RESEARCH PAPER
Future Research in AI & IoT, 2025, 1(2)
Homepage: https://frai.journals.umz.ac.ir/
DOI:

Blind Multiuser Detection in Asynchronous Variable processing gain in spread spectrum IoT systems

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Article Info
Received -----
Accepted -----
Available online -----

Keywords:
Asynchronous VPG DS-CDMA;
Secure Internet of things (IoT) Communication;
Autocorrelation-Based Detection;
Low Probability of Detection (LPD);
Physical layer Security.

Abstract:
In the context of rapidly expanding Internet of Things (IoT) deployments, ensuring reliable detection and decoding of low-power, wideband signals from numerous asynchronous devices is a critical challenge. This paper presents a novel blind multiuser detection technique for Variable Processing Gain Direct-Sequence CDMA (VPG-DS/CDMA) tailored to IoT networks. Building on prior fluctuation-based autocorrelation estimators, our method removes all constraints on individual spreading gains and operates effectively in multipath fading channels. By dynamically adjusting each device's spreading length, we demonstrate both an amplified periodic fluctuation signature and a direct relationship between fluctuation peak amplitude and spreading factor, enabling robust user separation even when signals are buried below the noise floor. Theoretical analysis proves reliable detection at extremely low SNR levels, a scenario common in battery-powered IoT sensors. We validate our approach via simulations over realistic IoT channel models and employ the Minimum Description Length (MDL) criterion to accurately estimate the active user count. Our results indicate that this blind multiuser detector can substantially improve network throughput and device scalability in dense IoT environments without prior synchronization or pilot overhead.

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Supplementary information: Supplementary information for this article is available at https://frai.journals.umz.ac.ir/
Please cite this paper as:

1. Introduction

The evolution of communication infrastructures to support the Internet of Things (IoT) has introduced complex demands on signal transmission technologies [1]. These systems must not only be energy-efficient but also capable of functioning in noisy and congested environments, all while maintaining secure data transmission [2]. Among various modulation schemes, Direct Sequence Spread Spectrum (DSSS) has emerged as a viable solution due to its ability to disperse signals over a broad frequency range, inherently reducing susceptibility to interference and enabling data recovery through correlation methods at the receiver side [3].

In multi-device networks, where simultaneous communication is essential, DSSS allows independent transmissions by assigning distinct spreading sequences to each terminal, a principle aligned with Code Division Multiple Access (CDMA) techniques [4]. This makes DSSS highly suitable for asynchronous, high-density IoT applications where synchronization cannot be guaranteed [5]. Recent efforts to improve DSSS performance in IoT settings include innovations in signal processing and detection mechanisms [6]. For instance, novel filtering methods utilizing time-domain transformations have shown promise in enhancing signal clarity and suppressing interference [7]. Likewise, artificial intelligence models, especially those based on neural networks, have been integrated into receivers to boost detection accuracy under harsh signal-to-noise conditions [9]. Security has also become a critical concern. Modifications to the statistical properties of DSSS signals, such as altering their spectral

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distribution, have proven effective in minimizing the probability of unauthorized interception or disruption [10]. Such adaptations are essential for IoT networks operating in contested or covert environments [11]. As wireless systems continue to scale, the need to support heterogeneous data rates and variable quality-of-service requirements grows [12]. CDMA systems can accommodate these needs using two primary methods: variable spreading factor schemes, where processing gain changes according to user data rate, and multi-code transmission, where high-rate data is partitioned into parallel lower-rate streams [13]. However, in scenarios where prior knowledge of system parameters is unavailable, such as blind detection in military or surveillance settings, these strategies face significant limitations [14]. A key challenge in such environments is the identification of the spreading code length, which plays a pivotal role in signal detection and synchronization [15, 16, 17]. This research proposes a blind multiuser detection framework designed specifically for asynchronous VPG DS-CDMA systems, eliminating the need for prior knowledge of processing gain or user count. The method is tailored to operate under multipath propagation and extremely low signal-to-noise ratios, conditions typical in dense IoT deployments.

This paper is organized as follows: Section II introduces the mathematical foundations and system architecture. Section III outlines the proposed blind detection algorithm. Section IV presents simulation results under various transmission scenarios, and Section V concludes with a summary of contributions and potential avenues for future exploration.

2. Method

2.1. Mathematical System Model

We consider a multiuser transmission model where each user operates within an asynchronous direct sequence CDMA system, employing a distinct processing gain. Let user i transmit a binary information sequence $\{b_i(j)\}$, where j indexes the bit position. This sequence is spread using a pseudo-random code $\{c_i(k)\}$ of length L_i, specific to the user's data rate.

The discrete-time baseband representation of the transmitted signal at the chip rate is formulated as:

$$x_i(k) == \sum_j b_i(j).c_i(k - jL_i) \qquad (1)$$

This model captures the spreading operation by associating each bit with a sequence of L_i chips. The transmitted waveform is constructed by modulating the data over these chip sequences. As the signal propagates through a multipath channel, its structure is distorted by time-varying impulse responses. Let $h_i(k)$ denote the baseband-equivalent channel impulse response for user i. The signal received at the destination is composed of the aggregate of these transmitted signals convolved with their respective channels, plus additive white Gaussian noise $n(k)$. Thus, the received discrete-time signal becomes:

$$r(k) = \sum_{i=1}^{N} x_i(k) * h_i(k) + n(k) \qquad (2)$$

The convolution in (2) accounts for the multipath propagation effects specific to each user's channel.

For analysis and detection purposes, it is often useful to define the effective impulse response as the combination of the spreading code and the channel impulse response. This effective channel, which captures both code modulation and channel distortion, is given by:

$$h_i^{eff}(k) = c_i(k) * h_i(k) \qquad (3)$$

This representation allows the received signal to be interpreted as a superposition of symbol sequences passed through effective linear systems, where detection can be approached via correlation, estimation, or blind techniques, depending on available information.

3. Novel Detection Approach

The proposed blind detection algorithm is designed to estimate the code length in asynchronous DS-CDMA systems with variable processing gains, even in the presence of noise and multipath propagation. It operates by adaptively selecting a data window and analyzing periodic fluctuations in the second-order statistics of the received signal.

The algorithm consists of two main components:

1. **Adaptive Window Selection** – to enhance the visibility of autocorrelation peaks related to the spreading sequence;

2. **Threshold Evaluation** – to discriminate between significant peaks and background noise.

The following steps summarize the complete procedure:

1. **Set a detection threshold (TL)** to differentiate between meaningful signal components and noise-induced fluctuations.

2. **Initialize a counter (TC)** to track the frequency of occurrence of potential code lengths across analysis windows.

3. **Construct a two-dimensional data structure** to store peak distances and support temporal averaging across multiple windows.

4. **Select a test range (TR)** for candidate code lengths. Adjust TR to ensure multiple peaks appear in each window; larger TR values correspond to detecting longer spreading sequences.

5. **Compute the difference between detected peaks** in each window and store these values in a matrix D, which quantifies the spacing between successive fluctuation peaks.

$D=\{d_{i,j}\}$ where $d_{i,j}$ =distance between peaks i and j (6)

6. **Assign likelihood values** to a matrix P, where each element $P_{i,j}$ reflects the probability that a specific code length corresponds to a real user. This is based on both the

amplitude of detected peaks and their frequency of occurrence:

$$p_{i,j} = f\,(d_{i,j}, A_{i,j}, R_{i,j}) \qquad (7)$$

Where $A_{i,j}$ is the amplitude of the j-th peak and $R_{i,j}$ represents its repetition count across windows.

7. **Aggregate the results** across multiple windows. The candidate code length with the highest cumulative probability in matrix P is selected as the estimated spreading factor.

4. Results

This section evaluates the effectiveness of the proposed code length estimation algorithm through numerical simulations under realistic operating conditions, including additive noise and multipath effects.

In the first experiment, we simulate a scenario with three active users, each assigned an m-sequence with a distinct length: 31, 63, and 127. These values correspond to different processing gains. The system operates with a chip rate of F_c =1.5MHz and a sampling frequency of F_s=10MHz. The signal-to-noise ratio is set to SNR =-5dB, and the number of users is fixed at K = 3. The simulation focuses on the uplink direction, where all users transmit asynchronously.

Figure 1 illustrates the correct detection of the pseudo-noise (PN) period in this 3-rate system, even under low SNR conditions.

Figure 2 presents the selection of the first adaptive analysis window when channel fading is introduced. The results show that the algorithm identifies the most probable spreading lengths with high accuracy. This is confirmed by the structure of the P and R matrices computed during detection:

$$P = \{p_{i,j}\},\ \mathrm{R} = \{r_{i,j}\} \qquad (9)$$

Where P contains the probability scores for each candidate code length, and R counts how often each value is detected across all windows.

In the **second experiment**, the simulation is extended to more complex systems. Here, spreading sequences are randomly generated (non-m-sequences) to mimic less structured real-world transmissions. A multipath channel is modeled using a finite impulse response filter. The MDL criterion is first used to estimate the number of active users. Once K is determined, the algorithm applies fluctuation-based detection to estimate the code lengths.

Figures 3 through 5 present the outcome of these tests under two scenarios: one with five users (5-rate) and another with eight users (8-rate), each employing a distinct random spreading code. These figures demonstrate that the detection process remains effective despite the use of non-ideal codes and variable user counts.

Lastly, Figure 6 plots the probability of accurate PN period detection versus SNR for multiple system configurations. It is evident that as the number of users and the rate diversity increase, the detection performance declines, particularly under poor signal conditions. However, the use of adaptive window sizes enables the algorithm to maintain satisfactory performance by enhancing the observability of periodic peaks.

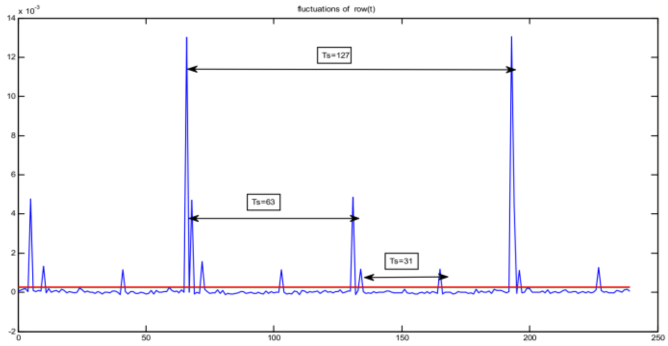

Figure 1. Estimation of PN period in 3-rate system under AWGN for SNR= -8dB.

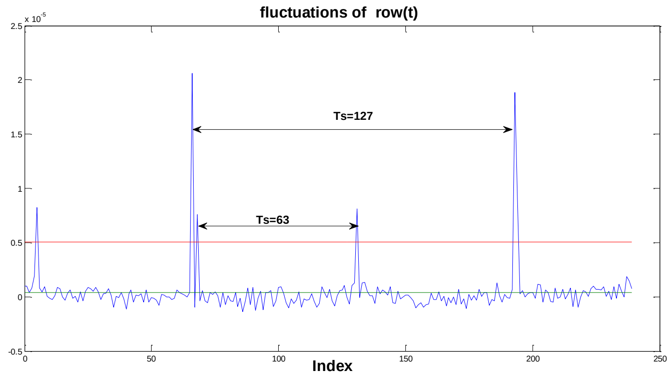

Figure 2. Initial adaptive window selection for PN detection in fading channel.

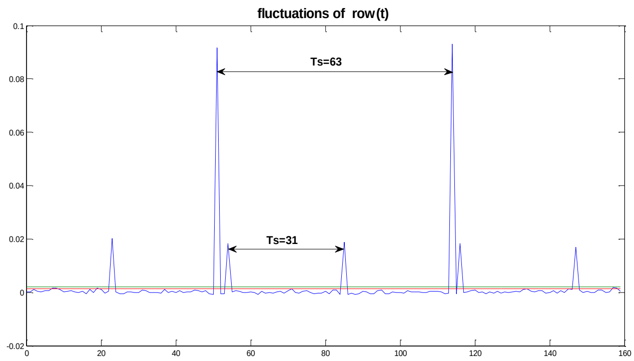

Figure 3. Secondary window adjustment in multipath fading.

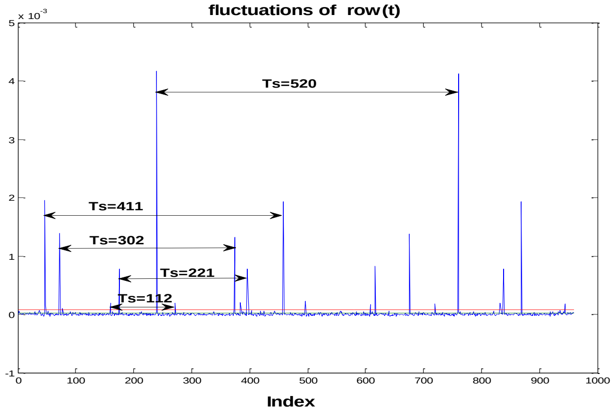

Figure 4. **Detection of PN period in 5- rate system at SNR=-5dB.**

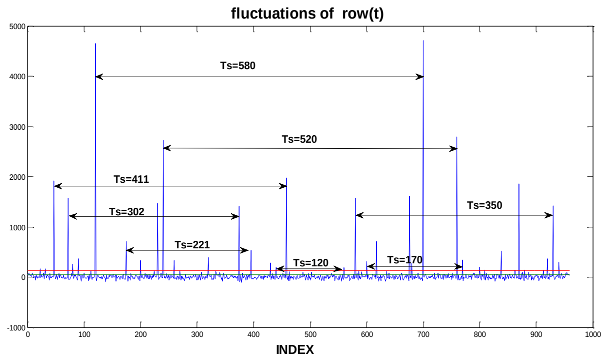

Figure 5. **Detection in 8- rate system under same SNR.**

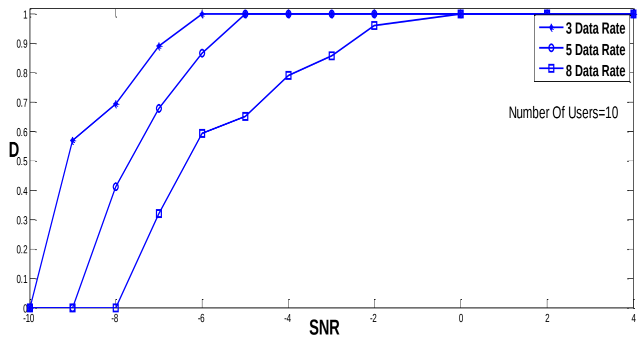

Figure 6. **Detection probability vs. SNR for systems with different rates.**

5. Conclusion

In this paper, a novel approach for estimating the pseudo-noise (PN) period in asynchronous VPG DS-CDMA systems under multipath channel conditions was presented. The proposed method leverages fluctuations in signal amplitudes and sequence lengths to construct a correlation matrix from data arranged within a single analysis window. Unlike previous studies, the adaptive selection of window length and number provides flexibility and enhanced performance under varying processing gain scenarios. This makes the technique particularly suitable for dynamic and heterogeneous environments such as the Internet of Things (IoT), where multiuser wideband signals are prevalent. The improved adaptability and robustness of the method offer a promising solution for efficient signal detection in future IoT-based communication systems.

6. Acknowledgement

To improve the language and enhance clarity, writing software, such as Grammarly, was employed in the process of manuscript preparation.

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