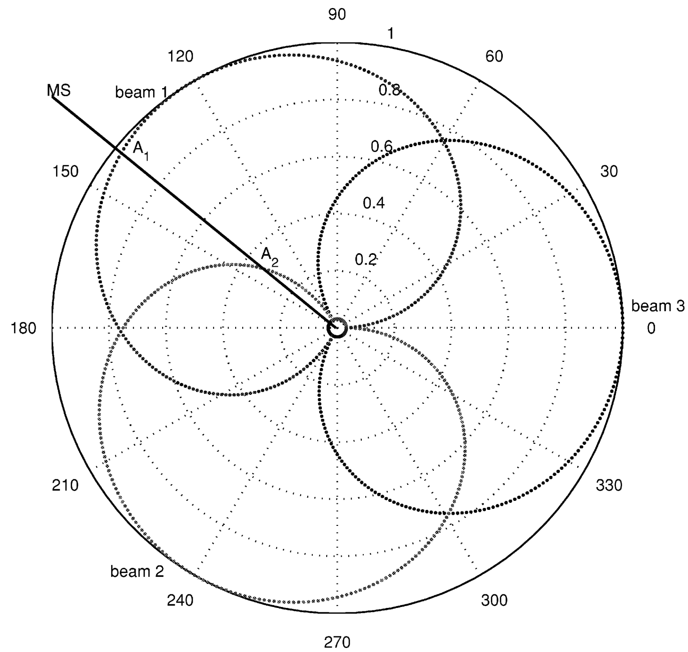

Fig. 1. Measured AmpOA level patterns (in dB) for a three-beam antenna versus the AOA (θ).

Accurate wireless channel parameter estimation is also a great challenge for mobile stations moving at a high speed. This is due to the rapid change in the received signal amplitude and phase that prohibits long signal averaging and accurate AmpOA estimation.

From the above discussion we conclude that in order to achieve high location accuracy, it is necessary to develop an accurate estimation technique for the received signal time and amplitude of arrival. This technique needs to be robust to both low SNR levels (encountered at BS's far from the MS or adjacent antenna beams) and to fast channel fading conditions. In the remainder of the paper, we develop one such technique.

III. Problem Formulation

Thus consider the problem of estimating an unknown delay τ^o of a known real-valued sequence $\{s(n,\tau^o)\}$ transmitted over a single path time varying channel,[3] from a measured sequence $\{r(n)\}_{n=1}^{K}$ that arises from the model

$$r(n) = A\, x^o(n)\, s(n,\tau^o) + v(n) \tag{1}$$

where $v(n)$ is additive white Gaussian noise, and $x^o(n)$ is a complex ergodic random process of known autocorrelation function $R_x(i)$ defined as

$$R_x(i) = \mathrm{E}\, x^o(n) x^o(n-i)$$

The sequence $\{x^o(n)\}$ accounts for the time-varying nature of the *fading* channel gain over which the sequence $\{s(n,\tau^o)\}$ is transmitted, while A is a constant *unknown* received signal amplitude that accounts for both the gain of the *static* channel if fading were not present and the antenna beam gain. Without loss of generality, we will assume that the sequence $\{x^o(n)\}$ has unit

[3]By a known sequence $\{s(n,\tau^o)\}$ we mean one for which the *dependency* on n and τ^o is known. The actual sequence itself does not need to be known. This means that only the parameter τ^o is unknown.

variance, i.e., $R_x(0) = 1$. The maximum likelihood (ML) estimates of $\{\tau^o, x^o(n)\}$ are defined by (see, e.g., [26])

$$\{\hat{\tau}, \hat{x}(n)\} = \arg \max_{\{\tau, x(n)\}} \left[P\left(r(1), \ldots, r(K) | \{\tau, x(n)\}\right)\right]$$

where the likelihood function $P(r|\{\tau, x(n)\})$ is of the form

$$C_1 \exp\left(-C_2 \frac{1}{K} \sum_{n=1}^{K} |r(n) - A\, x(n)\, s(n,\tau)|^2\right)$$

and C_1 and C_2 are positive constants that are independent of the unknowns $\{\tau, x(n)\}$. Thus, the ML estimates of $\{\tau^o, x^o(n)\}$ are given by

$$\{\hat{\tau}, \hat{x}(n)\} = \arg \max_{\{\tau, x(n)\}} \left[J_{\mathrm{ML}}\left(\tau, x(n)\right)\right]$$

where the cost function J_{ML} is defined by

$$J_{\mathrm{ML}}\left(\tau, x(n)\right) = \frac{2A}{K} \sum_{n=1}^{K} s(n,\tau) \mathrm{Re}\left(r(n) x^*(n)\right) - \frac{A^2}{K} \sum_{n=1}^{K} |x(n)|^2 s^2(n,\tau) \quad (2)$$

This construction requires an infinite dimensional search over $\{\tau, x(n)\}$, and is not feasible in practice even when τ and $x(n)$ are evaluated over a dense grid, which is generally the approach adopted in ML estimation over single path static channels (see, e.g., [16]).

IV. Proposed Estimator

We now develop an efficient ML estimator that requires a finite number of search bins. To arrive at this estimator, we make assumption A.1) in the case of slow channel variation as follows.

A.1) $x^o(n)$ is piecewise constant over intervals of N samples.

This means that fading is constant for every consecutive N samples. In other words, the first N samples have the same fading coefficient, while the following N samples have a different fading coefficient and so on. Here, N is a parameter that should clearly depend on the environment conditions. An optimal choice for N that is based on the available knowledge of the channel autocorrelation function $R_x(i)$ is discussed in the next section.

Now introduce a sequence $\{x^u(m)\}$ that is an N under-sampled version of $\{x^o(n)\}$, i.e.,

$$x^u(m) = x^o\left((m-1)N + 1\right)$$

for $m = 1, 2, \ldots, M$, where $M = K/N$ is assumed to be an integer. Using A.1) and (1), expression (2) becomes

$$J_{\mathrm{ML}} = \frac{1}{K} \sum_{m=1}^{M} A^2 \left[\left(x^{u*}(m) x(m) + x^u(m) x^*(m)\right) \times \left(\sum_{M}^{mN} s(n,\tau^o) s(n,\tau) \right) - |x(m)|^2 \left(\sum_{n=n_o}^{mN} s^2(n,\tau) \right) \right]$$

where $n_o = (m-1)N + 1$. Differentiating J_{ML} with respect to $x(m)$ and setting the derivative equal to zero we arrive at the conclusion that $\partial J_{\mathrm{ML}} / \partial x(m) = 0$ for

$$x(m) = \frac{\sum_{n=n_o}^{mN} s(n,\tau^o) s(n,\tau)}{\sum_{n=n_o}^{mN} s^2(n,\tau)} x^u(m).$$

In this case, the value of the cost function becomes

$$J_x(\tau) \triangleq \frac{1}{K} \sum_{m=1}^{M} A^2 |x^u(m)|^2 \frac{\left[\sum_{n=n_o}^{mN} s(n,\tau^o) s(n,\tau)\right]^2}{\sum_{n=n_o}^{mN} s^2(n,\tau).}$$

If we assume the sequence $\{s(n)\}$ to be ergodic and that N is large enough such that

$$\sum_{n=n_o}^{mN} s^2(n,\tau) = N R_s(0) \quad \text{for every } m$$

the maximization of $J_x(\tau)$ over τ reduces to maximizing the following cost function over τ:

$$J_1(\tau) \triangleq \frac{1}{K} \sum_{m=1}^{M} A^2 |x^u(m)|^2 \left[\sum_{n=n_o}^{mN} s(n,\tau^o) s(n,\tau) \right]^2.$$

We can now move the factor $A^2 |x^u(m)|^2$ inside the squared correlation term in the expression for $J_1(\tau)$ above. That is, using A.1) and (1), we easily find that

$$\begin{aligned} J_1(\tau) &= \frac{1}{K} \sum_{m=1}^{M} \left| \sum_{n=n_o}^{mN} A x^o(n) s(n,\tau^o) s(n,\tau) \right|^2 \\ &= \frac{1}{K} \sum_{m=1}^{M} \left| \sum_{n=n_o}^{mN} \left(r(n) s(n,\tau) - v(n) s(n,\tau)\right) \right|^2 \end{aligned}$$

To arrive at a feasible algorithm, we further make assumption A.2).

A.2) The partial cross correlation of $v(n)$ and $s(n,\tau)$ over N samples is considerably smaller than the partial autocorrelation of $s(n,\tau)$ over the same interval.

This assumption is practical since $v(n)$ and $s(n,\tau)$ are independent. In fact, it becomes true as N and $K \to \infty$. However, if N is small, the cross-correlation of $v(n)$ and $s(n,\tau)$ can introduce an additive bias term in the cost function. This bias will be studied in the next section. Note also that for practical values of M (which do not go to infinity), that bias will be stochastic in nature and will have a variance that decreases with N^2. This stochastic nature can lead to errors in the TOA estimation. For optimal estimation accuracy, the value of N should be chosen such that this bias variance (or power) is minimized with respect to the signal power. In the next section, we will select an optimal value of N based on this criterion.

Using A.2), our maximization problem is equivalent to maximizing the cost function

$$J(\tau) \triangleq \frac{1}{M} \sum_{m=1}^{M} \left| \frac{1}{N} \sum_{n=n_o}^{mN} r(n) s(n,\tau) \right|^2. \quad (3)$$

Thus, the optimal ML estimate for τ^o, when A.1 and A.2 hold, and for sufficiently large K, becomes

$$\hat{\tau} = \arg \max_{\tau} \frac{1}{M} \sum_{m=1}^{M} \left| \frac{1}{N} \sum_{n=n_o}^{mN} r(n) s(n,\tau) \right|^2. \quad (4)$$

A practical scheme for implementing (4) involves the following operations. A grid of τ values, say $\{\tau_1, \tau_2, \ldots, \tau_F\}$, is chosen and the correlation of the received sequence $\{r(n)\}$ with replicas $\{s(n,\tau_i\}$ are computed. We can see that this scheme only requires a one dimensional search, which is dramatically

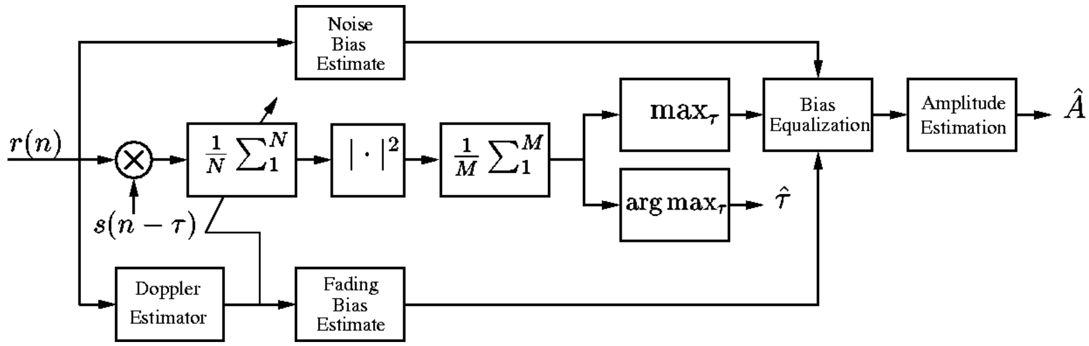

Fig. 2. The proposed time-delay estimation scheme for single-path fading channels.

simpler than the original ML estimator given in (2). We will term the correlation operation

$$\frac{1}{N}\sum_{n=n_o}^{mN} r(n)s(n,\tau)$$

coherent integration or coherent averaging since the phase of the samples of the sequence $\{r(n)s(n,\tau)\}$ is kept during this averaging process. In contrast, we will term the averaging operation over the M partial correlations

$$\frac{1}{M}\sum_{m=1}^{M} |\cdot|^2$$

noncoherent integration or noncoherent averaging since the phase of each of the correlation samples is removed by squaring before performing the averaging operation.

While this is not the ultimate scheme that we shall propose in this paper (see Fig. 2), we should mention that similar schemes have been used before in implementing CDMA channel searchers [27]. These schemes were designed to provide prompt channel estimates for online bit decoding and they cannot be used for wireless location applications for the following reasons:

1) The coherent integration period was limited to the symbol period (Number of samples per Walsh symbol, for IS-95 standards), which corresponds to N equal to the number of samples per symbol (N is equal to 64 multiplied by the number of samples per chip for IS-95 systems). In wireless location applications, coherent averaging can be extended far beyond the symbol interval.[4] Furthermore, we will show that in order for A.1) and A.2) to hold simultaneously, a careful choice of N should be made. In the next section, we derive an optimal value for N that would maximize the estimation accuracy of the algorithm.
2) Channel fading can be assumed constant during the relatively short estimation period of channel searchers, and is therefore totally ignored. On the other hand, location searchers use a much longer estimation period, which requires the searcher parameters to be adapted to an estimate of the channel maximum Doppler frequency as we will show in the next section.
3) Furthermore, we will introduce a bias correction technique for amplitude estimation that is not needed for channel searchers due to their relatively short estimation period during which the channel changes are not significant. The correction step, however, is necessary for wireless location applications.

After all is said and done, we shall arrive at the structure shown in Fig. 2. Here, we see that there are two bias estimation blocks and the value of N is adapted in accordance with the fading nature of the channel. We shall show in the next section how these blocks are designed and how N is chosen. Simulation results that we provide in Section VI will show a very significant performance enhancement of such scheme over conventional channel searchers.

V. Parameter Optimization and Amplitude Estimation

Up till now, we have shown that the maximum likelihood estimate of the TOA, τ^o, can be obtained using (4). We now finalize the proposed algorithm by providing a design equation for the parameter N. We also show how to estimate A by a simple peak picking operation, having the estimate for τ^o, from (4), in hand. In the following analysis, *assumptions* A.1 *and* A.2 *are not used*. Although these assumptions were used in deriving the estimation scheme, ignoring them in the following analysis will help us achieve the following goals: 1) Performance evaluation of the estimation scheme when assumptions A.1 and A.2 do not hold. 2) Arriving at an optimal value of the design parameter N. 3) Deriving an accurate estimation scheme for estimating the received signal amplitude A.

We will consider the case of an infinite received sequence length $(M \to \infty)$.[5] Thus, $J(\tau)$ in (3) becomes, by the law of large numbers

$$J(\tau) = E\left|\frac{1}{N}\sum_{n=1}^{N} r(n)s(n,\tau)\right|^2$$

[4]In wireless location applications, the received bits can be assumed to be known. This could be achieved by using known transmitted training sequences as in [23]. Another way is to use only received frames of perfect cyclic redundancy check (CRC) or to use the output decoded bits of the Viterbi decoder, which are at a high level of accuracy. This results in a delay of one frame period (20 ms for IS-95 systems), which is affordable for wireless location applications.

[5]This is a reasonable assumption for wireless location applications, where the estimation period can be on the order of a fraction of a second.
Note that in practice the total integration period, i.e. $K = NM$ is fixed. However, in this paper, we have only analyzed the case for the optimum N value. In general jointly optimizing N and M for a fixed duration K needs to be done. However, for large K values our method for determining N becomes optimum.

in terms of the expectation operator E. Using (1), one obtains

$$J(\tau) = E\left|\frac{1}{N}\sum_{n=1}^{N}(Ax^o(n)s(n,\tau^o)s(n,\tau) + v'(n,\tau))\right|^2 \quad (5)$$

where $v'(n,\tau) = v(n)s(n,\tau)$.

For mathematical tractability of the analysis, we impose the following assumption:

A.3) The sequence $\{s(n,\tau^o)\}$ is identically statistically independent (i.i.d), and is independent of the channel fading gain sequence $\{x^o(n)\}$.

Then, it can be shown (see Appendix A) that at $\tau = \tau^o$, the cost function $J(\tau^o)$ is given by

$$\dot{J}(\tau^o) = A^2\left(\frac{R_x(0)}{N} + \sum_{i=1}^{N-1}\frac{2(N-i)R_x(i)}{N^2}\right) + \frac{\sigma_v^2}{N} \quad (6)$$

where σ_v^2 is the variance of the noise term $v(n)$.

A. Optimal Coherent Integration

Equation (6) shows that as $M \to \infty$, the value of the cost function at $\tau = \tau^o$ is composed of two terms. The first term is proportional to A^2, while the second term is proportional to σ_v^2. Thus, a performance index that we can maximize is the signal-to-noise ratio (SNR), defined as the ratio of the signal and noise terms at $\tau = \tau^o$. This SNR (S) is given, from (6), by

$$S = \frac{A^2}{\sigma_v^2}\left(R_x(0) + \sum_{i=1}^{N-1}\frac{2(N-i)R_x(i)}{N}\right)$$

The SNR at the input of our scheme is A^2/σ_v^2. Thus, the SNR gain introduced by the algorithm (S_G) is given by

$$\begin{aligned} S_G &= \frac{S}{\frac{A^2}{\sigma_v^2}} \\ &= R_x(0) + \sum_{i=1}^{N-1}\frac{2(N-i)R_x(i)}{N} \end{aligned} \quad (7)$$

Fig. 3 is a plot of the SNR gain given by (7) versus N for a Rayleigh-fading channel, for which the autocorrelation function of the sequence $\{x^o(n)\}$, $R_x(i)$, is given by (see, e.g., [28]):

$$R_x(i) = J_o\left(2\pi f_D T_s|i|\right)$$

where $J_o(\cdot)$ is the first order Bessel function, T_s is the sampling period of the received sequence $\{r(n)\}$, and f_D is the maximum Doppler frequency of the Rayleigh-fading channel, which is directly related to the MS speed (v) and the carrier frequency f_c by

$$f_D = \frac{vf_c}{C}$$

where C denotes the speed of light. The plot of Fig. 3 is shown for several values of f_D. It can be seen that, for each f_D, there is a value of the coherent integration period, $N_{\rm opt}$, that maximizes the SNR gain. Increasing N beyond this optimum value, the SNR gain oscillates and then asymptotically approaches a fixed value that depends on f_D. We can also see that the optimal value of N decreases monotonically with f_D. Here we may add that although one would expect the signal power at the output of the estimation scheme to go to zero when N goes to infinity due to fading phase rotation, the SNR gain does not go to zero. This is because the noise power at the output of the estimation scheme also goes to zero at the same rate as N goes to infinity. Thus the SNR gain, which is the ratio between the signal and noise powers becomes insensitive to increasing N.

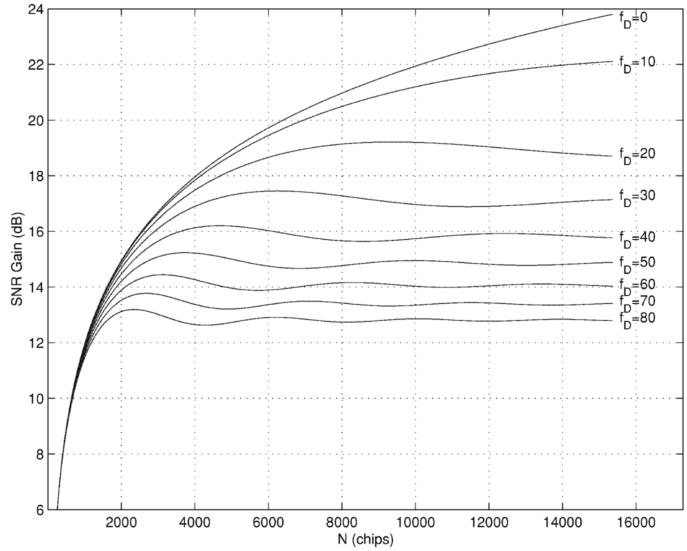

Fig. 3. SNR gain versus the coherent integration period N for a single-path Rayleigh-fading channel (f_D in Hz).

The optimal value of the coherent averaging period $(N_{\rm opt})$ is obtained by maximizing the SNR gain given in (7) with respect to N. Thus, $N_{\rm opt}$ is computed by equating

$$\frac{dS_G}{dN} = \sum_{i=1}^{N_{\rm opt}-1}\frac{2(N_{\rm opt}-i)R_x(i) - 2N_{\rm opt}R_x(i)}{N_{\rm opt}^2}$$

to zero, which directly leads to the equation[6]

$$\sum_{i=1}^{N_{\rm opt}-1} iR_x(i) = 0. \quad (8)$$

This shows that the coherent integration interval N *should be adapted* based on the available knowledge of the channel according to (8). For a Rayleigh-fading channel, we need only to estimate the MS speed, which can be obtained using many well-known techniques (see, e.g., [29]).

B. Amplitude Estimation

We will now use this analysis to obtain an accurate estimate of the amplitude A. Equation (6) shows that the amplitude of the output of our proposed estimation algorithm suffers from two biases. The first bias is an additive noise bias that increases with the noise variance. This bias is caused by noncoherent integration. Had we not squared the correlation term in (3), the effect of this noise bias would have been averaged out. This noise bias is given by

$$B_n = \frac{\sigma_v^2}{N} \quad (9)$$

and it vanishes as $N \to \infty$. The second bias is a multiplicative fading bias that arises from coherent averaging. If N were

[6]Here we assumed N to be a continuous variable. The optimal value $N_{\rm opt}$ is then chosen to be the closest integer to the zero crossing of dS_G/dN.

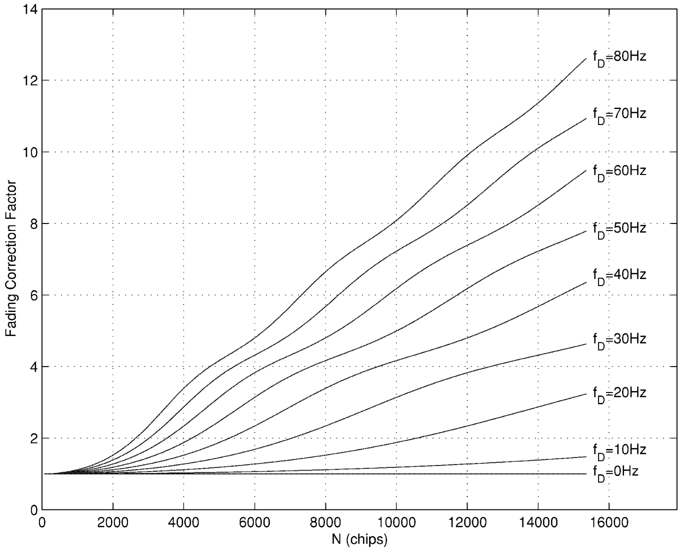

Fig. 4. Fading correction factor C_f versus f_D for a single-path Rayleigh-fading channel.

one, this term would have been constant and equal to unity (i.e., $B_f = R_x(0) = 1$). This fading bias is given from (6) by

$$B_f = \frac{R_x(0)}{N} + \sum_{i=1}^{N-1} \frac{2(N-i)R_x(i)}{N^2}. \tag{10}$$

It is clear that this multiplicative fading bias is less than or equal to unity (it is unity for static channels, which explains why previous conventional designs ignored this bias as fading was not considered in these designs—see [16]). The value of B_f is also unity for $N = 1$. This bias is due to phase misalignment of the complex channel coefficients at different time instants, which leads to a degradation in the coherent integration output. This multiplicative bias decreases with increasing f_D. In other words, the effect of this bias is enhanced with increasing f_D. For our purposes, it is more convenient to work with the inverse of B_f, say $C_f = 1/B_f$, i.e.,

$$C_f = \left[\frac{R_x(0)}{N} + \sum_{i=1}^{N-1} \frac{2(N-i)R_x(i)}{N^2}\right]^{-1}. \tag{11}$$

We shall refer to C_f as the fading correction factor. Fig. 4 plots C_f versus f_D for a Rayleigh-fading channel. It is clear that the need for this correction factor increases for higher Doppler frequencies.

If $\{B_n, C_f\}$ were known, then A could be obtained from (6) via

$$A = \sqrt{C_f \left[J(\tau^o) - B_n\right]}.$$

Obtaining accurate estimates for B_n and C_f is actually feasible in practical applications. A successful application for this correction technique is given in the next section in the context of CDMA location finding. We may also add that neither of these correction factors is needed for the estimation of τ^o.

VI. The CDMA Case

In the algorithm derivation we have presented so far, we did not pose any restrictions on the transmitted sequence $\{s(n, \tau^o)\}$. We now specialize our algorithm to the case of CDMA systems.[7] In this case, the transmitted sequence is a pulse-shaped pseudo noise (PN) binary sequence.

The value of C_f can be found from (11) by using the values of the channel auto-correlation sequence.[8] Moreover, since for CDMA signals the received SNR (chip energy-to-noise ratio E_c/N_o) is typically small and ranges from -17 dB at the main beam of the serving site to -40 dB at other sites or beams involved in the MS location process, the value of B_n can be estimated as follows. First, the noise variance σ_v^2 can be estimated *directly* from the received sequence $\{r(n)\}$ as

$$\widehat{\sigma_v^2} = \frac{1}{K_n} \sum_{i=1}^{K_n} |r(i)|^2$$

for some value $K_n \le K$. Here, we focused on reverse-link wireless location, where the MS signal parameters are estimated by various BSs. Then, an estimate for B_n is given, from (9), by

$$\widehat{B}_n = \frac{\widehat{\sigma_v^2}}{N} = \frac{1}{NK_n} \sum_{i=1}^{K_n} |r(i)|^2. \tag{12}$$

With $\{\widehat{B}_n, C_f\}$ so computed, we obtain an estimate for A via the expression

$$\widehat{A} = \sqrt{C_f \left[J(\widehat{\tau^o}) - \widehat{B}_n\right]} \tag{13}$$

Table I summarizes our estimation algorithm for the case of CDMA location finding.

A. Simulation Results

Figs. 6 and 7 show the estimation mean absolute TOA error and the AmpOA mean square error versus the received signal chip energy-to-noise ratio over a Rayleigh-fading channel for $M = 128$ and various values of the maximum Doppler frequency.

Fig. 5 compares the mean absolute time-delay estimation error of a conventional IS-95 searcher [16] with our proposed location searcher. The conventional searcher obtains an estimate of the TOA by multiplying the received sequence with replica of transmitted code sequence at various delays. The output of each despreading operation is coherently averaged over the symbol interval (Walsh symbol period), squared to get rid of bit ambiguity and noncoherently averaged afterwards over a frame duration (20 ms for IS-95). The searcher then picks the maximum of the various outputs and assigns its corresponding delay to the TOA estimate, and the square root of its value to the AmpOA estimate. The simulation results are given for $f_D = 40$ Hz, and various values of E_c/N_o. It is clear from these results that the mean absolute TOA error of the conventional acquisition technique is significant and in fact does not meet the FCC requirements. It is also clear from the figure that our proposed location searcher outperforms the conventional technique significantly even for very low values of M. We can also notice that increasing the value of M increases the accuracy of our technique considerably. However,

[7]Here, we may add that many location techniques for other TDMA cellular systems (see, e.g., [30], [31]), and which were originally designed for static channels, can directly be extended to fading channels by using our proposed framework.

[8]When f_D is estimated, we actually end up with an estimate for C_f.

TABLE I
LISTING OF THE PROPOSED ALGORITHM FOR ESTIMATING TIME AND AMPLITUDE OF ARRIVAL; OVER A SINGLE-PATH RAYLEIGH-FADING CDMA CHANNEL

Given a received sequence $\{r(n)\}_{n=1}^{K}$

$$r(n) = A\, x^o(n) s(n, \tau^o) + v(n)$$

an estimation algorithm for the time and amplitude of arrival (τ^o, A) that maximizes the signal-to-noise ratio gain at the output of the estimation scheme is given as follows:

1. Use the auto-correlation sequence $R_x(i)$ of the channel to determine the value N_{opt} that satisfies

$$\sum_{i=1}^{N_{opt}-1} i R_x(i) = 0$$

This may require an initial step for estimating the Doppler frequency f_D if $R_x(i)$ is not known.

2. Let $M = K/N_{opt}$ and evaluate the cost

$$J(\tau) = \frac{1}{M} \sum_{m=1}^{M} \left| \frac{1}{N_{opt}} \sum_{n_o=(m-1)N_{opt}+1}^{mN_{opt}} r(n) s(n, \tau) \right|^2$$

over a grid of values $\{\tau_i\}$. Pick the maximizing value

$$\hat{\tau} = \arg\max_{\tau} J(\tau)$$

and the resulting maximum cost $J(\hat{\tau})$.

3. Choose $K_n \leq N_{opt} M$ and compute the estimates

$$\widehat{\sigma_v^2} = \frac{1}{K_n} \sum_{i=1}^{K_n} |r(i)|^2 \qquad \widehat{B}_n = \frac{\widehat{\sigma_v^2}}{N_{opt}}$$

$$C_f = \left[\frac{R_x(0)}{N_{opt}} + \sum_{i=1}^{N_{opt}-1} \frac{2(N_{opt} - i) R_x(i)}{N_{opt}^2} \right]$$

4. Then set

$$\hat{A} = \sqrt{C_f \left(J(\hat{\tau}) - \widehat{B}_n \right)}$$

this value is dictated by the duration the 911 caller stays online. Furthermore, it is also limited by the speed at which the caller is moving. The total estimation time should be chosen such that the position of the caller does not significantly vary during the estimation period causing parameter drift.

Fig. 8 compares the amplitude estimation MSE results of the conventional channel estimation technique used in current IS-95 searchers and our proposed location searcher for various values of (N, M). The simulation results are given for $f_D = 80$ Hz and various values of E_c/N_o with fading correction only. We can see from the results that the amplitude MSE of the conventional channel estimation technique is considerably larger than that of our technique. We can also notice that increasing the value of M increases the accuracy of our technique considerably.

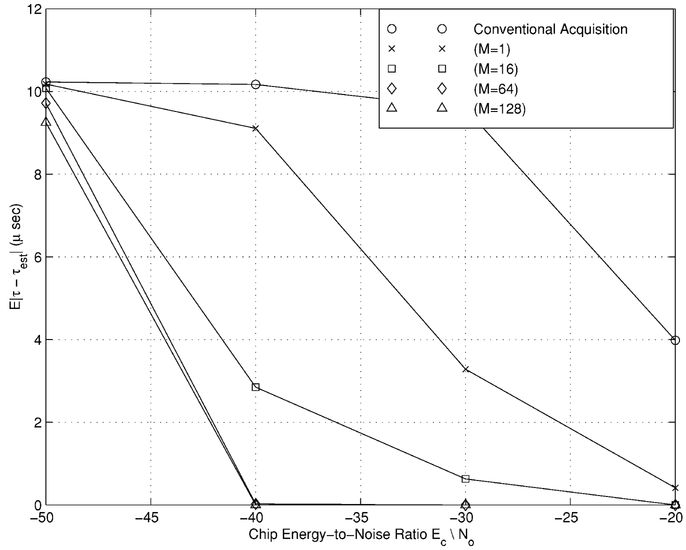

Fig. 5. Mean absolute TOA estimation error versus E_c/N_o for $f_D = 40\ Hz$ and $N = N_{\rm opt} = 4608\ chips$.

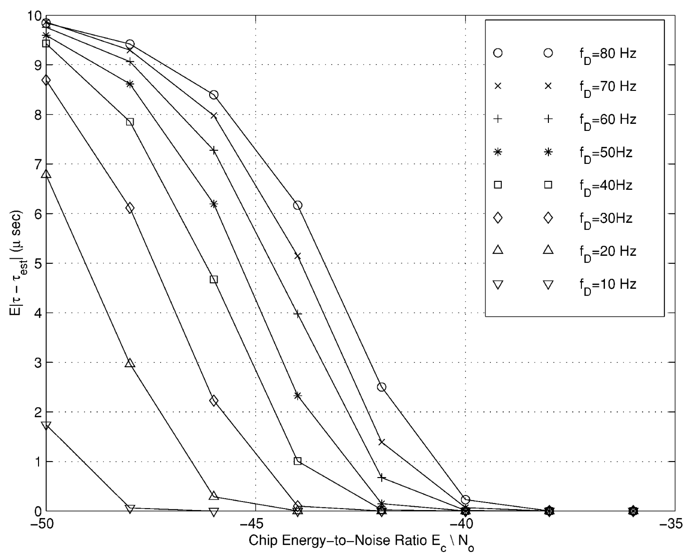

Fig. 6. Mean absolute TOA error versus E_c/N_o over a Rayleigh-fading channel with noncoherent integration interval length $M = 128$.

In order to appreciate the effect of the amplitude bias correction technique, the AmpOA MSE is plotted in Fig. 9 versus E_c/N_o with and without each of the two correction factors at $f_D = 80$ Hz. It is seen that noise correction only is not enough for high chip energy-to-noise ratios. This is due to the fact that at very low noise levels, the noise bias becomes negligible with respect to the fading bias. It is also seen that for very low chip energy-to-noise ratios, the uncorrected amplitude estimate is more precise than the corrected estimate. This is explained as follows. At very low chip energy-to-noise ratios, the error in noise estimation is boosted up by the fading correction factor causing more errors in the estimate. However, the estimation error in this region is very large and is not of interest. It is clear from the

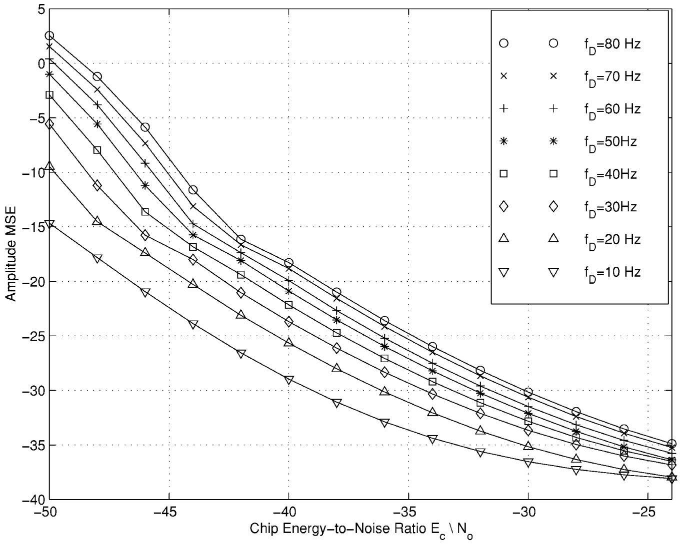

Fig. 7. AmpOA MSE error versus E_c/N_o over a Rayleigh-fading channel with noncoherent integration interval length $M = 128$.

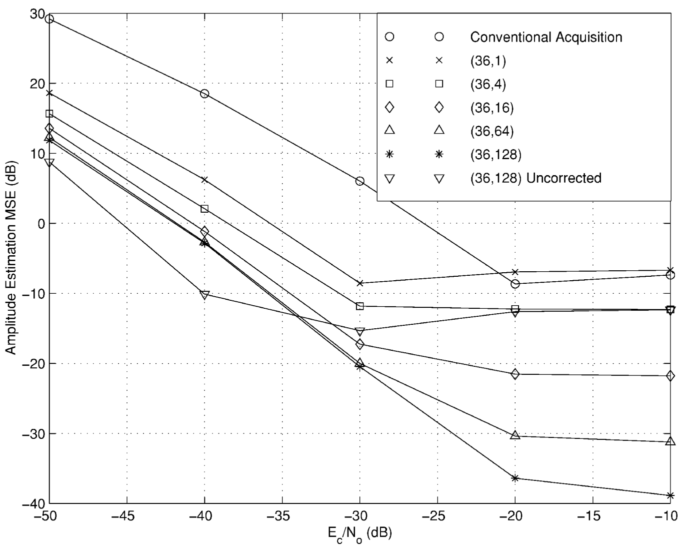

Fig. 8. AmpOA estimation MSE error versus E_c/N_o for $f_D = 80\ Hz$ and various values of (N, M) over a Rayleigh-fading channel.

figure that the proposed correction technique improves the precision of the AmpOA estimate significantly. Field trial results of the proposed algorithm are given in [32].

VII. Sensitivity to Doppler Estimation Errors

The simulation results given in the previous section assume perfect knowledge of the maximum Doppler frequency f_D. In this section, the effects of maximum Doppler frequency estimation errors on the precision of the TOA and AmpOA estimators are shown. It was mentioned in Section III that the SNR gain becomes approximately insensitive to N when it increases beyond its optimal value. Thus, only a *coarse* estimate of the maximum Doppler frequency is needed for the TOA estimation. Of course, a relatively large error in the maximum Doppler frequency would cause an error in N_{opt}. On the other hand, a relatively accurate maximum Doppler frequency estimate is needed for precise amplitude estimation. This is due to the need for the amplitude fading correction factor.

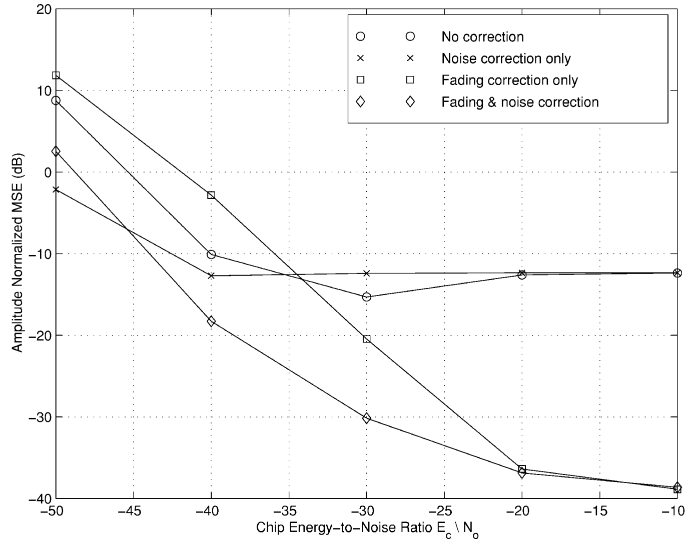

Fig. 9. Effect of Doppler estimation errors on amplitude estimation.

The amplitude estimation error, $|\Delta A_{f_D}|$, due to an error $|\Delta f_D|$ in the maximum Doppler frequency estimate, is given from (12) by

$$|\Delta A_{f_D}| = \left| A - \sqrt{C'_f \left[J(\tau^o) - B_n\right]} \right| \tag{14}$$

where C'_f is the fading correction factor calculated for an estimated maximum Doppler frequency $(f_D + \Delta f_D)$, and f_D is the actual maximum Doppler frequency. Here, we assumed no errors in the TOA estimate. The absolute normalized amplitude estimation error is then

$$\left| \frac{\Delta A_{f_D}}{A} \right| = \left| 1 - \sqrt{\frac{C'_f}{C_f}} \right| \tag{15}$$

where C_f is the fading correction factor calculated at the actual maximum Doppler frequency f_D. Fig. 10 shows the absolute relative amplitude error percentage versus the relative maximum Doppler frequency error percentage for different values of f_D. It is shown in the figure that the absolute relative amplitude error increases by approximately 0.5% for every 1% increase in the relative maximum Doppler frequency error. It is also seen that the amplitude estimate sensitivity to maximum Doppler frequency errors does not change significantly with the value of f_D. This indicates that the proposed estimation scheme is robust to errors in the maximum Doppler frequency estimation, so that a rough estimate of the MS speed would be adequate to obtain a reasonable accuracy in the TOA/AmpOA estimation process.

VIII. Conclusion

In this paper we developed an estimation strategy for the time and amplitude of arrival of a known transmitted sequence over a single-path fading channel in the presence of additive white Gaussian noise for wireless location purposes. The algorithm is

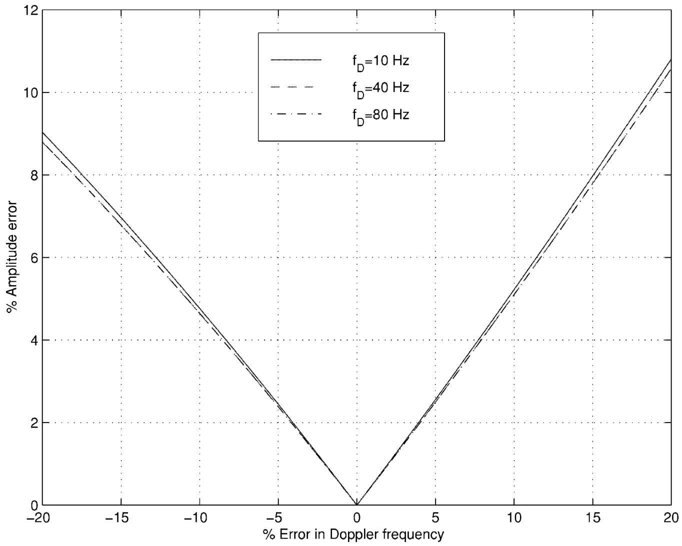

Fig. 10. AmpOA MSE with and without biases correction.

based on exploiting known channel information and a maximum Doppler frequency estimate to optimize the algorithm parameters in an adaptive manner. We also presented a bias correction technique for amplitude estimation. The algorithm was further specialized for CDMA signals and we presented simulation results that showed remarkable robustness of the proposed method to fast fading and high-noise levels.

APPENDIX A

Consider a transmitted sequence $\{s(n)\}$ of the form

$$s(n) = c(n) \star p(n)$$

where the symbol "$\star$" denotes the convolution operation, $c(n)$ is a binary sequence, and $p(n)$ is the wireless system pulse-shaping waveform. In order to obtain a compact representation, we assume that the variations in the channel gain sequence $\{x^o(n)\}$ within the duration of the pulse-shaping waveform, are negligible. This assumption is feasible for wireless systems even for fast channels. Then we can write

$$\begin{aligned} B &\triangleq \frac{1}{N}\sum_{n=1}^{N}\{Ax^o(n)s(n,\tau^o)s(n,\tau)\} \\ &= \frac{1}{N}\sum_{n=1}^{N}\{[Ax^o(n)c(n-\tau^o)\star p(n-\tau^o)] \\ &\quad \cdot [c(n-\tau)\star p(n-\tau)]\}\end{aligned}.$$

We can rewrite this autocorrelation in a convolution form as

$$B = \frac{A}{N}x^o(-n)c(-n+\tau^o)\star p(-n+\tau^o)\star c(n-\tau)\star p(n-\tau).$$

Using the properties of the convolution operation, we have

$$B = \frac{A}{N}R_p(\tau-\tau^o)x^o(-n)c(-n+\tau^o)\star c(n-\tau)$$

where $R_p(i)$ is the autocorrelation function of $p(n)$. Rewriting this term back as a correlation sum, we get

$$B = \frac{1}{N}\sum_{n=1}^{N} AR_p(\tau-\tau^o)x^o(n)c(n-\tau^o)\cdot c(n-\tau)$$

At $\tau = \tau^o$ and for a binary sequence $c(n)$, we have

$$B = \frac{1}{N}\sum_{n=1}^{N} Ax^o(n)$$

where we assumed, without loss of generality, that the pulse-shape waveform is normalized such that $R_p(0) = 1$. Substituting in (5), we obtain

$$J(\tau^o) = E\left|\frac{1}{N}\sum_{n=1}^{N}(Ax^o(n) + v'(n,\tau))\right|^2$$

Expanding the sum over n, squaring, applying the expectation operator, and using A.3), expression (6) directly follows.

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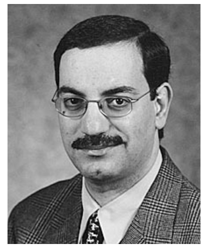

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