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Multiuser Channel Measurements For Wireless Localization

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Abstract

While transmitting information over multipath channels, multiple access interference cannot be easily eliminated. However, it is possible to design detectors that estimate the channel parameters accurately. The conventional detector may be unable to recover the transmitted information from the weaker users. The need for accurate parameter estimates in the presence of multiple access interference (MAI) has led the development of joint multiuser detectors/parameter estimators. These estimates are subsequently used for subscriber location estimation. Accurate and cost effective cellular localization would enable a diverse variety of new applications in the areas of tracking and tracing, access to emergency services, increased safety, monitoring, leisure, sports and entertainment. In this paper, the detector based on divided difference Kalman filter (DDF) algorithm in a closely spaced multipath fading channel is being investigated and analyzed for asynchronous direct-sequence (CDMA). The estimated delay is used to radio location purposes. The numerical analysis augmented by extensive simulations show that the proposed DDF based detector is simpler to implement, and more resilient to near-far interference in CDMA networks and is able to track closely spaced paths.

***Index Terms*—**CDMA Channel Estimation, Multiple Access Interference, multiuser detection, Non-linear state estimation, Kalman filters.

Introduction

In recent years, a lot of effort has been put in developing powerful channel estimation algorithms. In the real world wireless communication systems, the transmitted signals are impaired by a variety of phenomenon such as multipath, multiple access interference, frequency selective fading, time varying channel effects, synchronization problems and noise. At the receiver the received signal is represented as a function of unknown channel coefficients and time delays. If these parameters are known accurately, then the data symbol estimation improves dramatically.

Channel state information (CSI), which is typically represented by the channel parameters, is required for efficient communications. Many algorithms have been proposed to the joint estimation of the channel coefficients and delays. In particular, the joint estimation of the arriving multi-path time delays and corresponding channel tap gains is quite challenging, and has led the development of several joint multiuser parameter estimators. Joint amplitude/data estimation for the case of known delays has been proposed in [1]. A joint symbol detection and timing estimation based on particle filtering has been presented in [2]. Particle Filtering have also been applied to blind multiuser detection (MUD) over flat fast fading channels [3-4].

The Kalman filter framework based methods were considered in [5-12], where unscented Kalman filter (UKF) and extended Kalman filter (EKF) has been applied to parameter estimations. Filtering algorithms based on Kalman framework are used to estimate state of a system with noisy measurements. The EKF, that assumes the process noise and measurement noise to be zero-mean Gaussian white-noise, provides approximate solution when the models are nonlinear when the posterior density is non-Gaussian. The EKF linearizes the underlying model using first order Taylor series expansion. However, such an expansion introduces large errors in the estimation of covariance matrices and also it requires calculation of Jacobian matrices which may be difficult for nonlinear systems.

The DDF is based on the divided-difference approximation of the derivatives derived from Stirling's interpolation formula [13].When compared with the EKF and UKF, the second order DDF results in a more accurate posterior covariance from more accurate Gaussian statistics. Also DDF has a smaller absolute error in the fourth-order term and also guarantees positive semi-definiteness of the posterior covariance, while the UKF may result in a non-positive DDF has a smaller absolute error in the fourth-order term and also guarantees positive semi-definiteness of the posterior covariance, while the UKF may result in a non-positive.

Many of the algorithms presented in previous work have focused on single-user and/or single-path propagation models. However, in practice, the arriving signal typically consists of several epochs from different users, and it becomes therefore necessary to consider multi-user/multi-path channel models. The contribution in this paper is twofold: first, it presents a joint estimation algorithm for channel coefficients and time delays in CDMA environment using second order DDF with a particular emphasis on closely spaced paths in a multipath fading channel, and second, and more important, it shows the effect of pulse shaping on the accuracy of the estimated parameter.

The rest of the paper is organized as follows. In Section 2, the signal and channel models are presented. Section 3 provides a description of the nonlinear filtering method used for multiuser parameter estimation that utilizes divided difference filter. Section 4 describes computer simulation and performance discussion followed by the conclusion.

The System model

We consider a typical asynchronous CDMA system model where *K* users transmit over an *M*-path fading channel. The received baseband signal sampled at $t = lT_s$ is given by

$$r(l) = \sum_{k=1}^{K}\sum_{i=1}^{M} c_{l,i}(l) d_{l,m_l} a_k(l - m_l T_b - \tau_{k,i}(l)) + n(l) \qquad (1)$$

where $c_{k,i}(l)$ represents the complex channel coefficients, d_{k,m_l} is the m^{th} symbol transmitted by the k^{th} user, $m_l = \left[(l - \tau_k(l)/T_b\right]$, T_b is the symbol interval, $a_k(l)$ is the spreading waveform used by the k^{th} user, $\tau_{k,i}(l)$ is the time delay associated with the i^{th} path of the k^{th} user, and $n(l)$ represents Additive White Gaussian Noise (AWGN) assumed to have a zero mean and variance $\sigma^2 = E[|n(l)|^2] = N_0/T_s$ where T_s is the sampling time.

Implementation of DDF to CDMA Multiuser Parameter Estimation

Following the work in [6], we adopt a state-space model representation where the unknown channel parameters (path delays and gains) to be estimated are represented using the following $2KM \times 1$ vector,

$$\mathbf{x} = [\mathbf{c};\ \ ] \qquad (2)$$

with $c = [c_{11}, c_{12}, ..., c_{1M}, c_{21}, ..., c_{2M}, ..., c_{K1}, ..., c_{KM}]^T$

and $\tau = [\tau_{11}, \tau_{12}, ..., \tau_{1M}, \tau_{21}, ..., \tau_{2M}, ..., \tau_{K1}, ..., \tau_{KM}]^T$

The complex-valued channel amplitudes and real-valued time delays of the K users are assumed to obey a Gauss- Markov dynamic channel model [3], i.e.

$$c(l+1) = \mathbf{F}_c c(l) + \mathbf{v}_c(l) \qquad (3)$$

$$\tau(l+1) = \mathbf{F}_\tau \tau(l) + \mathbf{v}_\tau(l) \quad (4)$$

where $\mathbf{F}_c$ and $\mathbf{F}_\tau$ are $KM \times KM$ state transition matrices for the amplitudes and time delays respectively whereas $v_c(l)$ and $v_\tau(l)$ are $K \times 1$ mutually independent Gaussian random vectors with zero mean and covariance given by $\mathrm{E}\{v_c(i)v_c^T(j)\} = \delta_{ij}\mathbf{Q}_c$, $\mathrm{E}\{v_\tau(i)v_\tau^T(j)\} = \delta_{ij}\mathbf{Q}_\tau$, $\mathrm{E}\{v_c(i)v_\tau^T(j)\} = 0 \ \forall i, j$ with $\mathbf{Q}_c = \sigma_c^2\mathbf{I}$ and $\mathbf{Q}_\tau = \sigma_\tau^2\mathbf{I}$ are the covariance matrices of the process noise v_c and v_τ respectively, and δ_{ij} is the two-dimensional Kronecker delta function equal to 1 for $i = j$, and 0 otherwise.

The state model can be written as

$$\mathbf{x}(l+1) = \mathbf{F}\mathbf{x}(l) + \mathbf{v}(l) \quad (5)$$

where

$\mathbf{F} = \begin{bmatrix} \mathbf{F}_c & 0 \\ 0 & \mathbf{F}_\tau \end{bmatrix}, \mathbf{v} = \begin{bmatrix} \mathbf{v}_c^T & \mathbf{v}_\tau^T \end{bmatrix}, \mathbf{Q} = \begin{bmatrix} \mathbf{Q}_c & 0 \\ 0 & \mathbf{Q}_\tau \end{bmatrix}$ are $2KM \times 2KM$ state transition matrix, $2KM \times 1$ process noise vector with mean of zero and covariance matrix respectively.

The scalar measurement model follows from the received signal of (1) by

$$z(l) = h(\mathbf{x}(l)) + \eta(l) \quad (6)$$

where the measurement $z(l) = r(l)$,

and

$$h(\mathbf{x}(l)) = \sum_{k=1}^{K}\sum_{i=1}^{M} c_{k,i}(l) d_{k,m_l} a_k(l - m_l T_b - \tau_{k,i}(l)).$$

The scalar measurement $z(l)$ is a nonlinear function of the state $\mathbf{x}(l)$. Given the state-space and measurement models, we may find the optimal estimate of $\hat{\mathbf{x}}(l)$ denoted as $\hat{\mathbf{x}}(l \mid l) = E\{\mathbf{x}(l) \mid z^l\}$, with the estimation error covariance

$$\mathrm{P} = \mathrm{E}\left\{[\mathbf{x}(l) - \hat{\mathbf{x}}(l \mid l)][\mathbf{x}(l) - \hat{\mathbf{x}}(l \mid l)]^T \mid z^l\right\} \quad (7)$$

where z^l denotes the set of received samples up to time *l*, $\{z(l), z(l-1), ..., z(0)\}$.

DDF

DDF, unlike EKF, is a sigma point filter (SPF) where the filter linearizes the nonlinear dynamic and measurementfunctions by using an interpolation formula through systematicallychosen sigma points. The linearization is based onpolynomial approximations of the nonlinear transformationsthat are obtained by Stirling's interpolation formula, ratherthan the derivative-based Taylor series approximation [13].Conceptually, the implementation principle resembles that ofthe EKF, however, it is significantly simpler because uses afinite number of functional evaluations instead of analyticalderivatives. It is not necessary to formulate the Jacobianand/or Hessian matrices of partial derivatives of the nonlineardynamic and measurement equations. Thus, the new nonlinearstate filter, Divided Difference Filter (DDF), can also replacethe Extended Kalman Filter (EKF) and its higher-order estimatorsin practical real-time applications that require accurateestimation, but less computational cost. The derivative free, deterministic sampling based DDF outperforms the EKF interms of estimation accuracy, filter robustness and ease ofimplementation.

Consider the nonlinear equations

$$\mathbf{x}_{k+1} = \mathbf{f}(\mathbf{x}_k, \mathbf{w}_k, k)$$
$$\mathbf{y}_k = \mathbf{h}(\mathbf{x}_k, \mathbf{v}_k, k) \quad (8)$$

where $\mathbf{x}_k$ is the $n \times 1$ state vector, $\mathbf{y}_k$ is the $m \times 1$ observation vector, $\mathbf{w}_k$ is the state noise process vector and $\mathbf{v}_k$ is the $r \times 1$ measurement noise vector. It is assumed that the noise vectors are uncorrelated white Gaussian processes with expected means and covariances

$$E\{\mathbf{w}_k\} = \bar{\mathbf{w}}, \ E\left\{[\mathbf{w}_k - \bar{\mathbf{w}}_k][\mathbf{w}_j - \bar{\mathbf{w}}_k]^T\right\} = \mathbf{Q}_k$$
$$E\{\mathbf{v}_k\} = \bar{\mathbf{v}}, \ E\left\{[\mathbf{v}_k - \bar{\mathbf{v}}_k][\mathbf{v}_j - \bar{\mathbf{v}}_k]^T\right\} = \mathbf{R}_k$$

Let the square Cholesky factorizations

$$\mathbf{P}_0 = \mathbf{S_x S_x^T}$$
$$\mathbf{Q} = \mathbf{S_w S_w^T}$$

The predicted state vector is

$$\hat{\mathbf{x}}_{k+1}^- = \mathbf{f}(\hat{\mathbf{x}}_k, \bar{\mathbf{w}}_k, k)$$

The predicted state covariance is determined by the symmetric matrix product

$$\mathbf{P}_{k+1}^- = \mathbf{S}_\mathbf{x}^-(k+1)(\mathbf{S}_\mathbf{x}^-(k+1))^T \quad (9)$$

where

$$\mathbf{S}_\mathbf{x}^-(k+1) = \left[\mathbf{S}_{x\hat{x}}^{(1)}(k+1) \ \ \mathbf{S}_{xw}^{(1)}(k+1)\right]$$

with

$$\mathbf{S}_{x\hat{x}}^{(1)}(k+1) = \frac{1}{2h}\left\{\mathbf{f}_i(\hat{\mathbf{x}}_k + h\mathbf{s}_{x,j}, \bar{\mathbf{w}}_k) - \mathbf{f}_i(\hat{\mathbf{x}}_k - h\mathbf{s}_{x,j}, \bar{\mathbf{w}}_k)\right\}$$
$$\mathbf{S}_{xw}^{(1)}(k+1) = \frac{1}{2h}\left\{\mathbf{f}_i(\hat{\mathbf{x}}_k, \bar{\mathbf{w}}_k + h\mathbf{s}_{w,j}) - \mathbf{f}_i(\hat{\mathbf{x}}_k, \bar{\mathbf{w}}_k - h\mathbf{s}_{w,j})\right\}$$

where $\mathbf{s}_{x,j}$ is the column of $\mathbf{S_x}$ and $\mathbf{s}_{w,j}$ is the column of $\mathbf{S_w}$.

the square Cholesky factorizations are performed

$$\mathbf{P}_{k+1}^- = \mathbf{S}_\mathbf{x}^- \mathbf{S}_\mathbf{x}^{-T}$$
$$\mathbf{R} = \mathbf{S_v S_v^T}$$

The predicted observation vector $\hat{\mathbf{y}}_{k+1}^-$ and its predicted covariance are

$$\hat{\mathbf{y}}_{k+1}^- = \mathbf{h}(\hat{\mathbf{x}}_{k+1}^-, \bar{\mathbf{v}}_{k+1}, k+1) \quad (10)$$
$$\mathbf{P}_{k+1}^{vv} = \mathbf{S}_v(k+1)\mathbf{S}_v^T(k+1) \quad (11)$$

where

$$\mathbf{S}_v(k+1) = \left[\mathbf{S}_{y\hat{x}}^{(1)}(k+1) \ \ \mathbf{S}_{yv}^{(1)}(k+1)\right]$$
$$\mathbf{S}_{y\hat{x}}^{(1)}(k+1) = \frac{1}{2h}\left\{\mathbf{h}_i(\hat{\mathbf{x}}_{k+1} + h\mathbf{s}_{x,j}^-, \bar{\mathbf{v}}_{k+1}) - \mathbf{h}_i(\hat{\mathbf{x}}_{k+1}^- + h\mathbf{s}_{x,j}^-, \bar{\mathbf{v}}_{k+1})\right\}$$
$$\mathbf{S}_{yv}^{(1)}(k+1) = \frac{1}{2h}\left\{\mathbf{h}_i(\hat{\mathbf{x}}_{k+1}^-, \bar{\mathbf{v}}_{k+1} + h\mathbf{s}_{v,j}) - \mathbf{h}_i(\hat{\mathbf{x}}_{k+1}^-, \bar{\mathbf{v}}_{k+1} + h\mathbf{s}_{v,j})\right\}$$

where $\mathbf{s}_{x,j}^-$ is the column of $\mathbf{S}_\mathbf{x}^-$ and $\mathbf{s}_{v,j}$ is the column of $\mathbf{S_v}$. The innovation covariance $\mathbf{P}_{k+1}^{vv}$ is computed as

$$\mathbf{P}_{k+1}^{vv} = \mathbf{P}_{k+1}^{yy} + \mathbf{R}_{k+1} \quad (12)$$

with

$$\mathbf{P}_{k+1}^{yy} = \mathbf{S}_{y\hat{x}}^{(1)}(k+1)\left(\mathbf{S}_{y\hat{x}}^{(1)}(k+1)\right)^T \qquad (13)$$

Finally the cross covariance matrix is determined by

$$\mathbf{P}_{k+1}^{xy} = \mathbf{S}_{x}^{-}(k+1)\left(\mathbf{S}_{y\hat{x}}^{(1)}(k+1)\right)^T \qquad (14)$$

The filter gain K_{k+1}, the updated estimated state vector $\hat{\mathbf{x}}_{k+1}^{+}$ and the updated covariance $\mathbf{P}_{k+1}^{+}$ are computed using

$$\mathrm{K}_{k+1} = \mathbf{P}_{k+1}^{xy}(\mathbf{P}_{k+1}^{vv})^{-1} \qquad (15)$$

$$\hat{\mathbf{x}}_{k+1}^{+} = \hat{\mathbf{x}}_{k+1}^{-} + \mathrm{K}_{k+1}\left(\mathbf{y}_{k+1} - \hat{\mathbf{y}}_{k+1}\right) \qquad (16)$$

$$\mathbf{P}_{k+1}^{+} = \mathbf{P}_{k+1}^{-} - \mathrm{K}_{k+1}\mathbf{P}_{k+1}^{vv}\mathrm{K}_{k+1}^{T} \qquad (17)$$

The second-order divided difference filter (DDF2) is obtained by using the calculation of the mean and covariance in the second-order polynomial approximation section. First, the following additional matrices containing divided difference are defined

$$\mathbf{S}_{x\hat{x}}^{(2)}(k+1) = \frac{\sqrt{\gamma-1}}{2\gamma}\left\{\mathbf{f}_i(\hat{\mathbf{x}}_k + h\mathbf{s}_{x,j}, \bar{\mathbf{w}}_k) + \mathbf{f}_i(\hat{\mathbf{x}}_k - h\mathbf{s}_{x,j}, \bar{\mathbf{w}}_k) - 2\mathbf{f}_i(\hat{\mathbf{x}}_k, \bar{\mathbf{w}}_k)\right\}$$

$$\mathbf{S}_{xw}^{(2)}(k+1) = \frac{\sqrt{\gamma-1}}{2\gamma}\left\{\mathbf{f}_i(\hat{\mathbf{x}}_k, \bar{\mathbf{w}}_k + h\mathbf{s}_{w,j}) + \mathbf{f}_i(\hat{\mathbf{x}}_k, \bar{\mathbf{w}}_k - h\mathbf{s}_{w,j}) - 2\mathbf{f}_i(\hat{\mathbf{x}}_k, \bar{\mathbf{w}}_k)\right\}$$

where $\mathbf{s}_{x,j}$ is the jth column of $\mathbf{S}_{\mathbf{x}}$, $\mathbf{s}_{w,j}$ is the jth column of $\mathbf{S}_{\mathbf{w}}$ and $\gamma = h^2$ is a constant parameter. The predicted state equation is

$$\begin{aligned}\hat{\mathbf{x}}_{k+1}^{-} &= \frac{\gamma-(n_x+n_w)}{\gamma}\mathbf{f}(\hat{\mathbf{x}}_k, \bar{\mathbf{w}}_k) \\ &+ \frac{1}{2\gamma}\sum_{p=1}^{n_x}\left\{\mathbf{f}(\hat{\mathbf{x}}_k + h\mathbf{s}_{s,p}, \bar{\mathbf{w}}_k) + \mathbf{f}_i(\hat{\mathbf{x}}_k - h\mathbf{s}_{s,j}, \bar{\mathbf{w}}_k)\right\} \\ &+ \frac{1}{2\gamma}\sum_{p=1}^{n_x}\left\{\mathbf{f}(\hat{\mathbf{x}}_k, \bar{\mathbf{w}}_k + h\mathbf{s}_{w,p}) + \mathbf{f}_i(\hat{\mathbf{x}}_k, \bar{\mathbf{w}}_k - h\mathbf{s}_{s,p})\right\}\end{aligned} \qquad (18)$$

where n_x denotes the dimension of the state vector, and n_w is the dimension of process noise vector. The Cholesky factorization of the predicted covariance is computed as

$$\mathbf{S}_{\mathbf{x}}^{-}(k+1) = \left[\mathbf{S}_{x\hat{x}}^{(1)}(k+1)\ \ \mathbf{S}_{xw}^{(1)}(k+1)\ \ \mathbf{S}_{x\hat{x}}^{(2)}(k+1)\ \ \mathbf{S}_{xw}^{(2)}(k+1)\right]$$

The predicted covariance is computed using

$$\mathbf{P}_{k+1}^{-} = \mathbf{S}_{\mathbf{x}}^{-}(k+1)(\mathbf{S}_{\mathbf{x}}^{-}(k+1))^T$$

the predicted observation vector

$$\begin{aligned}\hat{\mathbf{y}}_{k+1}^{-} &= \frac{\gamma-(n_x+n_v)}{\gamma}\mathbf{h}(\hat{\mathbf{x}}_{k+1}^{-}, \bar{\mathbf{v}}_{k+1}) \\ &+ \frac{1}{2\gamma}\sum_{p=1}^{n_x}\left\{\mathbf{h}(\hat{\mathbf{x}}_{k+1}^{-} + h\mathbf{s}_{x,p}^{-}, \bar{\mathbf{v}}_{k+1}) + \mathbf{h}(\hat{\mathbf{x}}_{k+1}^{-} - h\mathbf{s}_{x,p}^{-}, \bar{\mathbf{v}}_{k+1})\right\} \\ &+ \frac{1}{2\gamma}\sum_{p=1}^{n_x}\left\{\mathbf{h}(\hat{\mathbf{x}}_{k+1}^{-}, \bar{\mathbf{v}}_{k+1} + h\mathbf{s}_{v,p}) + \mathbf{h}(\hat{\mathbf{x}}_{k+1}^{-}, \bar{\mathbf{v}}_{k+1} - h\mathbf{s}_{v,p})\right\}\end{aligned} \qquad (19)$$

where n_v is the dimension of the measurement noise, $\mathbf{s}_{x,p}^{-}$ is the pth column of $\mathbf{S}_{\mathbf{x}}^{-}$, and $\mathbf{s}_{v,p}$ is the pth column of $\mathbf{S}_{\mathbf{v}}$. The innovation covariance matrix is given by

$$\mathbf{P}_{k+1}^{vv} = \mathbf{S}_v(k+1)\mathbf{S}_v^T(k+1)$$

with

$$\mathbf{S}_v(k+1) = \left[\mathbf{S}_{y\hat{x}}^{(1)}(k+1)\ \ \mathbf{S}_{yv}^{(1)}(k+1)\ \ \mathbf{S}_{y\hat{x}}^{(2)}(k+1)\ \ \mathbf{S}_{yv}^{(2)}(k+1)\right]$$

$$\mathbf{S}_{y\hat{x}}^{(2)}(k+1) = \frac{\sqrt{\gamma-1}}{2\gamma}\left\{\mathbf{h}_i(\hat{\mathbf{x}}_{k+1}^{-} + h\mathbf{s}_{x,j}^{-}, \bar{\mathbf{v}}_{k+1}) + \mathbf{h}_i(\hat{\mathbf{x}}_{k+1}^{-} - h\mathbf{s}_{x,i}^{-}, \bar{\mathbf{v}}_{k+1}) - 2\mathbf{h}_i(\hat{\mathbf{x}}_{k+1}^{-}, \bar{\mathbf{v}}_{k+1})\right\}$$

$$\mathbf{S}_{yv}^{(2)}(k+1) = \frac{\sqrt{\gamma-1}}{2\gamma}\left\{\mathbf{h}_i(\hat{\mathbf{x}}_{k+1}^{-}, \bar{\mathbf{v}}_{k+1} + h\mathbf{s}_{x,j}^{-}) + \mathbf{h}_i(\hat{\mathbf{x}}_{k+1}^{-}, \bar{\mathbf{v}}_{k+1} - h\mathbf{s}_{x,j}^{-}) - 2\mathbf{h}_i(\hat{\mathbf{x}}_{k+1}^{-}, \bar{\mathbf{v}}_{k+1})\right\}$$

The cross correlation matrix is

$$\mathbf{P}_{k+1}^{xy} = \mathbf{S}_{\hat{x}}^{(1)}(k+1)\left(\mathbf{S}_{y\hat{x}}^{(1)}(k+1)\right)^T \tag{20}$$

The filter gain K_{k+1}, the updated estimated state vector $\hat{\mathbf{x}}_{k+1}^{+}$ and the updated covariance $\mathbf{P}_{k+1}^{+}$ are computed using

$$\mathrm{K}_{k+1} = \mathbf{P}_{k+1}^{xy}(\mathbf{P}_{k+1}^{vv})^{-1} \tag{21}$$

$$\hat{\mathbf{x}}_{k+1}^{+} = \hat{\mathbf{x}}_{k+1}^{-} + \mathrm{K}_{k+1}\left(\mathbf{y}_{k+1} - \hat{\mathbf{y}}_{k+1}\right) \tag{22}$$

$$\mathbf{P}_{k+1}^{+} = \mathbf{P}_{k+1}^{-} - \mathrm{K}_{k+1}\mathbf{P}_{k+1}^{vv}\mathrm{K}_{k+1}^{T} \tag{23}$$

Simulation Results:

For the purpose of simulation we have considered two pulse shapes i.e. rectangular, and raised cosine pulse. The spreading codes length is chosen to be 32 with 16 samples per chip. The simulations have been carried out for a Rayleigh fading channel for three users each with three closely spaced paths with nominal powers of 1.0, 0.9 and 0.5 respectively. The state transition matrix is assumed to be $\mathbf{F} = 0.999\mathbf{I}$ and $\mathbf{Q} = 0.001\mathbf{I}$ where $\mathbf{I}$ is the identity matrix. We note that the data bits, $d_{k,m}$, are not included in the estimation process, but are assumed unknown apriori. In the simulations, we assume that the data bits are available from decision-directed adaptation, where the symbols $d_{k,m}$ are replaced by the $d_{k,m}$ decisions shown in Figure 1. We also assumed that the filter is initialized by an estimator close to the true values. Large and random data sets were used to evaluate the performance degradation. The tracking for the weaker user for the 1st path has been carried out where the true delay is $\tau = 111$ samples. Figure 2 shows the timing epoch of the first arriving path in a multiuser scenario with three multipath separated byhalf a chip. We have considered the case of the weaker user and two pulse shapes have been compared. Proposed estimator converges to the close to the true in the presence of MAI and is able to track desired user delay even when the paths are closely spaced. Also the estimator shows better performance for the raised cosine pulse. Similarly the observation can be made for the channel coefficients as well which have been shown in Figure (3) for the RRC pulse only.

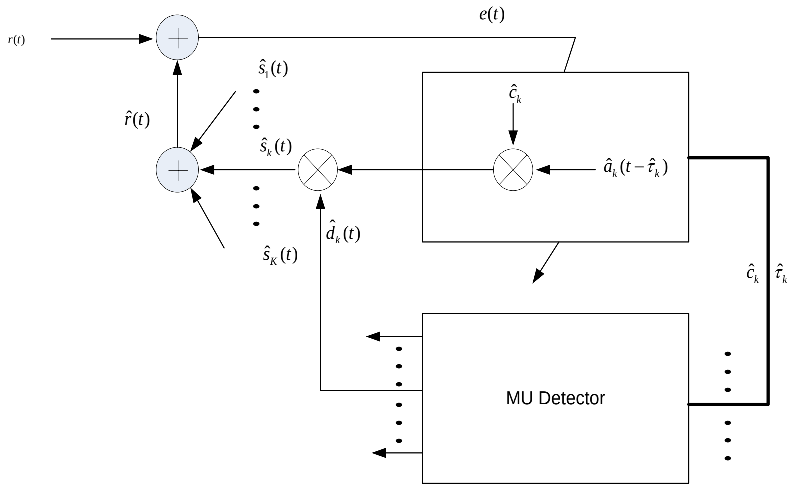

Figure 1 Multiuser parameter estimation receiver

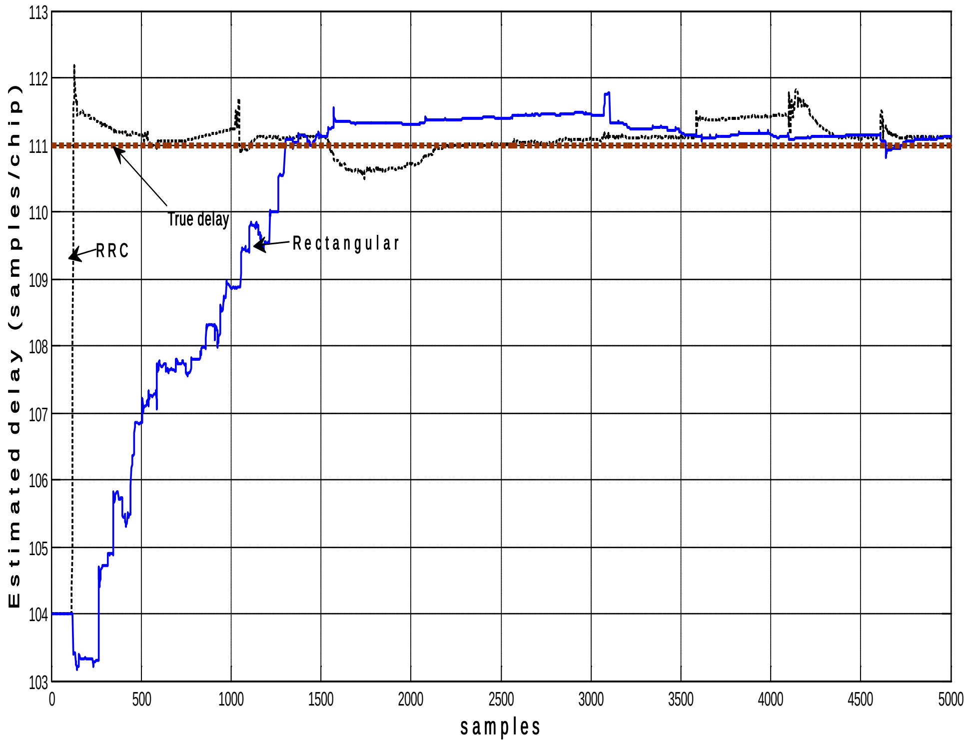

Figure 2. Time delays tracking of the weaker path

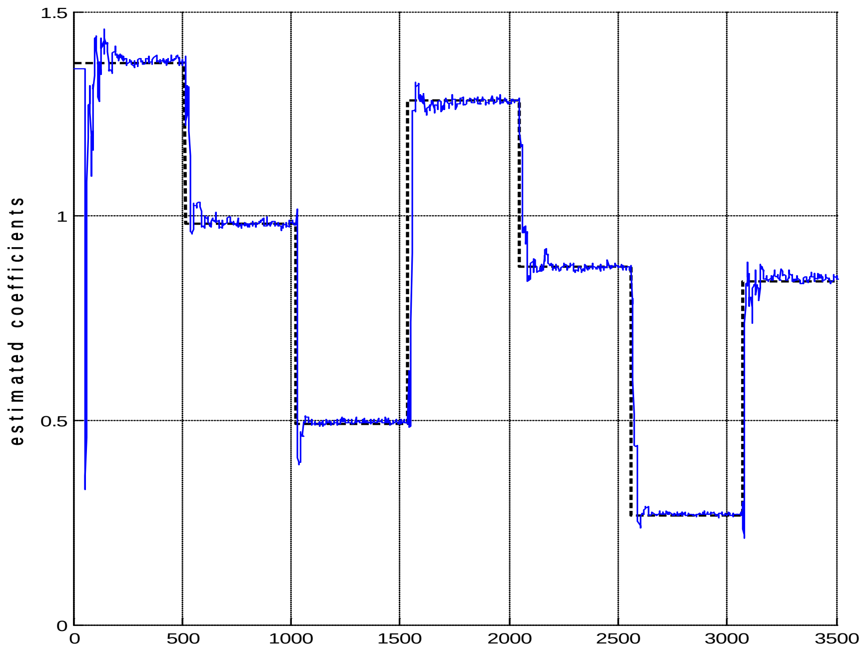

Figure 3. Time varying channel amplitude tracking of the weaker path

Multiuser Radiolocation

For the radio channel between the mobile and base station we assume that the mobile signal is subject to attenuation including distance path loss and lognormal shadowing [14],

$$\alpha(d_{BS_i}, \xi_{BS_i}) = p(d_{BS_i})10^{\xi_{BS_i}/10} \quad (24)$$

where $p(d)$ is the distance path loss, and ξ_{BS_i} is the shadowing variable. The path loss part follows a two-segment model with breakpoint at d_o

$$p(d) = 10n\log_{10}(d) \quad (25)$$

where n is the path loss slope assumed to take two different values, depending on whether the mobile is within or beyond the given breakpoint. In the subsequent numerical simulations, we use the slopes $n = 2$ and a breakpoint at 200m, with a cell radius of 2km. For a given mobile, shadowing vis-à-vis the different base stations is partially correlated, and given by: $\xi_{BS_i} = a\xi_c + b\xi_i$ where ξ_c and ξ_i are the common and independent terms, respectively, and $a^2 + b^2 = 1$. In the numerical results, we assume the shadowing variables are log-normal with standard deviation $\sigma_{sh} = 8dB$, and 50% correlation $(a = b = 1/\sqrt{2})$.

Since time-of-arrival estimation accuracy strongly depends on the received MAI levels, this issue can be a limiting factor in mobile radiolocation which typically requires TOA data from at least three base stations. For example, if we assume that the mobile is served by the center base station BS1 and will be located by the strongest seven base stations BS1, BS2, . . . , BS7 (sorted in a descending order from the base station that receives the highest average received power), then we define the ratio of its average received power as BS_i compared to BS1 as $\beta_i = P_i / P_1$ where P_i is the received power in BS_1 and $\beta_1 = 1 \geq \beta_2 \geq \beta_3 \geq \ldots \geq \beta_7$. [14].

It is found that this ratio can fluctuate widely depending on the mobile position relative to the base stations of interest. As an illustration, we present examples for four scenarios (cases 1, 2 and 3) that will be used in the subsequent numerical results. Case-1 refers to a mobile located in close proximity to its "serving" BS1, with a signal at least 10dB above that at the other two base stations. Case-2 represents a two-way soft handover scenario, with the mobile power at base station 2 within 3dB (as an example) from that at BS1, and case-3 denotes the 3-way soft handover situation where the mobile signal is within 3dB at both BS2 and BS3 compared to BS1[14].

In this paper, we are considering only line-of-sight (LOS) propagation, and base stations assumed synchronized. The TOA measurements recorded at each BS is directly proportional to the mobile-base distance. We follow the approximate maximum likelihood (AML)[14] for the purpose of radiolocation. Figure 4 shows the cumulative distribution function (CDF) of the mobile position estimation error for the three cases outlined in Section 2 (with their relevant parameters in Table 1. It is clearly seen that the case for 3-way soft handover gives the best performance, followed by 2-way soft handover one, and the case when the mobile is closest to its own base station is worst. This is because the MS, closer to the serving BS, needs to transmit at lower power levels to maintain the fixed received power at the serving BS. This is due to the fact that as the distance to the neighboring BSs increases, the signal experiences greater path loss. So the received signal power at the neighboring BSs reaches lower levels, making position location error to rise sharply.

	β_1	β_2	β_3	β_4	β_5	β_6	β_7
Case 1	1	0.0216	0.0113	0.0069	0.0045	0.0031	0.0021
Case 2	1	0.6982	0.2215	0.1202	0.0735	0.0485	0.0331
Case 3	1	0.7922	0.6353	0.2993	0.1701	0.1065	0.0706
Averages of β-factors for various soft-handover link conditions							
when shadowing st.dev. $\sigma_{sh} = 8dB$ and the cell radius is 2km [14]							

TABLE I

Averages of the Beta Factors

Figure 4. Cumulative distribution function (CDF) for the residual mobile positioning error for 3cases using DDF

Conclusion

In this paper, we have evaluated the performance of a DDF parameter estimation accuracy in an asynchronous CDMA has been evaluated in the presence of MAI and additive Gaussian noise. It is shown that the DDF achieves better performance and enjoys moderate complexity when employed to estimate the channel parameters on the received signals in multiuser/multipath scenarios. A general derivation the processing steps was presented, followed by a specialization to the case of time delay and channel gain estimation for multipath CDMA signals, with particular focus on closely spaced multipath epochs. Such estimates result in higher accuracy in multiuser radiolocation scenario.

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