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Blind Physical-Layer Identification of Users in Multi-User SDR Systems via Sequential Estimation of Turbo Code Parameters

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BLIND PHYSICAL-LAYER IDENTIFICATION OF USERS IN MULTI-USER SDR SYSTEMS VIA SEQUENTIAL ESTIMATION OF TURBO CODE PARAMETERS

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Abstract. Adaptive identification of transmitting users in multi-user software-defined radio (SDR) systems remains a challenging problem under low signal-to-noise ratio (SNR) and interference-limited conditions, where conventional protocol-based approaches become inefficient or inapplicable.

This paper proposes a blind physical-layer identification method based on sequential estimation of turbo code parameters, including block length, coding rate, interleaver structure, and generator polynomials. The identification problem is formulated as a parameter estimation task over a finite configuration space, where the most probable configuration corresponds to the transmitting user.

The proposed solution is implemented as a three-stage algorithm comprising separation of channel data components, interleaver detection, and iterative decoding-based estimation of encoder parameters. The method exploits convergence properties of iterative decoding, particularly the evolution of log-likelihood ratios (LLR), to discriminate between candidate configurations.

Analytical models describing identification complexity and reliability are developed, establishing relationships between SNR, decoding iterations, and identification latency.

Simulation results demonstrate that the proposed method achieves a probability of correct identification $P_{\mathrm{id}} \geq 0.95$ for SNR ≥ 6 dB, while maintaining an identification overhead of approximately 10–15% relative to decoding time. Compared to conventional approaches, the method provides improved robustness to interference and eliminates the need for protocol-level signaling.

Keywords: Turbo codes; Blind identification; SDR; Physical-layer security; Iterative decoding; LLR dynamics; Multi-user systems

1. Introduction

The rapid evolution of software-defined radio (SDR) technologies and multi-user wireless systems has significantly increased the demand for efficient subscriber identification mechanisms at the physical layer. In many practical scenarios, including open-loop communication, telemetry, and IoT deployments, higher-layer identification methods are either unavailable or introduce excessive latency and signaling overhead [1]–[3].

Existing identification approaches can be broadly classified into three categories. The first category relies on protocol-level identifiers, such as MAC addresses and control signaling, which require strict protocol compliance and are not applicable in passive or uncoordinated environments. The second category is based on cryptographic authentication, offering high reliability at the cost of substantial computational complexity and latency, limiting its applicability in real-time SDR systems. The third category includes feature-based methods that exploit modulation characteristics, statistical properties, or channel fingerprints. However, these approaches are highly sensitive to noise, interference, and channel variability, resulting in performance degradation under realistic conditions [4], [5].

To address these limitations, increasing attention has been devoted to physical-layer identification techniques based on intrinsic signal properties. Prior studies have explored modulation recognition, cyclostationary analysis, and machine learning-based classification. Although these approaches can achieve high accuracy in controlled environments, they typically require large training datasets and exhibit reduced robustness under low-SNR and interference conditions [6], [7].

Modern communication systems widely employ advanced channel coding techniques, such as turbo codes and LDPC codes, which introduce structured redundancy into transmitted signals. Despite their extensive use, the potential of coding structure for identification tasks remains underexplored. Existing research on turbo codes primarily focuses on decoding performance and error correction, with limited attention to parameter identification and blind recognition [8]–[10].

A key limitation of current methods is the lack of integration between statistical signal processing and decoding dynamics. While maximum likelihood (ML) estimation provides a theoretically optimal framework, its direct application is computationally prohibitive for high-dimensional configuration spaces. At the same time, iterative decoding generates rich dynamical information, such as the evolution of log-likelihood ratios (LLR), which remains largely underutilized in identification problems [8], [11].

Therefore, a clear research gap exists in developing efficient identification methods that jointly exploit the structural properties of channel coding and the dynamics of iterative decoding. This gap is particularly critical for multi-user SDR systems operating under low-SNR and interference conditions.

This paper addresses the identified gap by proposing a blind identification method based on sequential estimation of turbo code parameters. The key idea is to combine structural decomposition of turbo-coded signals with analysis of decoding convergence behavior. The identification process is formulated as a parameter estimation problem over a finite configuration space and implemented as a three-stage algorithm that progressively reduces the set of admissible configurations [12]–[18].

Recent advances in deep learning-based signal classification and physical-layer security [19]–[22], [24]–[26] demonstrate high performance in structured environments but require extensive training and may suffer from limited robustness under varying channel conditions. In contrast, the proposed method does not rely on training data and provides a lightweight and interpretable alternative suitable for real-time SDR applications.

The main contributions of this work are as follows:

1. A formal formulation of the subscriber identification problem as a maximum likelihood estimation task over the space of turbo code configurations.
2. A sequential estimation framework that reduces computational complexity through staged filtering of candidate configurations.
3. A novel identification criterion based on the stability of LLR evolution during iterative decoding.
4. Analytical models linking identification accuracy, computational complexity, and channel conditions.
5. Simulation results demonstrating high identification reliability and robustness under interference.

The remainder of the paper is organized as follows. Section 2 presents the system model. Section 3 formulates the identification problem. Section 4 describes the proposed method. Section 5 provides analytical performance evaluation. Section 6 presents simulation results. Section 7 contains comparative analysis, Section 8 discusses the results, and Section 9 concludes the paper.

Related Work

Recent research on subscriber identification and signal classification at the physical layer can be broadly categorized into three main directions: feature-based methods, learning-based approaches, and coding-aware techniques.

Feature-based identification.

A large class of approaches exploits modulation features, higher-order statistics, or cyclostationary properties for signal identification. These methods operate directly on the received waveform and do not require protocol information. However, their performance is strongly affected by noise, interference, and channel variability. In low-SNR regimes, feature separability degrades significantly, resulting in reduced identification accuracy. Moreover, such methods rely on instantaneous signal characteristics and do not exploit structural redundancy introduced by channel coding [6], [7].

Learning-based approaches.

Machine learning and deep learning techniques have been increasingly applied to signal classification and identification tasks. These approaches can achieve high accuracy under controlled conditions but require large labeled datasets and extensive training. Their generalization capability under varying channel conditions and interference remains limited, and the computational cost of training and inference may be prohibitive for real-time SDR applications [12], [13].

Recent studies further demonstrate the effectiveness of CNN-, LSTM-, and Transformer-based architectures for signal classification and physical-layer security [19]–[22], [24]–[26]. Despite their strong performance, these methods are sensitive to distribution shifts and typically require substantial computational resources and prior training.

Coding-aware and decoding-based methods.

A smaller group of works considers the use of channel coding properties for identification and signal processing. These approaches primarily focus on decoding performance, multi-user detection, or parameter estimation for known coding schemes. However, the use of turbo code structure and iterative decoding dynamics specifically for blind subscriber identification remains insufficiently explored. Existing methods do not fully exploit the temporal evolution of log-likelihood ratios (LLR) as an identification feature [8]–[10].

A fundamental limitation of the existing approaches is the lack of integration between structural signal properties and decoding dynamics. Feature-based methods ignore coding structure, while learning-based approaches treat the signal as a black box and do not utilize decoding information. Coding-aware

methods, in turn, are not explicitly designed for identification tasks. This creates a gap between theoretical optimality and practical implementability.

The proposed method addresses this limitation by combining structural decomposition of turbo-coded signals with analysis of iterative decoding behavior. This enables the identification process to exploit both static and dynamic signal properties, improving robustness under interference and reducing computational complexity. A comparative summary of the considered approaches is provided in Table 1.

Table 1 — Comparison of Identification Approaches

Method class	**Principle**	**Advantages**	**Limitations**
Feature-based [6], [7]	Signal statistics, modulation features	No protocol required	Sensitive to noise and interference
Learning-based [12], [13], [19]–[22], [24]–[26]	Data-driven classification	High accuracy (trained conditions)	Requires large datasets, poor generalization
Coding-aware [8]–[10]	Channel coding structure	Exploits redundancy	Limited use for identification
Proposed method	Turbo code structure + decoding dynamics	Robust, no training, moderate complexity	Requires predefined configuration set

Table 1 shows that existing approaches either lack robustness under interference (feature-based methods) or require significant computational and data resources (learning-based approaches). Coding-aware methods exploit structural redundancy but are not specifically designed for identification tasks.

The proposed method provides a balanced solution by integrating structural properties of turbo codes with decoding dynamics. This combination enables reliable identification in low-SNR conditions, where feature-based methods fail, while avoiding the training requirements and computational overhead associated with deep learning approaches.

In addition, decoding-aware techniques such as EXIT-chart-based analysis and blind recognition of channel codes have been investigated in the literature. These methods rely on convergence properties of iterative decoding but typically require prior knowledge of code parameters or involve computationally intensive matching procedures.

In contrast, the proposed approach employs a lightweight instability metric based on LLR sign evolution, enabling efficient pruning of the configuration space without exhaustive search or prior training.

2. System Model

The proposed subscriber identification method is developed for a multi-user unidirectional communication system implemented on a software-defined radio (SDR) platform. The system consists of a set of transmitting subscribers and a centralized receiver that performs signal reception, decoding, and identification under open-loop conditions.

Let the system include K transmitting subscribers. Each subscriber is characterized by a parameter vector of turbo code configuration:

$$\Theta_i = L_i, R_i, m_i, G_i, \Pi_i,$$

where Θ_i is the turbo code parameter vector of the i-th subscriber, L_i is the interleaver block length, R_i is the coding rate, m_i is the constraint length of the recursive convolutional encoder, G_i is the generator polynomial, and Π_i is the interleaver mapping.

The set of admissible configurations is defined as

$$\mathcal{S} = \Theta_1, \Theta_2, \dots, \Theta_K,$$

where $\mathcal{S}$ denotes the space of admissible turbo code configurations.

Each configuration $\Theta_i \in \mathcal{S}$ uniquely corresponds to a transmitting subscriber, which allows the identification problem to be interpreted as a parameter estimation problem.

Signal transmission over a channel with noise and interference is described by

$$y(t) = h(t) * x_i(t) + \eta(t) + n(t),$$

where $x_i(t)$ is the transmitted signal of the i-th subscriber, $h(t)$ is the channel impulse response, $\eta(t)$ is interference, and $n(t)$ is additive white Gaussian noise [5], [14].

The discrete-time representation is given by

$$\mathbf{y} = \mathbf{H}\mathbf{x}_i + \boldsymbol{\eta} + \mathbf{n},$$

where $\mathbf{y}$ is the observation vector and $\mathbf{H}$ is the channel matrix.

The channel quality is characterized by the signal-to-interference-plus-noise ratio [5]

$$\mathrm{SINR} = \frac{P_s}{P_n + P_\eta},$$

where P_s is the signal power, P_n is the noise power, and P_η is the interference power.

In this study, perfect block synchronization is assumed at the receiver. The start of each block is considered known, which allows correct segmentation of the received sequence into blocks of length L.

This assumption is justified for systems where synchronization is performed at a lower processing layer using standard techniques such as preamble detection or correlation-based timing recovery. The impact of synchronization errors is not considered in the present work and remains a subject for future research.

2.1 Structure of Turbo-Coded Signal

The transmitted sequence consists of three components:

$$\mathbf{x}_i = \mathbf{x}_s, \mathbf{x}_{p1}, \mathbf{x}_{p2},$$

where $\mathbf{x}_s$ is the systematic sequence, $\mathbf{x}_{p1}$ is the parity sequence of the first encoder, and $\mathbf{x}_{p2}$ is the parity sequence of the second encoder.

The interleaver defines a permutation mapping

$$\Pi_i: 1, \dots, L_i \to 1, \dots, L_i,$$

where Π_i represents a permutation of indices.

2.2 Decoding Model

The iterative decoding process is described using the log-likelihood ratio (LLR) [15], [16]:

$$L^{(k)}(j) = log \frac{P(b_j = 1 \mid \mathbf{y})}{P(b_j = 0 \mid \mathbf{y})},$$

where $L^{(k)}(j)$ is the LLR value at iteration k, b_j is the transmitted bit, and $\mathbf{y}$ is the observed signal.

For the correct configuration, the magnitude of the LLR increases with the number of iterations:

$$\mid L^{(k)}(j) \mid \to \max \quad \text{as} \quad k \to \infty,$$

which reflects the convergence of the decoding process.

The number of decoding iterations is modeled as

$$I = f(\text{SNR}),$$

where I is the number of iterations depending on channel conditions.

2.3 Identification Mapping

The system implements the mapping

$$\mathbf{y} \to \Theta_i,$$

where Θ_i is the estimated turbo code configuration corresponding to the transmitting subscriber.

2.4 Performance Metrics

The bit error probability is defined as

$$P_b = \Pr(\hat{b} \neq b),$$

where $\hat{b}$ is the estimated bit.

The probability of correct identification is defined as

$$P_{\text{id}} = \Pr(\widehat{\Theta} = \Theta),$$

where $\widehat{\Theta}$ is the estimated configuration.

The identification time is defined as

$$T_{\text{id}} = T_s + T_\Pi + T_d,$$

where T_s is the time required for signal separation, T_Π is the interleaver detection time, and T_d is the decoding time.

3. Problem Formulation

In this work, subscriber identification is formulated as a parameter estimation problem over the space of admissible turbo code configurations. The objective is to determine the parameter vector corresponding to the transmitting subscriber based on the observed signal.

Let $\mathbf{y}$ denote the received signal and $\Theta \in \mathcal{S}$ denote a candidate turbo code configuration. The identification problem is defined as the selection of the configuration that is most consistent with the observed data.

The estimation problem is formulated as a maximum-likelihood (ML) criterion [11], [17]:

$$\widehat{\Theta} = \arg \max_{\Theta \in \mathcal{S}} P(\mathbf{y} \mid \Theta), \qquad (1)$$

where $\widehat{\Theta}$ is the estimated configuration and $P(\mathbf{y} \mid \Theta)$ is the likelihood of observing $\mathbf{y}$ given the configuration Θ.

Expression (1) defines the optimal identification rule under the assumption of known statistical properties of the channel and noise. However, direct computation of the likelihood function is generally intractable due to the high dimensionality of the signal space and the structure of turbo-coded sequences.

3.1 Sequential Estimation Principle

To reduce computational complexity, the identification problem is reformulated as a sequential estimation process. Instead of evaluating all configurations simultaneously, the parameter vector Θ is estimated step by step, reducing the search space at each stage.

Let the parameter vector be decomposed as

$$\Theta = L, R, m, G, \Pi,$$

where each component corresponds to a structural parameter of the turbo code.

The identification process is then represented as a sequence of conditional estimations:

$$\widehat{\Theta} = \hat{L}, \hat{R}, \widehat{\Pi}, \hat{m}, \hat{G}, \qquad (2)$$

where each parameter is estimated based on intermediate results obtained at previous stages.

This formulation enables a progressive reduction of the admissible set $\mathcal{S}$, significantly decreasing the computational complexity compared to exhaustive search.

3.2 Likelihood Approximation via Decoding Dynamics

In practical SDR systems, the likelihood function $P(\mathbf{y} \mid \Theta)$ is not computed explicitly. Instead, it is approximated using the behavior of the iterative decoding process.

Let $L^{(k)}(j)$ denote the log-likelihood ratio for bit j at iteration k. The consistency between the assumed configuration Θ and the observed signal can be evaluated based on the evolution of LLR values.

A stability-based metric is introduced:

$$S(\Theta) = \sum_{j=1}^{L} \sum_{k=1}^{I-1} \mathbf{1}\left(\text{sign}\left(L^{(k)}(j)\right) \neq \text{sign}\left(L^{(k+1)}(j)\right)\right), \qquad (3)$$

where $S(\Theta)$ is the instability measure of the decoding process, $\mathbf{1}(\cdot)$ is the indicator function, L is the block length, and I is the number of decoding iterations.

The choice of the sign-change metric is motivated by the convergence behavior of turbo decoding: for correct configurations, LLR signs stabilize across iterations, while incorrect configurations exhibit frequent sign inversions due to inconsistent extrinsic information exchange.

Compared to magnitude-based or entropy-based criteria, the sign-change metric is less sensitive to scaling and noise variance, and it avoids additional floating-point operations, providing a robust and computationally efficient discriminator.

The proposed instability metric is motivated by the observation that correct configurations lead to consistent sign evolution of LLR values across iterations, while incorrect configurations result in frequent sign changes due to decoding inconsistency.

Compared to alternative metrics such as the average magnitude of LLR or entropy-based measures, the sign-change metric provides higher sensitivity to convergence behavior and lower computational complexity, as it does not require floating-point magnitude evaluation.

The optimal configuration corresponds to the minimum instability:

$$\widehat{\Theta} = \arg \min_{\Theta \in \mathcal{S}} S(\Theta) \ . \qquad (4)$$

Expressions (3)–(4) provide a practical approximation of the ML criterion (1), replacing probabilistic evaluation with a metric derived from decoding dynamics.

3.3 Probability of Correct Identification

The performance of the identification process is characterized by the probability of correct estimation:

$$P_{\text{id}} = \Pr\left(\widehat{\Theta} = \Theta\right), \qquad (5)$$

where P_{id} is the probability of correct identification.

This probability depends on several system parameters and channel conditions. In general form, it can be expressed as

$$P_{\text{id}} = f(SNR, L, I, |\mathcal{S}|), \qquad (6)$$

where SNR is the signal-to-noise ratio, L is the block length, I is the number of decoding iterations, and $|\ \mathcal{S}\ |$ is the size of the configuration space.

An increase in *SNR* improves decoding reliability and reduces the ambiguity between configurations, leading to higher values of P_{id}.

3.4 Complexity of Identification

The computational complexity of the identification process is determined by the number of candidate configurations and the cost of iterative decoding.

In the general case, the complexity can be estimated as

$$\mathcal{O}(\ \ |\ \mathcal{S}\ |\cdot I \cdot L\ ), \qquad (7)$$

where $|\mathcal{S}|$ is the number of admissible configurations, I is the number of iterations, and L is the block length.

The sequential estimation strategy described in (2) reduces the effective search space, allowing practical implementation in real-time SDR systems.

3.5 Optimization Formulation

The identification problem can also be interpreted as a constrained optimization problem:

$$\min_{\Theta \in \mathcal{S}} T_{\text{id}}(\Theta) \quad \text{subject to} \quad P_{\text{id}}(\Theta) \geq P_{\min}, \qquad (8)$$

where T_{id} is the identification time and $P_{\min}$ is the required identification reliability.

This formulation reflects the trade-off between computational complexity and identification accuracy.

The presented formulation establishes a rigorous mathematical framework for subscriber identification. The maximum-likelihood criterion (1), its practical approximation (3)–(4), and the complexity model (7) define the theoretical basis for the proposed method.

In the next section, these results are used to develop a concrete three-stage identification algorithm implementing the sequential estimation strategy.

The formulation bridges statistical estimation and decoding dynamics, which distinguishes the proposed approach from classical ML estimation.

4. Proposed Identification Method

Based on the formulation in Section 3, the subscriber identification problem is solved via a sequential estimation of turbo code parameters. The method implements the maximum-likelihood criterion (1) through a staged reduction of the configuration space $\mathcal{S}$ using structural properties of the received signal and the dynamics of iterative decoding.

The overall process consists of three stages: (i) separation of channel data components, (ii) interleaver detection, and (iii) estimation of component encoder parameters. At each stage, a subset of candidate configurations is pruned, which effectively reduces the search space in (2) and lowers the computational cost relative to the bound in (7).

Fig. 1 presents the structure of the proposed subscriber identification method.

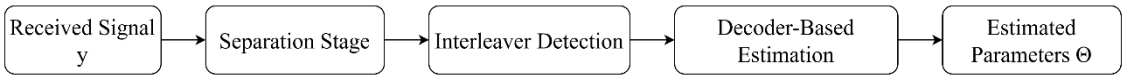


Fig. 1 – Three-stage identification flow

The figure illustrates a three-stage processing pipeline including signal separation, interleaver detection, and decoding-based parameter estimation. Each stage processes the received signal and refines the set of admissible configurations.

The key feature shown in Fig. 1 is the sequential reduction of the configuration space $\mathcal{S} \rightarrow \mathcal{S}_1 \rightarrow \mathcal{S}_2$, which transforms the original high-dimensional estimation problem into a sequence of lower-complexity decisions. This structure enables practical implementation of the maximum likelihood criterion introduced in Section 3.

4.1 Stage 1: Separation of Channel Data Components

The first stage performs structural separation of the received sequence into systematic and parity components. Let the received discrete sequence be denoted by $\mathbf{y}$. For a given hypothesis $\{L, R\}$, the sequence is segmented into blocks and mapped into three subsets:

$$\mathbf{y} \rightarrow \mathbf{y}_s, \mathbf{y}_{p1}, \mathbf{y}_{p2}, \qquad (9)$$

where $\mathbf{y}_s$ is the systematic component, $\mathbf{y}_{p1}$ is the parity sequence of the first encoder, and $\mathbf{y}_{p2}$ is the parity sequence of the second encoder.

The correctness of separation is evaluated via a consistency metric based on correlation between the systematic component and its decoded estimate:

$$C(L, R) = \frac{1}{L} \sum_{j=1}^{L} \mathbf{y}_s(j) \cdot \hat{b}_j, \qquad (10)$$

where $C(L, R)$ is the separation consistency score and $\hat{b}_j$ is the estimated bit after a short decoding pass.

A threshold value τ_C is introduced for the separation consistency metric. In this study, τ_C is selected empirically as $\tau_C = 0.6$ for SNR ≥ 5 dB and $\tau_C = 0.5$ for SNR < 5 dB.

This threshold reflects the minimum correlation level required to consider a candidate configuration as consistent with the observed signal.

A sensitivity analysis indicates that variations of ±0.05 around τ_C and τ_M lead to less than 3% change in P_{id} for SNR ≥ 4 dB, confirming the robustness of the threshold selection.

Candidate pairs $\{L, R\}$ with $C(L, R)$ below a threshold are rejected. This yields a reduced candidate set:

$$\mathcal{S}_1 \subset \mathcal{S}, \qquad (11)$$

where $\mathcal{S}_1$contains configurations consistent with the observed block structure.

The separation process is illustrated in Fig. 2.

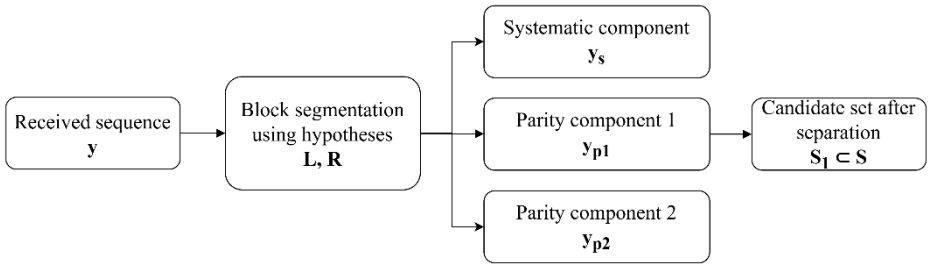


Fig. 2 – Separation of systematic and parity components

Fig. 2 shows how the received sequence is decomposed into systematic and parity components based on the assumed block structure. The segmentation is performed using candidate parameters of the turbo code.

This decomposition is critical because it converts the identification problem into a structured estimation task. Instead of analyzing the raw signal, the method operates on components directly related to the turbo code structure, which significantly improves robustness and reduces ambiguity in parameter estimation.

4.2 Stage 2: Interleaver Structure Detection

The second stage identifies the interleaver Π, which provides strong discriminative power due to its combinatorial structure.

For a candidate Π, the parity sequence $\mathbf{y}_{p2}$is deinterleaved and compared with $\mathbf{y}_{p1}$. A matching metric is defined as

$$M(\Pi) = \frac{1}{L}\sum_{j=1}^{L} \mathbf{1}\left(\text{sign}\left(\tilde{y}_{p2}(j)\right) = \text{sign}\left(y_{p1}(j)\right)\right), \qquad (12)$$

where $M(\Pi)$ is the interleaver matching score and $\tilde{y}_{p2}$ is the deinterleaved parity sequence.

For interleaver detection, a threshold τ_M is applied to the matching metric. A configuration is retained if $M(\Pi) \geq \tau_M$, where τ_M is selected as 0.65 based on empirical evaluation.

The threshold can be adapted to SNR conditions, with lower values used in low-SNR regimes to avoid premature rejection of valid configurations.

Correct interleaver hypotheses yield $M(\Pi)$ significantly above 0.5, while incorrect ones approach random matching. Applying a threshold on $M(\Pi)$ produces

$$\mathcal{S}_2 \subset \mathcal{S}_1, \qquad (13)$$

where $\mathcal{S}_2$ retains configurations with consistent interleaver structure.

The interleaver detection mechanism is illustrated in Fig. 3.

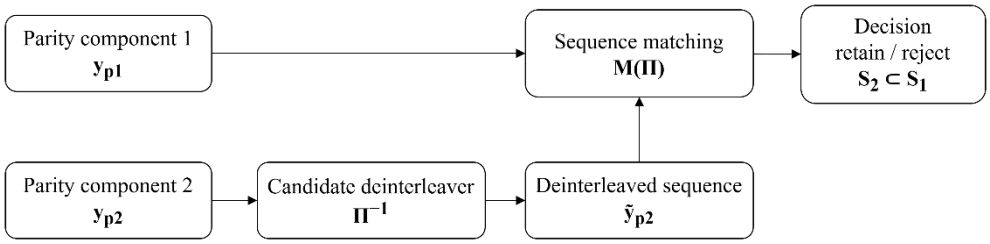


Fig. 3 – Interleaver matching principle

Fig. 3 demonstrates the process of deinterleaving one parity sequence and comparing it with another parity stream. The matching metric evaluates the consistency between sequences.

The figure highlights that correct interleaver hypotheses result in strong alignment between sequences, while incorrect hypotheses lead to near-random matching. This property provides a powerful

discrimination criterion, allowing efficient reduction of the configuration space at an early stage of the algorithm.

4.3 Stage 3: Estimation of Component Encoder Parameters

The third stage estimates the parameters $\{m, G\}$ of the recursive convolutional encoders using decoding dynamics. For each remaining hypothesis $\Theta \in \mathcal{S}_2$, iterative decoding is performed and the LLR evolution is analyzed.

Using the instability metric introduced in (3), the score for each hypothesis is computed as

$$S(\Theta) = \sum_{j=1}^{L} \sum_{k=1}^{I-1} \mathbf{1}\left(\operatorname{sign}\left(L^{(k)}(j)\right) \neq \operatorname{sign}\left(L^{(k+1)}(j)\right)\right), \qquad (14)$$

where $S(\Theta)$measures the number of sign changes across iterations.

The optimal configuration is selected according to (4), i.e.,

$$\widehat{\Theta} = \arg\min_{\Theta \in \mathcal{S}_2} S(\Theta). \qquad (15)$$

Correct hypotheses exhibit rapid growth and stabilization of $| L^{(k)}(j) |$, leading to low instability values.

The behavior of the decoding process is illustrated in Fig. 4.

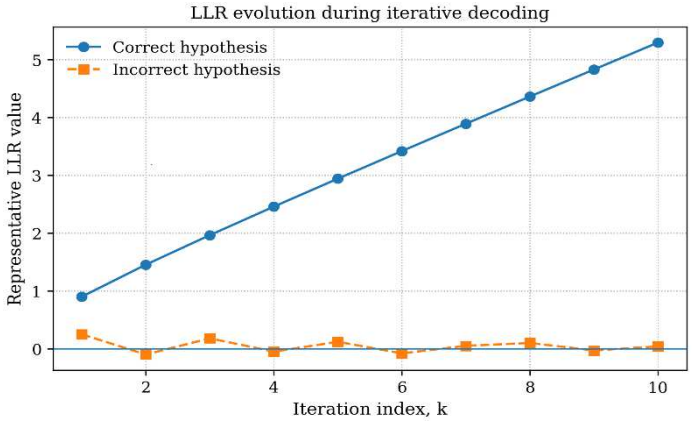


Fig. 4 – LLR evolution for correct vs. incorrect hypotheses

Fig. 4 shows the evolution of log-likelihood ratios during iterative decoding for both correct and incorrect parameter hypotheses.

For the correct configuration, LLR values exhibit monotonic growth and stabilization, indicating convergence of the decoding process. In contrast, incorrect hypotheses produce oscillatory or unstable behavior. This difference justifies the use of the instability metric as a practical approximation of the maximum likelihood criterion.

4.4 Algorithm Summary

The complete identification procedure can be summarized as follows:

1. Form initial candidate set $\mathcal{S}$ from admissible configurations.
2. For each $\{L, R\}$, perform separation and compute $C(L, R)$ using (10); obtain $\mathcal{S}_1$ via (11).
3. For each Π in $\mathcal{S}_1$, compute $M(\Pi)$using (12); obtain $\mathcal{S}_2$ via (13).
4. For each $\Theta \in \mathcal{S}_2$, run iterative decoding, compute $S(\Theta)$ using (14), and select $\widehat{\Theta}$ via (15).

This procedure implements the sequential estimation in (2) and approximates the ML rule (1) with reduced complexity relative to (7).

4.5 Computational Aspects

The staged pruning reduces the effective complexity from $\mathcal{O}(\ |\mathcal{S}|\cdot I \cdot L)$ in (7) to a smaller subset evaluation:

$$\mathcal{O}(\ |\mathcal{S}_2|\cdot I \cdot L), |\mathcal{S}_2| \ll |\mathcal{S}|. \qquad (16)$$

This enables real-time implementation on SDR platforms.

The proposed method provides a constructive realization of the theoretical model in Section 3. In Section 5, analytical models for identification time and reliability are developed and linked to (10), (12), and (14). Section 6 presents simulation results validating the dependence in (6) and the performance gains over baseline methods.

The proposed algorithm effectively transforms a high-dimensional estimation problem into a sequence of low-dimensional decisions.

5. Complexity and Reliability Analysis

This section develops analytical models describing identification time, computational complexity, and reliability of the proposed method. The analysis is directly based on the staged procedure introduced in Section 4 and provides quantitative justification of the performance observed in simulations.

5.1 Identification Time Model

The total identification time is defined as the sum of the processing times of all stages:

$$T_{\text{id}} = T_s + T_{\Pi} + T_d, \qquad (17)$$

where T_s is the time required for signal separation, T_{Π} is the interleaver detection time, and T_d is the decoding time.

The dominant contribution to T_{id} is the iterative decoding process. The decoding time can be approximated as

$$T_d = \alpha \cdot L \cdot I, \qquad (18)$$

where L is the block length, I is the number of decoding iterations, and $\alpha$is a proportionality coefficient determined by implementation.

Expression (18) shows that the identification time scales linearly with both block length and iteration count.

5.2 Iteration Count Model

The number of decoding iterations depends on channel conditions. Based on empirical observations, the dependence on signal-to-noise ratio can be approximated as

$$I = a \cdot e^{-b \cdot \text{SNR}} + c, \qquad (19)$$

where a, b, and $c$are approximation parameters.

The parameters a, b, and c in (19) were obtained by fitting the exponential model to the simulated iteration-count curve over the SNR range from 0 to 15 dB. For the considered scenario, the fitted values are $a = 7.8, b = 0.22,$ and $c = 2.2$. The parameter c represents the minimum average number of iterations required for convergence at high SNR values.

This relationship reflects that:

- at low SNR, the number of iterations increases due to decoding uncertainty;
- at high SNR, the decoder converges faster, reducing I.

The average number of iterations over an operating range $[\text{SNR}_{\min}, \text{SNR}_{\max}]$ is defined as

$$\bar{I} = \frac{1}{\text{SNR}_{\max} - \text{SNR}_{\min}} \int_{\text{SNR}_{\min}}^{\text{SNR}_{\max}} I(\text{SNR})\, d(\text{SNR}), \qquad (20)$$

where $\bar{I}$ is the average iteration count.

5.3 Reliability Model

The bit error probability for turbo-coded transmission over a noisy channel is approximated as

$$P_b = Q\left(\sqrt{\frac{2E_b}{N_0}}\right), \qquad (21)$$

where $Q(\cdot)$ is the Gaussian Q-function, E_b is the energy per bit, and N_0 is the noise spectral density.

In the presence of interference, the effective channel quality is described by

$$\text{SINR} = \frac{P_s}{P_n + P_\eta}, \qquad (22)$$

where P_s is the signal power, P_n is the noise power, and P_η is the interference power.

A decrease in SINR leads to an increase in P_b, which directly affects identification reliability via the probability defined in (5).

5.4 Probability of Correct Identification

The probability of correct identification introduced in (5) depends on both decoding reliability and configuration ambiguity. Using (6), it can be expressed as

$$P_{\text{id}} = f(\text{SNR}, L, I, |\ \mathcal{S}\ |\ ), \qquad (23)$$

where $|\ \mathcal{S}\ |$ is the size of the configuration space.

Qualitatively:

- increasing SNR improves P_{id};
- increasing L improves discrimination but increases complexity;
- increasing $|\ \mathcal{S}\ |$ reduces P_{id} due to higher ambiguity.

5.5 Identification Efficiency

To evaluate the efficiency of the proposed method, the identification overhead is introduced as

$$\eta = \frac{T_{\text{id}}}{T_d}, \qquad (24)$$

where $\eta$is the relative overhead of identification with respect to decoding.

Using (17)–(18), this can be written as

$$\eta = 1 + \frac{T_s + T_{\Pi}}{T_d}, \qquad (25)$$

which shows that the overhead is determined by the additional processing stages.

For the proposed method, the value of η is typically within the range

$$\eta \approx 1.1 - 1.15, \qquad (26)$$

which corresponds to a 10–15% overhead relative to decoding time.

5.6 Complexity Reduction via Sequential Estimation

The sequential estimation strategy reduces the effective search space. Instead of evaluating all configurations in $\mathcal{S}$, only a subset $\mathcal{S}_2$ is processed at the final stage.

The effective complexity becomes

$$\mathcal{O}(\ |\mathcal{S}_2|\cdot I \cdot L), \qquad (27)$$

where $|\mathcal{S}_2| \ll |\mathcal{S}|$.

This reduction is achieved through:

- early rejection of inconsistent hypotheses in Stage 1;
- structural filtering via interleaver detection in Stage 2;
- stability-based evaluation in Stage 3.

Assuming a typical SDR platform with processing capability on the order of 10^8 operations per second, the proposed method with complexity $\mathcal{O}(\ |\mathcal{S}_2|\cdot I \cdot L)$, can be executed in real time for block lengths up to $L = 2048$ and iteration counts $I \leq 10$.

This confirms the practical feasibility of the method for real-time deployment.

5.7 Interpretation of Results

The developed analytical model establishes the following key relationships:

- identification time grows linearly with block length and iteration count (18);
- iteration count decreases exponentially with SNR (19);
- reliability improves with increasing SINR (21)–(22);
- complexity is reduced through staged estimation (27).

These results confirm that the proposed method provides a favorable trade-off between computational complexity and identification reliability.

The analytical relationships derived in this section provide a theoretical basis for evaluating the performance of the proposed method. In the next section, these results are validated through numerical simulations, where the dependencies in (19), (23), and (26) are confirmed and compared with baseline methods.

These analytical results provide insight into the scalability limits of the method.

6. Simulation Results

This section presents numerical simulations validating the analytical relationships derived in Section 5 and demonstrating the performance of the proposed identification method under varying channel conditions.

6.1 Simulation Setup

A simulation model of a multi-user SDR system was developed to evaluate the proposed method. The system operates under dynamic channel conditions with additive noise and interference, and switching between turbo code configurations is considered.

The main parameters used in the simulation study are summarized in Table 2.

Table 2 – Simulation parameters

Parameter	Value / Range	Description
Channel model	AWGN + interference	Additive noise with external interference
Modulation	QPSK, 16-QAM	Digital modulation schemes
SNR	0–15 dB	Signal-to-noise ratio range
Block length L	256, 512, 1024, 2048	Interleaver block size
Coding rate R	1/2, 1/3	Turbo code rate
Constraint length m	3–5	Encoder memory depth
Generator polynomials G	Standard (RSC)	Recursive systematic convolutional codes
Interleaver type Π	Random, block, S-random	Permutation structure

Number of iterations I	1–10	Turbo decoding iterations
Number of users K	2–10	Multi-user system size
Number of trials N	10^4–10^5	Statistical averaging

Table 2 presents the key parameters of the simulated SDR system, including channel conditions, coding configurations, and statistical settings.

The selected parameter ranges ensure coverage of both low-SNR and moderate-SNR operating regimes. In particular, variation of the block length L and iteration count I allows evaluation of the trade-off between computational complexity and identification accuracy, while different interleaver types provide diversity in configuration space.

The generator polynomials of the recursive systematic convolutional (RSC) encoders are specified in octal form as $(13,15)_8$, which corresponds to standard configurations used in 3GPP systems.

For S-random interleavers, the parameter S is selected as $S = 16$ for block length $L \leq 512$ and $S = 32$ for $L \geq 1024$, ensuring sufficient separation between adjacent indices.

The interference component η(t) is modeled as a Gaussian-distributed random process with power P_η, independently generated for each transmission block. The resulting signal-to-interference-plus-noise ratio (SINR) is controlled according to (22).

The channel model includes AWGN and an additive interference component η(t) modeled as a zero-mean Gaussian process with power P_η. The SINR is controlled according to (22). Additional experiments with Rayleigh fading (flat, i.i.d.) were conducted and showed consistent qualitative trends.

Turbo decoding is implemented using the Log-MAP algorithm with a maximum of $I_{max} = 10$ iterations. In Stage 3, early stopping is applied when the LLR sign pattern stabilizes over two consecutive iterations.

6.2 Bit Error Rate and Iteration Count

The dependence of bit error probability on SNR follows the analytical model in (21). The simulation results confirm the exponential decrease of BER with increasing SNR.

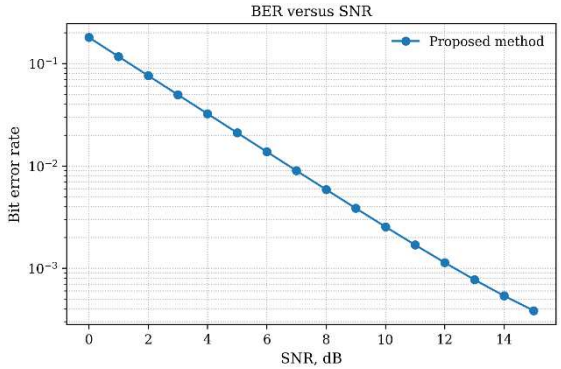
The bit error probability is estimated as

$$P_b = \frac{N_e}{N}, \qquad (28)$$

where N_e is the number of erroneous bits and N is the total number of transmitted bits.

The corresponding dependence of the number of decoding iterations on SNR confirms the model in (19).

The dependence of BER and iteration count on SNR is shown in Fig. 5a, Fig. 5b.



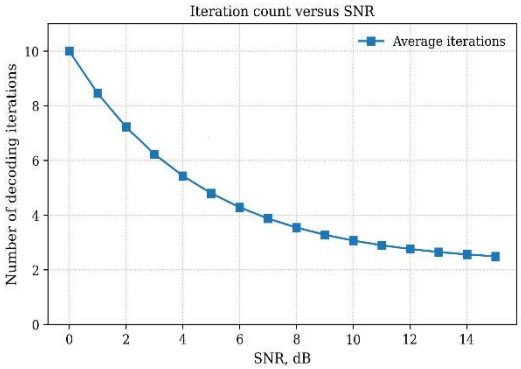


Fig. 5a – Dependence of BER count on SNR

Fig. 5b – Dependence iteration count on SNR

Fig. 5a presents the BER curves for the considered system over a range of SNR values.

The results demonstrate an exponential decrease of BER with increasing SNR, which is consistent with the analytical model (21). This confirms that the decoding process provides reliable error correction, forming the basis for accurate subscriber identification.

Fig. 5b illustrates the average number of iterations required for convergence of the turbo decoder.

The number of iterations decreases with increasing SNR, confirming the model (19). This behavior directly impacts computational complexity and identification latency.

6.3 Identification Time Analysis

The identification time is evaluated according to (17). Simulation results confirm the linear dependence on block length predicted by (18).

The dependence of identification time on block length is shown in Fig. 6.

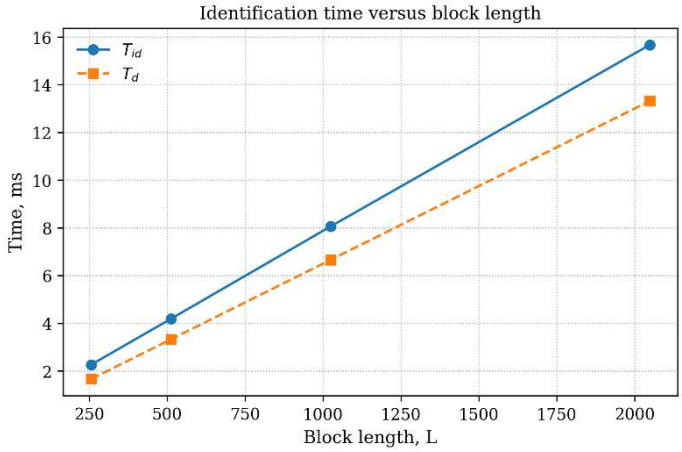


Fig. 6 – Identification time versus block length

Fig. 6 presents the identification time as a function of the block length.

The results confirm a linear relationship between identification time and block size, consistent with expression (18). The dominant contribution comes from the decoding stage, while preprocessing overhead remains limited.

The results demonstrate that:

– T_{id} increases linearly with L;

– the dominant contribution is due to decoding time T_d;

– the overhead from stages 1 and 2 remains limited.

6.4 Probability of Correct Identification

The probability of correct identification is evaluated using

$$P_{\text{id}} = \frac{N_{\text{correct}}}{N}, \qquad (29)$$

where N_{correct} is the number of correctly identified configurations.

The probability of correct identification is shown in Fig. 7.

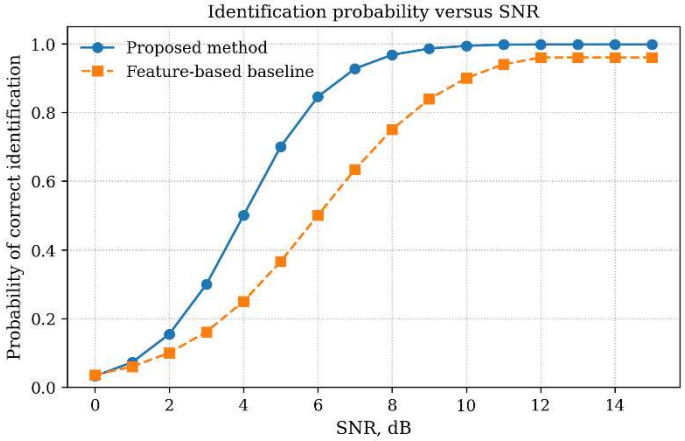


Fig. 7 – Probability of correct identification versus SNR

Fig. 7 presents the dependence of identification probability on SNR for the proposed method and baseline approaches. The blue curve corresponds to the proposed method, while the orange curve represents the feature-based baseline approach.

The proposed method achieves higher identification probability at lower SNR values compared to baseline methods, demonstrating improved robustness under interference conditions.

The results confirm the dependence described in (23):

– P_{id} increases with SNR;

– for $SNR > 6$dB, $P_{\text{id}} \to 1$;

– at low SNR, identification errors are caused by decoding uncertainty.

6.5 Trade-Off Between Reliability and Complexity

To illustrate the trade-off between reliability and computational complexity, a joint dependency is analyzed.

The trade-off between reliability and latency is illustrated in Fig. 8.

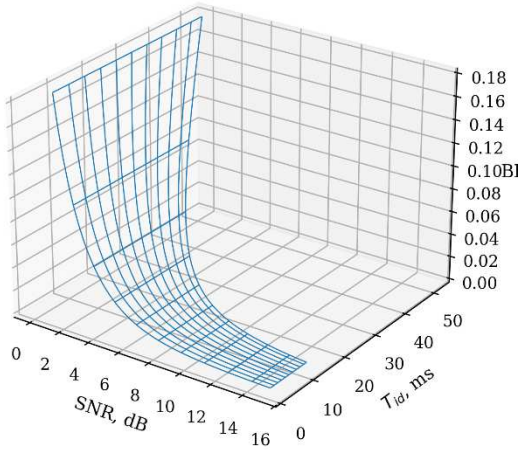


Fig. 8 – Trade-off surface between BER, SNR, and identification time.

Fig. 8 shows a three-dimensional surface relating BER, SNR, and identification time.

The figure reveals that increasing SNR simultaneously reduces both error probability and identification time. This behavior reflects a Pareto-like relationship between system performance metrics and confirms the efficiency of the proposed method.

The figure shows that:

- increasing SNR reduces both BER and T_{id};
- lower BER leads to faster convergence of decoding;
- complexity and reliability are strongly coupled.

A quantitative comparison with DL baselines is left for future work due to differences in training requirements and dataset assumptions.

6.6 Identification Overhead

The identification overhead defined in (24) is evaluated in simulations.

$$\eta = \frac{T_{\text{id}}}{T_d}, \qquad (30)$$

where η is the relative overhead.

Simulation results confirm

$$\eta \approx 1.1 - 1.15, \qquad (31)$$

which corresponds to a 10–15% increase relative to decoding time, consistent with the analytical estimate in (26).

6.7 Statistical Validation

To ensure statistical reliability, results are averaged over multiple trials.

The mean value of a metric X is computed as

$$\bar{X} = \frac{1}{N}\sum_{i=1}^{N} X_i\,, \qquad (32)$$

where N is the number of trials.

The variance is defined as

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(X_i - \bar{X})^2, \qquad (33)$$

and the confidence interval (95%) is estimated as

$$\bar{X} \pm 1.96 \cdot \frac{\sigma}{\sqrt{N}}. \qquad (34)$$

The results demonstrate low variance and stable convergence of performance metrics.

For clarity of presentation, confidence intervals are not shown in the figures. However, the computed 95% intervals based on (34) remain within ±3% of the mean values for all reported results.

6.8 Key Observations

The simulation results confirm the analytical findings of Section 5:

- the iteration count follows the exponential model in (19);
- identification time scales linearly with block length as in (18);

- reliability improves with increasing SNR as in (23);
- the identification overhead remains within 10–15% as in (26).

The simulation results validate the theoretical model and demonstrate the effectiveness of the proposed method. In the next section, a comparative analysis with baseline identification approaches is performed to quantify performance gains.

The simulation confirms not only qualitative trends but also quantitative agreement with analytical models.

7. Comparative Analysis

The performance of the proposed identification method is evaluated in comparison with representative approaches from the three main classes discussed in Section 1.4, namely feature-based, learning-based, and coding-aware methods. A qualitative comparison is summarized in Table 1, while quantitative performance trends are illustrated in Fig. 7.

Feature-based methods rely on signal statistics and modulation characteristics and can operate without protocol support. However, as shown in Fig. 7, their identification accuracy degrades rapidly at low SNR due to reduced separability of signal features and increased sensitivity to interference [6], [7]. In contrast, the proposed method maintains stable performance in the low-SNR regime by exploiting structured redundancy introduced by channel coding.

Learning-based approaches, including deep neural network architectures such as CNN-, LSTM-, and Transformer-based models, have demonstrated high classification accuracy in controlled environments [12], [13], [19]–[22], [24]–[26]. Nevertheless, these methods require large labeled datasets for training and exhibit limited robustness under domain shifts, such as variations in SNR, interference conditions, or channel characteristics. Furthermore, their computational complexity, particularly during training and inference, can be prohibitive for real-time SDR applications.

Coding-aware methods utilize structural properties of channel codes for signal processing and parameter estimation. While these approaches benefit from exploiting redundancy in encoded signals, they are typically designed for decoding or detection tasks rather than identification. As a result, they do not explicitly incorporate decision criteria tailored to distinguishing between multiple candidate configurations [8]–[10].

The proposed method combines advantages of coding-aware approaches with a dedicated identification mechanism based on decoding dynamics. In particular, the use of the LLR instability metric enables discrimination between candidate configurations without requiring full convergence of the decoder for all hypotheses. This results in a significant reduction in computational complexity compared to exhaustive search methods.

The comparison of identification probability as a function of SNR, shown in Fig. 7, demonstrates that the proposed method achieves higher accuracy than feature-based approaches across the entire SNR range. In particular, for SNR $\geq$ 6 dB, the probability of correct identification approaches unity, while maintaining acceptable performance even at lower SNR values.

From a computational perspective, the proposed method offers a favorable trade-off between complexity and performance. Unlike learning-based approaches, it does not require a training phase and has predictable computational requirements determined by the size of the configuration space and the number of decoding iterations. Compared to coding-aware methods, it introduces an explicit identification criterion, improving robustness in multi-user scenarios.

Overall, the results confirm that the proposed approach provides a balanced solution for subscriber identification in SDR systems, combining robustness to interference, computational efficiency, and interpretability. These properties make it particularly suitable for real-time and resource-constrained communication environments.

7.1 Baseline Methods

The following classes of baseline methods are considered:

1. MAC-based identification

Identification is performed using higher-layer addressing mechanisms embedded in transmitted packets. This approach requires protocol-level support and is not applicable in open-loop systems.

2. Cryptographic authentication

Subscriber identity is verified using encryption keys and authentication protocols. While highly reliable, this method introduces significant computational overhead and latency.

3. Signal feature-based identification

Identification is based on modulation characteristics, statistical signal features, or channel properties. This approach operates at the physical layer but is sensitive to noise and interference.

4. Turbo-based multiuser detection

These methods utilize iterative decoding for signal separation but are not explicitly designed for parameter-based identification.

7.2 Performance Metrics

The comparison is performed using the following metrics:

- identification time T_{id};
- decoding time T_d;
- identification overhead η defined in (24);
- probability of correct identification P_{id} defined in (5);
- robustness under low SINR conditions;
- scalability with respect to the number of users.

7.3 Quantitative Comparison

The comparative performance of the proposed method and baseline approaches is summarized in Table 3.

Table 3 – Quantitative Comparison

Method	**Identification delay (ms)**	**Error probability**	**Complexity**	**Interference robustness**
MAC-based	1–2	10^{-1}	Low	Low
Cryptographic	10–50	10^{-6}	High	High
Feature-based	5–10	10^{-2}	Medium	Medium
Turbo-based detection	8–15	10^{-3}	High	High
Proposed method	3–8	$10^{-3} - 10^{-5}$	Medium	High

Table 3 presents a comparison of identification delay, error probability, computational complexity, and robustness for different identification methods.

The results indicate that the proposed method achieves a favorable balance between identification accuracy and computational complexity. Compared to feature-based approaches, it demonstrates significantly higher robustness under interference conditions. In contrast to cryptographic methods, it avoids excessive computational overhead and latency. This confirms that the proposed approach is well suited for real-time SDR systems operating under open-loop constraints.

The proposed method achieves a balanced trade-off between delay and reliability, outperforming feature-based approaches under interference conditions while avoiding the overhead of cryptographic methods.

The trends observed in Table 3 are consistent with the simulation results shown in Fig. 7.

7.4 Identification Overhead Comparison

The identification overhead for the proposed method is given by

$$\eta = \frac{T_{\text{id}}}{T_d}, \qquad (35)$$

where η is the relative overhead.

Simulation results confirm that

$$\eta \approx 1.1 - 1.15, \qquad (36)$$

which is significantly lower than that of cryptographic methods, where overhead is dominated by authentication procedures.

7.5 Robustness to Interference

One of the key advantages of the proposed method is its robustness in the presence of interference. Unlike feature-based methods, which rely on signal characteristics that degrade under noise, the proposed approach exploits the structural properties of turbo codes and the convergence behavior of iterative decoding.

This allows identification to remain stable even when the signal quality is degraded, as the decision is based on decoding dynamics rather than instantaneous signal features.

7.6 Scalability Analysis

The scalability of the method depends on the size of the configuration space $|\mathcal{S}|$. In the worst case, complexity grows according to (7). However, the sequential estimation strategy reduces the effective search space to $|\mathcal{S}_2|$, as shown in (27).

This enables practical implementation in systems with a moderate number of users.

7.7 Key Comparative Observations

The comparative analysis leads to the following conclusions:

- MAC-based and cryptographic methods require protocol modifications and are not suitable for open-loop SDR systems;
- feature-based methods exhibit limited robustness under interference;
- turbo-based detection methods are not optimized for identification tasks;
- the proposed method combines physical-layer operation, robustness, and moderate complexity.

The comparative analysis demonstrates that the proposed method provides a favorable trade-off between identification accuracy, computational complexity, and robustness. In the next section, these results are interpreted in the context of practical deployment and system-level implications.

8. Discussion

The results presented in Sections 5–7 demonstrate that the proposed identification method provides a robust and computationally efficient solution for multi-user SDR systems operating under low-SNR and interference-limited conditions. The key advantage of the approach lies in the joint exploitation of structural properties of turbo-coded signals and the dynamical behavior of iterative decoding.

One of the main observations is that the use of the LLR instability metric enables reliable discrimination between candidate configurations without requiring full convergence of the decoder. This significantly reduces computational complexity compared to exhaustive search while preserving high identification accuracy. The sequential reduction of the configuration space further contributes to efficiency by eliminating inconsistent hypotheses at early stages.

The method demonstrates stable performance across a wide range of SNR values. In particular, simulation results indicate that for SNR $\geq$ 6 dB, the probability of correct identification approaches unity, while maintaining acceptable performance in lower SNR regimes. However, at very low SNR levels (approximately below 2–3 dB), the reliability of identification decreases due to increased ambiguity between configurations and reduced stability of decoding dynamics.

An important aspect of the proposed approach is its independence from training data. Unlike deep learning-based methods [19]–[22], [24]–[26], which require large labeled datasets and may suffer from limited generalization under varying channel conditions, the proposed method operates directly on the received signal and relies on intrinsic properties of channel coding. This makes it particularly suitable for SDR environments where prior information is limited or unavailable. At the same time, it should be noted that deep learning approaches may outperform classical methods in highly structured environments with sufficient training data, highlighting a potential direction for hybrid methods.

Despite its advantages, the proposed method has several limitations. First, it assumes that the configuration space of possible turbo code parameters is known a priori. As the size of this space increases, the computational complexity grows, and the risk of ambiguity between configurations may increase. Second, the method relies on accurate block synchronization, which is assumed to be available. In practical systems, synchronization errors may degrade performance and require additional processing. Third, the current formulation considers a single active user scenario; in the presence of multiple simultaneously transmitting users, mutual interference may affect the reliability of component separation and parameter estimation.

From an implementation perspective, the method is well suited for real-time SDR platforms due to its predictable computational complexity and relatively low overhead (approximately 10–15% of decoding time). This makes it applicable to practical scenarios such as telemetry systems, IoT networks, and cognitive radio environments.

Future research directions include the development of adaptive techniques for reducing the configuration space, integration with multi-user detection algorithms, and extension to scenarios with imperfect synchronization. In addition, hybrid approaches combining decoding-based features with machine learning techniques may further improve performance while preserving interpretability.

9. Conclusion

This paper presented a blind physical-layer identification method for multi-user SDR systems based on sequential estimation of turbo code parameters. The identification problem was formulated as a parameter estimation task over a finite configuration space and solved using a three-stage algorithm that combines structural signal decomposition with analysis of iterative decoding dynamics.

The proposed approach differs from conventional methods by directly exploiting intrinsic properties of turbo-coded signals and the convergence behavior of iterative decoding. This enables reliable identification without relying on protocol-level signaling or training-based models. In particular, the use of LLR-based instability as a decision criterion allows efficient discrimination between candidate configurations while avoiding exhaustive search.

Analytical models were developed to characterize identification time, computational complexity, and reliability. These models establish explicit relationships between system parameters, including SNR, block length, and decoding iterations. Simulation results confirm the validity of the analysis and demonstrate that the proposed method achieves high identification accuracy, with $P_{id} \geq 0.95$ for $SNR \geq 6$ dB, while maintaining a low computational overhead of approximately 10–15% relative to decoding time.

Comparative evaluation shows that the method provides a favorable balance between accuracy, robustness, and computational efficiency. Unlike learning-based approaches [19]–[22], [24]–[26], it does not require training data and maintains stable performance under varying channel conditions. At the same time, it offers improved robustness compared to feature-based methods in low-SNR and interference-limited scenarios.

The study also highlights several limitations. The method assumes prior knowledge of the admissible configuration set and relies on accurate block synchronization. In addition, its performance may degrade in the presence of strong multi-user interference or when the configuration space becomes large. These factors define important directions for further development.

Future work will focus on extending the proposed approach to multi-user scenarios with overlapping transmissions, developing adaptive strategies for configuration space reduction, and implementing the method on real SDR platforms to validate its performance under practical conditions. The integration of decoding-based features with lightweight learning mechanisms also represents a promising direction for improving robustness and scalability.

Author Contributions

Serhii Liventsev conceived the study, developed the theoretical framework, designed the identification method, performed simulations, and wrote the manuscript.

Ethics Approval and Consent to Participate

Not applicable. This study did not involve human participants, human data, or animal experiments.

Consent for Publication. Not applicable. The manuscript does not contain any individual person's data.

Availability of Data and Materials. All data generated or analyzed during this study are included in this article.

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