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Research Article

Equalization of Multiuser Wireless CDMA Downlink Considering Transmitter Nonlinearity Using Walsh Codes

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Transmitter nonlinearity has been a major issue in many scenarios: cellular wireless systems have high power RF amplifier (HPA) nonlinearity at the base station; satellite downlinks have nonlinear TWT amplifiers in the satellite transponder and multipath conditions in the ground station; and radio-over-fiber (ROF) systems consist of a nonlinear optical link followed by a wireless channel. In many cases, the nonlinearity is simply ignored if there is no out-of-band emission. This results in poor BER performance. In this paper we propose a new technique to estimate the linear part of the wireless downlink in the presence of a nonlinearity using Walsh codes; Walsh codes are commonly used in CDMA downlinks. Furthermore, we show that equalizer performance is significantly improved by taking into account the presence of the nonlinearity during channel estimation. This is shown by using a regular decision feedback equalizer (DFE) with both wireless and RF amplifier noise. We perform estimation in a multiuser CDMA communication system where all users transmit their signal simultaneously. Correlation analysis is applied to identify the channel impulse response (CIR) and the derivation of key correlation relationships is shown. A difficulty with using Walsh codes in terms of their correlations (compared to PN sequences) is then presented, as well as a discussion on how to overcome it. Numerical evaluations show a good estimation of the linear system with 54 users in the downlink and a signal-to-noise ratio (SNR) of 25 dB. Bit error rate (BER) simulations of the proposed identification and equalization algorithms show a BER of 10^{-6} achieved at an SNR of $\sim$25 dB.

1. INTRODUCTION

The quality of channel estimation has a prominent impact on the accuracy of equalization and hence system performance. The general wireless CDMA downlink for cellular networks is shown in Figure 1. In order to properly equalize this channel, an accurate estimation of both the nonlinear and linear channel parameters is required. Some example systems are cellular CDMA network downlink, radio-over-fiber (ROF) [1] downlink, and satellite downlink. In all these cases, the system of interest consists of a mildly nonlinear part followed by a linear part, in that particular order. This interconnection is considered a Hammerstein system. The breakdown of the nonlinear/linear downlink systems as described above is the following:

(1) *wireless CDMA network downlink*: RF amplifier/wireless channel;
(2) *satellite downlink*: TWT amplifier/wireless channel;
(3) *ROF downlink*: optical channel/wireless channel.

Some of the dominant issues associated with the above systems include intersymbol interference (ISI), RF amplifier nonlinearity, and the presence of noise. In order to limit the effects of these distortions, estimation and subsequently equalization of the concatenated channel should be done. The most common approach is to ignore the nonlinearity and just attempt to estimate the linear channel. This will result in inferior equalization performance. The goal in this paper is to estimate first the channel parameters, and then devise appropriate equalization.

Some work in identifying Hammerstein systems has been done by Billings and Fakhouri [2]. In [2], the Hammerstein model was analyzed in a single control signal (or single user) continuous-time baseband environment. Correlation analysis was used to decouple the identification of the linear and nonlinear component subsystems by using white Gaussian inputs. The generation of white noise inputs has practical difficulties, therefore in this paper we substitute the white Guassian inputs with the summation of multiple Walsh code

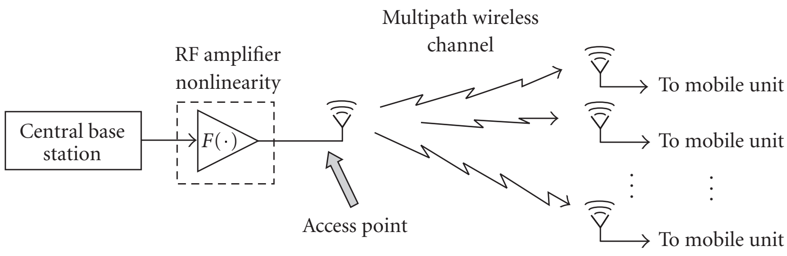
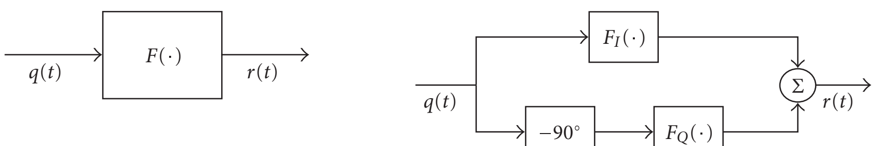


Figure 1: General wireless downlink.



(a) Single complex-valued system.

(b) Two real-valued systems.

Figure 2: Inphase and quadrature phase model for a nonlinear system.

sequences. We then apply the concept of Hammerstein representation and correlation analysis to a multiuser CDMA discrete-time passband communication system. The use of Walsh codes for estimation of the downlink is attractive because these spreading codes are already widely used in spread spectrum communications [3].[1] Any mildly nonlinear system that can be described by an lth-order polynomial can be identified using our technique. Other Hammerstein system identification methods involve frequency domain techniques [5], subspace-based state-space system identification [6], and noniterative algorithms based on orthonormal functions [7].

The wireless downlink has a nonlinear element (e.g., HPA) common to all users, but each user will have a separate multipath wireless channel. We considered this multiuser scenario, where a summation of Walsh codes travels through this concatenated channel. Following the channel estimation, the downlink is equalized. A decision feedback equalizer (DFE) is used to equalize for the wireless channel dispersion. It is shown that equalizing for the nonlinearity is not a strict requirement, however, consideration of the nonlinearity is required for the accurate estimation and equalization of the linear channel.

Although the work in this paper is tailored to a multiuser CDMA communication system, it can also be applied to areas outside of the communication field where a parallel connection of multiple linear systems is encountered in series with a single nonlinearity.

[1] 3G systems use scrambling codes as opposed to Walsh codes. Our approach is still justified since 3G downlink systems use both an initial channelization code spreading (i.e., orthogonal Walsh code) followed by a scrambling code spreading [4]. So in 3G downlink systems, Walsh codes are still used, only in combination with scrambling codes, and we believe that system identification with Walsh codes will be of interest to researchers in this area.

2. MULTIUSER CDMA DOWNLINK SYSTEM MODEL

In this section the theory for a multiuser CDMA downlink will be presented with the help of discrete-time nonlinear systems theory discussed in [2]. But before proceeding with the estimation theory, a short section regarding complex notation will be discussed.

2.1. Passband complex consideration

Communication signals and systems are passband. In order to use baseband signal processing, communication signals in the passband (i.e., real-valued signals [8]) must be appropriately translated from the passband to the baseband. Generally, this translation results in complex-valued baseband signals [8]. Therefore, in a passband system, the signals as well as the channel impulse response (CIR) and nonlinear component are complex valued. We now show how these complex-valued quantities can be split into real-valued quadrature components for easy handling.

When an RF signal undergoes a nonlinear transformation one of the major concerns is the AM-AM and AM-PM distortions. The complex-valued nonlinear system in Figure 2(a) introduces both of these distortions [9]. It has been shown in [10, 11] that a bandpass memoryless nonlinearity can be modeled with a baseband complex nonlinear model. Then the nonlinear distortion can be expressed by inphase and quadrature phase components that are real. Let the input signal in Figure 2(a) be given as

$$q(t) = A(t)\cos\left[\omega_c t + \theta(t)\right]. \tag{1}$$

Then the output $r(t)$ is

$$r(t) = R[A(t)]\cos\{\omega_c t + \theta(t) + \phi[A(t)]\}, \tag{2}$$

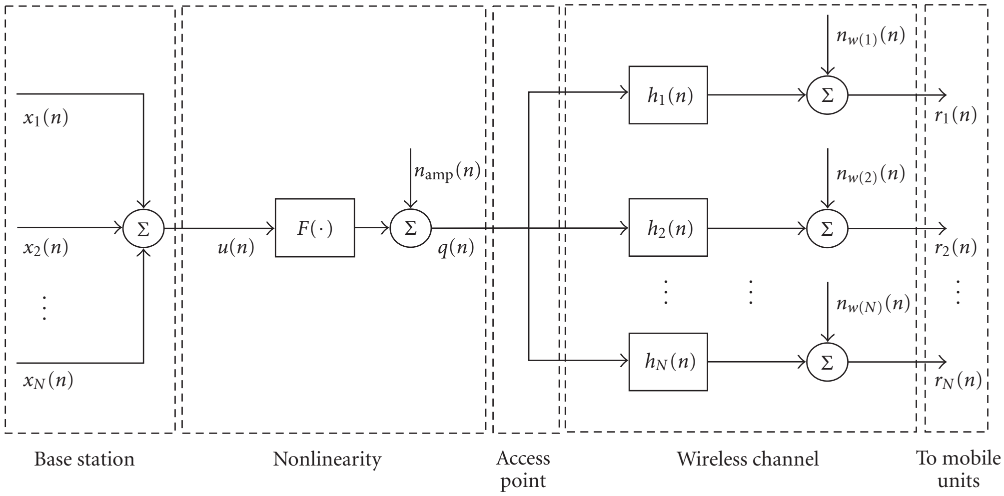


FIGURE 3: Downlink in a multiuser CDMA environment with a single nonlinearity (amplifier) and separate wireless channels for each user.

where R is the AM-AM distortion and ϕ is the AM-PM distortion. The output $r(t)$ can also be expressed as

$$\begin{aligned} r(t) = {} & R[A(t)]\cos(\phi[A(t)])\cos(\omega_c t+\theta(t)) \\ & - R[A(t)]\sin(\phi[A(t)])\sin(\omega_c t+\theta(t)), \end{aligned} \tag{3}$$

using the trigonometric identity $\cos(A+B) = \cos(A)\cos(B) - \sin(A)\sin(B)$. Equation (3) can then be written as

$$\begin{aligned} r(t) = {} & r_i[A(t)]\cos(\omega_c t+\theta(t)) \\ & - r_q[A(t)]\sin(\omega_c t+\theta(t)), \end{aligned} \tag{4}$$

where

$$\begin{aligned} r_i[A(t)] &= R[A(t)]\cos(\phi[A(t)]), \\ r_q[A(t)] &= R[A(t)]\sin(\phi[A(t)]). \end{aligned} \tag{5}$$

Equation (4) shows that the bandpass nonlinearity can be separated into an inphase component and a quadrature phase component with only AM-AM distortion. Therefore, the two real-valued systems shown by the quadrature model in Figure 2(b) are equivalent to the complex-valued system shown in Figure 2(a). Similarly, the bandpass CIR can also be separated into inphase and quadrature phase components [8].

Mathematically, real quantities are easier to work with and therefore the quadrature model is the representation of choice in this paper. As a result of this, it can be stated that for the linear system in this paper the real-valued inphase and quadrature phase components are estimated individually. All variables introduced hereafter are real quantities unless otherwise specified.

2.2. *Wireless channel estimation theory*

This section presents an investigation into the estimation of the *wireless channel* of the downlink in a multiuser CDMA environment using Walsh codes. As mentioned in Section 1, the system of interest consists of a mildly nonlinear part (HPA) followed by a linear part (wireless channel), which can be modeled by a Hammerstein system. An investigation into the single signal estimation of a Hammerstein system has been covered in [2], but Gaussian inputs were used and there was no extraction of the term $\mathfrak{R}_{uw_1}(\sigma)$. In this section, the theory is extended to the multiuser case where varying wireless channels are encountered for each mobile user. It is also shown that multilevel testing (via the Vandermonde matrix) alleviates anomalies that would otherwise be encountered with direct correlation.

TABLE 1: Symbol descriptions for the downlink.

Symbol	Description
$x_j(n)$	Input Walsh code spreading sequence, $1 \le j \le N$
$u(n)$	Compound Walsh signal input
$F(\cdot)$	Nonlinear function
$n_{amp}(n)$	RF amplifier Gaussian noise
$q(n)$	Signal sent through multiple wireless channels
$h_j(n)$	Wireless channel impulse response, $1 \le j \le N$
$n_{w(j)}(n)$	Wireless channel Gaussian noise, $1 \le j \le N$
$r_j(n)$	Signal sent to mobile units, $1 \le j \le N$

The scenario of a multiuser CDMA downlink is shown in Figure 3 (all signals used in analyzing the downlink, along with their descriptions, are shown in Table 1). In this scenario: (1) the base station generates an independent Walsh code for each user and combines them, (2) the combined signal is then transmitted through the common nonlinear link followed by the addition of HPA noise, (3) the signal is then transmitted through separate wireless channels followed by the addition of an independent wireless channel noise,[2] and

[2] Different "initial seed" settings are used during simulation to ensure independence.

finally, (4) the signal is sent to the mobile user for further processing. This scenario generates a multitude of signal impairments such as: (1) ISI from the wireless channels, (2) different path loss affecting dynamic range, (3) addition of wireless and RF amplifier noise, and (4) carrier regrowth, inband distortion, and cross-multiplication of terms, all resulting from the nonlinearity.

The channel of interest in the estimation theory to follow will be that of the first user, and so the output signal used in all following derivations will be $r_1(n)$. The first step in the estimation is to define the output of the system. According to the theorem of Weierstrass [12], any function which is continuous within an interval may be approximated to any required degree of accuracy by polynomials in this interval. Therefore, the output of the nonlinear system plus the amplifier noise is given by a polynomial of the form

$$q(n) = A_1 u(n) + A_2 u^2(n) + \cdots + A_l u^l(n) + n_{\text{amp}}(n), \qquad (6)$$

where $u(n)$ is a compound input of Walsh codes (of length N_w) that can be written as

$$u(n) = x_1(n) + x_2(n) + \cdots + x_N(n), \qquad (7)$$

where N is the number of Walsh codes (or equivalently the number of users). The system output $r_1(n)$ can be expressed by the convolution

$$r_1(n) = q(n) * h_1(n) + n_{w(1)}(n). \qquad (8)$$

Substituting for $q(n)$ from (6) and expanding the convolution give

$$\begin{aligned} r_1(n) = {} & A_1 \sum_{m=-\infty}^{\infty} h_1(m) u(n-m) + A_2 \sum_{m=-\infty}^{\infty} h_1(m) u^2(n-m) \\ & + \cdots + A_l \sum_{m=-\infty}^{\infty} h_1(m) u^l(n-m) \\ & + \sum_{m=-\infty}^{\infty} h_1(m) n_{\text{amp}}(n-m) + n_{w(1)}(n), \end{aligned} \qquad (9)$$

which can be written in a more compact form as

$$\begin{aligned} r_1(n) = {} & \sum_{k=1}^{l} \left(A_k \sum_{m=-\infty}^{\infty} h_1(m) u^k(n-m) \right) \\ & + \underbrace{\sum_{m=-\infty}^{\infty} h_1(m) n_{\text{amp}}(n-m) + n_{w(1)}(n)}_{\text{noise terms}}. \end{aligned} \qquad (10)$$

As a summation of the output of the isolated lth order kernel, the above equation becomes

$$r_1(n) = w_1(n) + w_2(n) + w_3(n) + \cdots + w_l(n) + \text{noise terms}. \qquad (11)$$

Expressing the output in the form of (11) is a crucial step in developing the correlation relationships that follow. By studying the correlation between the output $r_1(n)$ and the input $u(n)$, as well as the output of the first-order kernel $w_1(n)$ and the input $u(n)$, the linear and nonlinear systems can be estimated.

3. CORRELATION RELATIONSHIPS

The next step in the estimation of the concatenated channel is to further process the input-output relations, as defined above, by utilizing correlation relationships.

3.1. Generalized input-output correlation

A commonly defined output is used in this derivation. The output is given by $r(n)$, where $r(n) = r_j(n)$, $1 \le j \le N$. Using the input $u(n)$ and the general output $r(n)$, the cross-covariance between them can be written as

$$\mathfrak{R}_{ur}(\sigma) = \overline{\big(r(n) - \overline{r(n)}\big)\big(u(n-\sigma) - \overline{u(n-\sigma)}\big)}. \qquad (12)$$

The cross-covariance relationship is used widely throughout this section. From this point onward, $r(n)$, $q(n)$, $n_{\text{amp}}(n)$, $u(n)$, and $x_j(n)$, $n_{w(j)}(n)$ for $1 \le j \le N$ will refer to their respective signals with the mean removed. In some cases [12], a mean level is added to the input to ensure that both odd and even terms in (11) contribute to the first-order input-output cross-correlation. However, in this case, only the output of the first-order kernel is of interest (discussed shortly) and hence a mean level is not needed. With means removed, the cross-covariance can be written as

$$\mathfrak{R}_{ur}(\sigma) = \overline{r(n) u(n-\sigma)}. \qquad (13)$$

Substituting (11) into the above equation and assuming the input and noise processes to be statistically independent, that is, $\overline{n_{\text{amp}}(n) u(n-\sigma)} = 0$ for all σ and $\overline{n_{w(j)}(n) u(n-\sigma)} = 0$ for all σ, give

$$\begin{aligned} \mathfrak{R}_{ur}(\sigma) &= \overline{\big[w_1(n) + w_2(n) + \cdots + w_l(n)\big]\big[u(n-\sigma)\big]} \\ &= \overline{w_1(n)u(n-\sigma) + w_2(n)u(n-\sigma) + \cdots + w_l(n)u(n-\sigma)} \\ &= \overline{w_1(n)u(n-\sigma)} + \overline{w_2(n)u(n-\sigma)} + \cdots + \overline{w_l(n)u(n-\sigma)} \\ &= \mathfrak{R}_{uw_1}(\sigma) + \mathfrak{R}_{uw_2}(\sigma) + \cdots + \mathfrak{R}_{uw_l}(\sigma), \end{aligned} \qquad (14)$$

which can be written in a more compact form as

$$\mathfrak{R}_{ur}(\sigma) = \sum_{k=1}^{l} \mathfrak{R}_{uw_k}(\sigma). \qquad (15)$$

However, if $\mathfrak{R}_{ur}(\sigma)$ is evaluated directly as defined above, the terms $\sum_{k=2}^{l} \mathfrak{R}_{uw_k}(\sigma)$ give rise to anomalies associated with multidimensional autocovariances [13]. This problem can be overcome by isolating $\mathfrak{R}_{uw_1}(\sigma)$ using multilevel input testing. This step is crucial for successful estimation of the wireless channel. Multilevel testing is possible under the condition that the output can be expressed by (11). It should be noted that if the channels were linear there would be no need to isolate $\mathfrak{R}_{uw_1}(\sigma)$ because $\mathfrak{R}_{uw_1}(\sigma) = \mathfrak{R}_{ur}(\sigma)$.

Multilevel testing is implemented prior to the nonlinearity by using the signal $\alpha_m u(n)$, where $\alpha_m \ne \alpha_l$ for all $m \ne l$, and repeating l times. For example, with a third-order nonlinearity, the output at the mobile user can be written as

$$\begin{aligned}
r(n) &= \left[\left(A_1 u(n) + A_2 u^2(n) + A_3 u^3(n) + n_{\text{amp}}(n)\right) * h_1(n)\right] \\
&\quad + n_{w(j)}(n) \\
&= A_1 u(n) * h_1(n) + A_2 u^2(n) * h_1(n) \\
&\quad + A_3 u^3(n) * h_1(n) + n_{\text{amp}}(n) * h_1(n) + n_{w(j)}(n) \\
&= w_1(n) + w_2(n) + w_3(n) + \text{noise terms}.
\end{aligned} \tag{16}$$

With the multilevel input $\alpha_1 u(n)$, the above equation becomes

$$\begin{aligned}
r_{\alpha_1}(n) &= \left[\left(A_1 \alpha_1 u(n) + A_2 \alpha_1^2 u^2(n) + A_3 \alpha_1^3 u^3(n) + n_{\text{amp}}(n)\right)\right. \\
&\quad \left. * h_1(n)\right] + n_{w(j)}(n) \\
&= A_1 \alpha_1 u(n) * h_1(n) + A_2 \alpha_1^2 u^2(n) * h_1(n) \\
&\quad + A_3 \alpha_1^3 u^3(n) * h_1(n) + n_{\text{amp}}(n) * h_1(n) + n_{w(j)}(n) \\
&= \alpha_1 w_1(n) + \alpha_1^2 w_2(n) + \alpha_1^3 w_3(n) + \text{noise terms},
\end{aligned} \tag{17}$$

which when used to find $\Re_{ur}(\sigma)$ gives the following modified form of (15):

$$\boxed{\Re_{ur_{\alpha_m}}(\sigma) = \sum_{k=1}^{l} \alpha_m^k \Re_{uw_k}(\sigma), \quad m = 1, 2, \ldots, l} \tag{18}$$

where r_{α_m} is the response of the system to multilevel inputs.

An important condition when using multilevel inputs is that the number of multilevel inputs used should be equal to the highest polynomial order. This ensures that the algorithm works in the presence of any order nonlinear function. Representing (18) in matrix form gives

$$\begin{bmatrix} \Re_{ur_{\alpha_1}}(\sigma) \\ \Re_{ur_{\alpha_2}}(\sigma) \\ \cdot \\ \cdot \\ \Re_{ur_{\alpha_l}}(\sigma) \end{bmatrix} = \begin{bmatrix} \alpha_1 & \alpha_1^2 & \cdot & \cdot & \alpha_1^l \\ \alpha_2 & \alpha_2^2 & \cdot & \cdot & \alpha_2^l \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \alpha_l & \alpha_l^2 & \cdot & \cdot & \alpha_l^l \end{bmatrix} \begin{bmatrix} \Re_{uw_1}(\sigma) \\ \Re_{uw_2}(\sigma) \\ \cdot \\ \cdot \\ \Re_{uw_l}(\sigma) \end{bmatrix}. \tag{19}$$

To check the above α matrix for singularities, it is divided into two matrices as follows:

$$\begin{bmatrix} \alpha_1 & 0 & \cdot & \cdot & 0 \\ 0 & \alpha_2 & 0 & \cdot & 0 \\ \cdot & 0 & \cdot & \cdot & 0 \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ 0 & 0 & \cdot & \cdot & \alpha_l \end{bmatrix} \begin{bmatrix} 1 & \alpha_1 & \alpha_1^2 & \cdot & \alpha_1^{l-1} \\ 1 & \alpha_2 & \alpha_2^2 & \cdot & \alpha_2^{l-1} \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ 1 & \alpha_l & \alpha_l^2 & \cdot & \alpha_l^{l-1} \end{bmatrix}. \tag{20}$$

The matrix on the left-hand side (LHS) of (20) is clearly nonsingular for $\alpha_m \neq 0$. The matrix on the right-hand side (RHS) of (20) is the Vandermonde matrix which has a nonzero determinant given by

$$\prod_{1 \le i < j \le l} (\alpha_j - \alpha_i), \tag{21}$$

for $\alpha_i \neq \alpha_j$. Therefore, for every value of σ, (19) has a unique solution for $\Re_{uw_i}(\sigma)$, $i = 1, 2, \ldots, l$. Now that $\Re_{uw_1}(\sigma)$ (the input-kernel correlation) can be extracted, the final step in the identification process is to find how $\Re_{uw_1}(\sigma)$ relates to the CIR.

3.2. *Difficulties with the input-kernel correlation*

The cross-covariance between the compound input $u(n)$ and $w_1(n)$ can be written as

$$\Re_{uw_1}(\sigma) = \overline{w_1(n) u(n - \sigma)}. \tag{22}$$

Substituting for $w_1(n)$ from (10) and expanding $u(n)$ give

$$\begin{aligned}
\Re_{uw_1}&(\sigma) \\
&= \overline{\left(A_1 \sum_{m=-\infty}^{\infty} h_1(m) u(n-m)\right)(u(n-\sigma))} \qquad (23) \\
&= A_1 \sum_{m=-\infty}^{\infty} h_1(m) \overline{u(n-m) u(n-\sigma)} \\
&= A_1 \sum_{m=-\infty}^{\infty} h_1(m) \overline{(x_1(n-m) + x_2(n-m) + \cdots + x_N(n-m))} \\
&\quad \times \overline{(x_1(n-\sigma) + x_2(n-\sigma) + \cdots + x_N(n-\sigma))}.
\end{aligned} \tag{24}$$

The above equation can be considered in two ways: (1) by expanding $u(n)$, giving (24), and (2) without expanding $u(n)$, giving (23).

3.2.1. *Expanding $u(n)$*

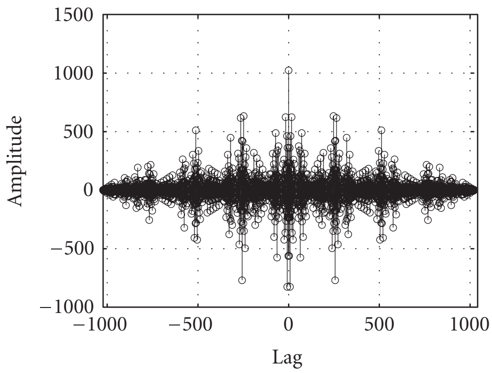
Simplifying (24) using correlation notation gives

$$\begin{aligned}
\Re_{uw_1}&(\sigma) \\
&= A_1 \sum_{m=-\infty}^{\infty} h_1(m) \left(\Re_{x_1 x_1}(m-\sigma) + \Re_{x_2 x_2}(m-\sigma)\right. \\
&\quad \left. + \cdots + \Re_{x_N x_N}(m-\sigma) + \Re_{x_i x_{j(j \neq i)}}(m-\sigma)\right).
\end{aligned} \tag{25}$$

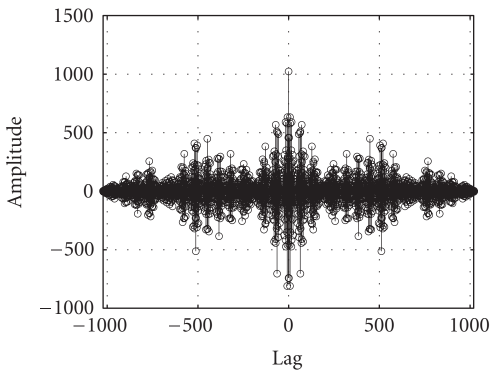
Since Walsh codes do not have well-defined mathematical correlation properties, the above equation cannot be further simplified. Individually, Walsh codes have good correlation properties only when tightly synchronized and even then it is only at the zeroth lag. As the lag moves away from zero, the correlation becomes unacceptable. This is represented in Figure 4. This figure shows the autocovariance and cross-covariance properties of two individual Walsh codes, one with a code index of 396 and the other with a code index of 882. From Figures 4(a) and 4(b) it is clear that the autocovariance properties of individual Walsh codes are unacceptable. For this reason, identification of the concatenated channel in a single user Walsh code environment is difficult. But the situation drastically changes when many users are considered at once.

3.2.2. *Without expanding $u(n)$*

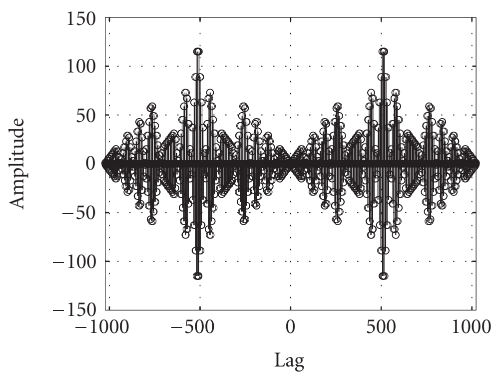
The covariance properties of the *summation* of Walsh codes are very much different from that of the covariance of individual Walsh codes. It has been found through simulations



(a) Autocovariance of Walsh code of index 396.



(b) Autocovariance of Walsh code of index 882.



(c) Cross-covariance of the above two Walsh codes.

Figure 4: Covariance properties of individual Walsh codes of length 2^{10} for two different code indices.

that, as more and more users are added, this compound input of Walsh codes starts to resemble a white noise-like process. This is an interesting outcome because it is known that identification of the downlink is possible under the condition that the input is white noise-like (see [2, 13]). The autocovariance of the input $u(n)$ is shown in Figure 5. There is some resemblance observed between this autocovariance and that of a PN sequence, given by $\Re_{x_i x_i}(\lambda) = N_c \delta_i(\lambda)$. Aside from the amplitudes at nonzero lags, the autocovariance of the summation of Walsh codes can be approximated by the

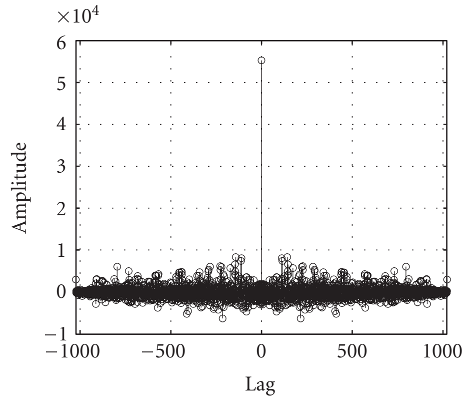


Figure 5: Autocovariance of a summation of Walsh codes.

relationship[3]

$$\Re_{uu}(\lambda) \approx N_w N \delta(\lambda), \tag{26}$$

where N is the number of Walsh codes. Applying the above approximation to (23) gives

$$\Re_{uw_1}(\sigma) = A_1 N_w N \sum_{m=0}^{N_w-1} h_1(m)\delta(m-\sigma). \tag{27}$$

Using the convolution properties of the impulse function gives

$$\boxed{\Re_{uw_1}(\sigma) = A_1 N_w N h_1(\sigma)} \tag{28}$$

where the estimated CIR can be found by solving the above expression. Therefore, it has been shown that the CIR can be estimated by utilizing the autocovariance property of summed Walsh codes. Using a greater number of Walsh codes results in even better covariance properties and hence a more accurate identification.

4. ESTIMATION: SIMULATION RESULTS AND DISCUSSION

The simulation package used for all simulations herein was MATLAB with Simulink. The simulations were performed with Figure 3 implemented as a Simulink model. The Simulink model was used mainly as a means to gather the input-output data of the system. All the initializations and identification calculations (i.e., correlations) were performed in MATLAB by sending the Simulink inputs/outputs to the MATLAB workspace.[4]

[3] Under the condition that the code indices for the Walsh codes occupy the entire range of indices available for that certain code length, in equal intervals.

[4] MATLAB and Simulink are the trade names of their respective owners.

4.1. Simulation parameters and channel characteristics

4.1.1. CIR and polynomial

All CIRs used in the simulations satisfied the property of unit energy, that is, $\sum_n |h(n)|^2 = 1$. This ensured no amplification from the wireless channel.

The major source of nonlinearity is the RF amplifier, which can be modeled using an lth-order polynomial. Any mildly nonlinear system that can be described by an lth-order polynomial can be identified using our technique. For example, in the case of ROF, the polynomial is third-order with a saturating characteristic (see [14, 15]).

4.1.2. Number of users and Walsh code length

Fifty four users were simulated at the base station. Simulations were performed with a Walsh code length of 1024 ($N_w = 2^{10}$).

4.1.3. Noise

The SNR between the base station and access point was set to 25 dB, and the wireless noise power for each mobile user was set equal to the amplifier noise power.

4.1.4. Cross-covariance

Lang and Chen showed in [16] that, for 10th degree sequences, the average Walsh code cross-covariances are approximately 2.53 times larger than PN sequence cross-covariances. However, the adverse effect of these cross-covariances is minimal because they are relatively small when compared to the large autocovariance value. This can also be seen by comparing Figures 4(c) and 5. From these figures it is found that the maximum amplitude of the cross-covariance is approximately 0.208% of the maximum autocovariance.

4.1.5. Quality of fit

The quality of fit of the estimated CIR to the actual CIR was measured by defining a normalized estimation error parameter

$$\rho = \frac{\sum_{k=0}^{L} \left[h_{\text{actual}}(k) - h_{\text{est}}(k)\right]^2}{L_{\max}}, \tag{29}$$

where $L_{\max}$ is the largest CIR memory amongst all users. Dividing by $L_{\max}$ makes ρ independent of CIR memory. A smaller ρ means a better CIR estimate.

4.1.6. Synchronous communication

Synchronization can be achieved for all signals in the downlink. The buffer period needed for the simulation of asynchronous communication is not needed. All signals can start at the same time and data is collected from the start of the simulation to the end (i.e., the time needed to cover one period, N_w).

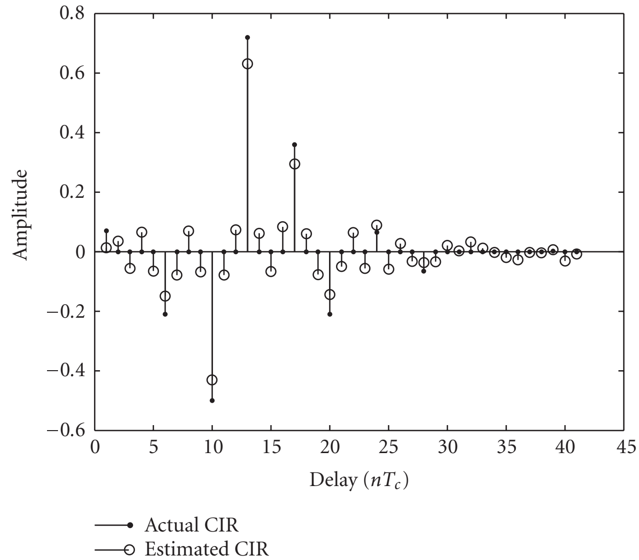


Figure 6: "Poor" channel impulse response (CIR) estimate.

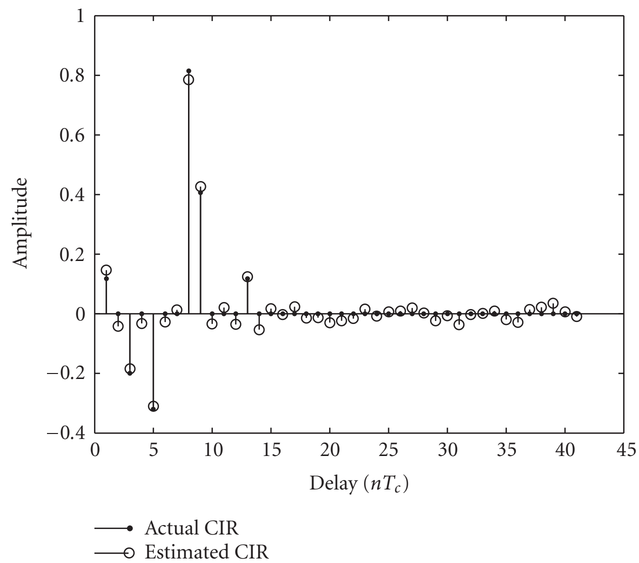


Figure 7: "Good" channel impulse response (CIR) estimate with $\rho = 1.462 \times 10^{-4}$.

4.2. Wireless channel identification

Two CIR estimates are presented in this section, they are defined as "good" and "poor." The reason for this is to show that at this point there is still an inconsistency between estimates and that the quality of the estimate depends on the characteristics of the CIR (a major factor being the spread between multipath arrivals). Note that the linear CIRs have been estimated in the presence of a nonlinearity. We performed a large number of trials by varying the gain of each path using the Rayleigh fading model. The worst and the best case estimation errors from these trials were $\rho = 4.241 \times 10^{-3}$ and $\rho = 1.462 \times 10^{-4}$. These two cases are shown in Figures 6 and 7, respectively. Most of the time ρ was smaller than the

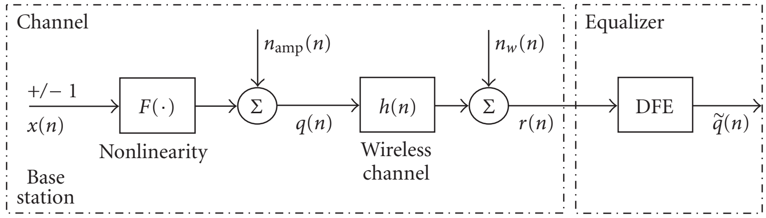


Figure 8: Block diagram for downlink equalization.

mean value, which we found gives a reasonably good channel estimate. Note that since there is a greater spread between multipath arrivals in the "poor" estimate of Figure 6, the algorithm is not so accurate but it is still able to recover the general structure of the desired CIR.

4.3. Nonlinearity identification

Once the CIRs are known, the internal signal $q(n)$ must be estimated so that polynomial fitting can be done between the signals $u(n)$ and $\tilde{q}(n)$. The accuracy of the nonlinear identification is highly dependent on the CIR estimates and so it is important that the CIR estimation algorithm works well. One possible method to estimate the internal signal is by deconvolving $h_{1,\ldots,N}(n)$ with their respective outputs $r_{1,\ldots,N}(n)$. Estimating the nonlinearity is left for future work.

5. HAMMERSTEIN-TYPE DOWNLINK EQUALIZATION

The downlink has a static nonlinearity followed by a dynamic linear time dispersive wireless channel. This is a Hammerstein system. Although the nonlinear portion of the Hammerstein system has not been estimated, equalization can still be performed on the linear wireless channel of the downlink. The structure of the equalizer is shown in Figure 8. The receiver consists only of a DFE arrangement that compensates solely for the wireless channel dispersion. Even though the polynomial is not compensated for, the simulation results of the equalization still show a good improvement in terms of bit error rate (BER). Note that the equalization is done for a single user, but the channel is estimated under a multiuser environment. The nonlinearity is common for all the users; however, the wireless channel varies for different users.

The number of DFE taps was derived based on the memory of the CIR (L was varied from 9 to 13). In order to completely eliminate postcursor interference, the number of FBF taps must satisfy the condition $K_2 \geq L$ [8]. The number of FFF taps is chosen to be approximately $2L$ (which is common in the literature). Hence, the DFE parameters for the simulations were as follows: FFF taps were varied from 18 to 26 and FBF taps were varied from 9 to 13.

A large number of error rate simulations were performed and the BER from an "average" CIR estimate was found. Simulations were also done to find the BER resulting from not taking the nonlinearity into account during the channel estimation process. These two BERs are plotted in Figure 9. We can see from this figure that a very good improvement in the BER can be achieved with the proposed algorithm which takes the nonlinearity into account during channel estimation.

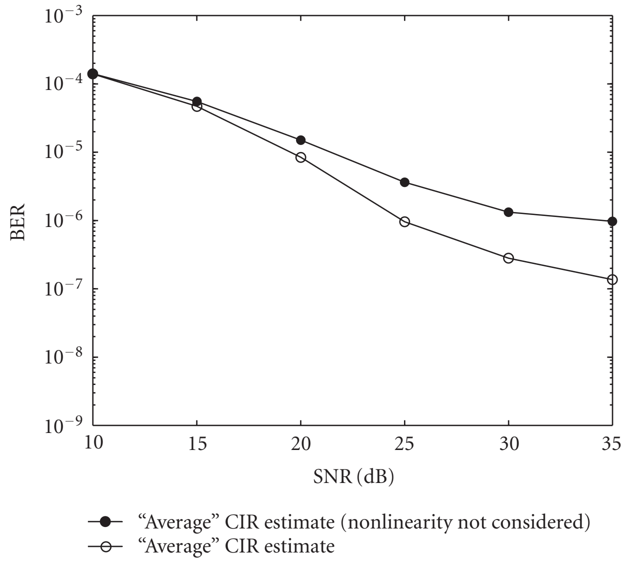


Figure 9: BER of the downlink using the "average" CIR estimate; this is the most realistic outcome.

When the channel has a few strong paths (typical in a rural environment with few buildings) the proposed nonlinear channel estimation works very well. Figure 10 shows this best case (when the estimation error is small). Under this scenario the performance error is even better. An acceptable BER for transmitting data is 10^{-6}. Our algorithm can achieve this BER at an SNR of about 25 dB (with the "good" CIR estimate), which is comparable to the DFE BER curves obtained in [8, 17].

This paper shows the usefulness of an estimation algorithm that takes into account the nonlinear nature of the channel.

6. CONCLUSION

This paper presented a method for identification of the multiuser CDMA downlink using the correlation properties of Walsh codes. We improved the single user identification performed in [2] to accommodate multiple users and we showed

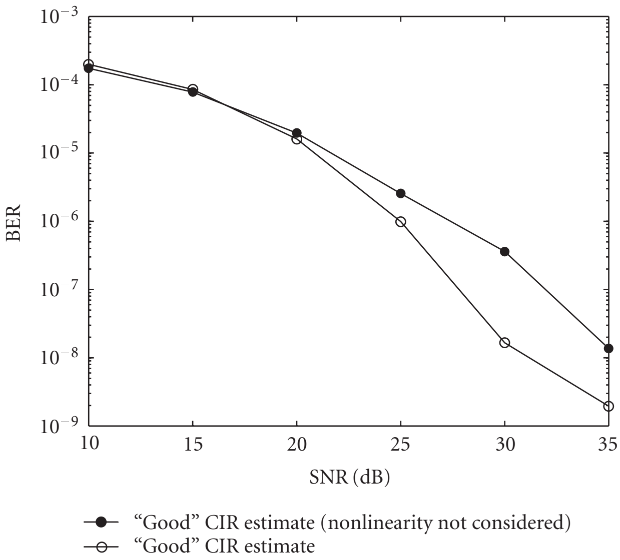


Figure 10: BER of the downlink using the "good" CIR estimate.

the effect of both wireless and RF amplifier noise. It was shown that using a summation of Walsh codes, as opposed to single Walsh codes, makes identification of the Hammerstein system possible. In a synchronous CDMA environment, the proposed identification algorithm works well with 54 users, and even better with additional users because the correlation property improves. Equalization of the downlink showed a BER of 10^{-6} achieved at an SNR of ~ 25 dB.

Some concerns regarding the practicality of the estimation algorithm arise when considering the effect that multilevel testing has at the system level. However, with power control algorithms used in CDMA systems, the multilevel transmission is inherently done. For example, when a mobile unit moves away from the base station, its received power will drop; the base station will then increase the transmitted power (typically in 1 dB steps) until the power is acceptable. So, one of our ideas to overcome this problem of multilevel testing is to record data during the adjustment of power with power control algorithms. Assuming there is little change in the wireless channel impulse response while gathering data, this technique can provide the multilevel testing required for estimation.

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