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MULTI-USER SUBSCRIBER IDENTIFICATION USING TURBO CODES ON PROGRAMMABLE RADIO PLATFORMS

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Abstract. This paper proposes a method for subscriber identification in a multi-user unidirectional data transmission system based on software-defined radio (SDR). Unlike conventional approaches relying on protocol-level signaling or cryptographic mechanisms, the proposed method operates at the physical layer by exploiting structural parameters of turbo codes (TC), including block length, coding rate, interleaver type, and generator polynomial.

The identification problem is formulated as a sequential parameter estimation task and implemented through a three-stage algorithm comprising channel data separation, interleaver detection, and iterative decoding-based parameter inference. A mathematical model describing identification complexity and reliability is developed, including analytical approximations of the average number of decoding iterations under varying signal-to-noise ratio (SNR) conditions.

Simulation results demonstrate that the proposed method ensures reliable subscriber identification in low-SNR and impulsive interference environments, while reducing identification overhead to 10–15% of the total decoding time. The approach enables implicit identification without modifying transmission protocols and can be integrated into SDR-based multi-user systems, including 5G NR scenarios.

The proposed solution provides a unified mechanism for combining error-correcting coding and subscriber identification, improving system efficiency, robustness, and security.

The method can be interpreted as a constrained optimization problem over the space of turbo code configurations.

Keywords. Cognitive radio, turbo codes, subscriber identification, software-defined radio (SDR), multi-user systems, interference robustness, iterative decoding, 5G NR

Introduction. The rapid development of software-defined radio (SDR) technologies and next-generation wireless systems, including 5G and IoT networks, has significantly increased the complexity of multi-user communication environments. In such systems, heterogeneous devices operate under dynamically changing conditions, including variable channel quality, interference, and resource constraints. Ensuring reliable and efficient identification of transmitting users in these environments remains a critical challenge, particularly for unidirectional or open-loop communication systems, where feedback or protocol-level coordination is limited or unavailable.

Conventional approaches to subscriber identification are typically based on higher-layer mechanisms, such as MAC addressing, protocol signaling, or cryptographic authentication. While these methods provide reliable identification, they introduce additional overhead, increase latency, and may require modifications to existing communication protocols. Moreover, in low signal-to-noise ratio (SNR) conditions and in the presence of impulsive interference, their effectiveness may degrade due to synchronization and signaling constraints.

An alternative direction is the use of physical-layer features for implicit identification. Existing methods in this class rely on signal characteristics such as modulation patterns, channel state information, or statistical properties of the received signal. However, such approaches often suffer from limited robustness, high variability under interference, and insufficient discriminative capability in multi-user scenarios.

In this context, turbo codes (TC), widely used for error correction in modern communication systems, provide an additional structural dimension that can be exploited for identification purposes. The parameters of turbo codes, including block length, coding rate, interleaver structure, and generator polynomial, define the internal configuration of the encoding and decoding process and can serve as implicit identifiers of transmitting devices. Despite extensive research on turbo decoding and multi-user detection, the use of TC parameters for subscriber identification remains insufficiently explored.

The key idea of this work is to treat subscriber identification as a problem of sequential estimation of turbo code parameters from the received signal. Let the set of TC parameters be defined as

$$\Theta = \{N, R, v, G, \Pi\},$$

where N is the block length, R is the coding rate, v is the constraint length, G is the generator polynomial, and Π denotes the interleaver structure. The identification task can then be formulated as the problem of estimating the most probable configuration

$\widehat{\Theta}$ based on the observed signal, which implicitly determines the transmitting subscriber.

To solve this problem, a three-stage identification procedure is proposed, including separation of channel data, detection of the interleaver type, and estimation of the component encoder parameters using iterative decoding. The approach combines structural analysis of the received sequence with properties of iterative decoding, in particular the behavior of a priori information during decoding iterations.

To illustrate the considered communication scenario, Fig. 1 presents the structure of a multi-user unidirectional communication system.

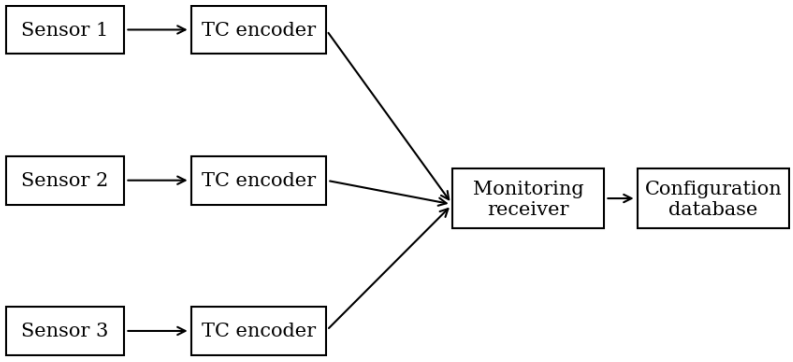


Fig. 1. Structure of a multi-user unidirectional communication system

The system consists of multiple transmitting sensors, each using a unique turbo code configuration, and a centralized receiver that performs signal reception, decoding, and subscriber identification using a configuration database.

The main contributions of this paper are as follows:

– formulation of subscriber identification as a physical-layer parameter estimation problem based on turbo code structure;

– development of a three-stage algorithm for sequential determination of TC parameters;

– derivation of analytical relationships describing identification complexity and its dependence on SNR and code parameters;

– demonstration of the method's robustness under low-SNR and impulsive interference conditions;

– validation of the approach through simulation, showing reduced identification overhead relative to decoding time.

The proposed method enables implicit subscriber identification without modifications to the transmission protocol and can be integrated into SDR-based multi-user systems, including modern 5G NR architectures. In contrast to traditional approaches, it combines error-correcting coding and identification within a unified framework, improving system efficiency and robustness.

To position the proposed approach within existing research, Table 1 summarizes and compares the main classes of subscriber identification methods used in multi-user communication systems.

Table 1. Comparison of existing subscriber identification methods

Method	Layer	Identification principle	Protocol modification	Complexity	Robustness to interference	Key references (DOI)
MAC-based identification	Network	Address-based identification (MAC)	Required	Low	Low	—
Cryptographic authentication	Application	Key-based authentication	Required	High	High	—
Signal feature-based methods	Physical	Modulation / channel feature analysis	Not required	Medium	Medium	10.1109/JSAC.2004.839380
Turbo-based multiuser detection	Physical	Iterative decoding of multiuser signals	Not required	High	High	10.1017/CBO9780511542937
Proposed method	Physical	Turbo code parameter estimation	Not required	Medium	High	This work

As shown in Table 1, existing approaches either require protocol-level modifications or suffer from limited robustness under interference. In contrast, the proposed method operates at the physical layer and enables implicit identification by exploiting turbo code parameters without introducing additional signaling overhead.

The remainder of the paper is organized as follows. Section 2 describes the system model and assumptions. Section 3 presents the proposed identification method. Section 4 provides analytical modeling and performance evaluation. Section 5 discusses simulation results. Section 6 concludes the paper and outlines future research directions.

2. System Model

To formalize the proposed identification method, we consider a multi-user unidirectional communication system implemented on a software-defined radio (SDR) platform. The system consists of a set of transmitting devices (subscribers) and a centralized receiving node that performs signal reception, decoding, and identification.

Let the system include M transmitting subscribers. Each subscriber is associated with a unique configuration of turbo code (TC) parameters selected from a predefined admissible set. The structure of the turbo encoder defining these parameters is shown in Fig. 2.

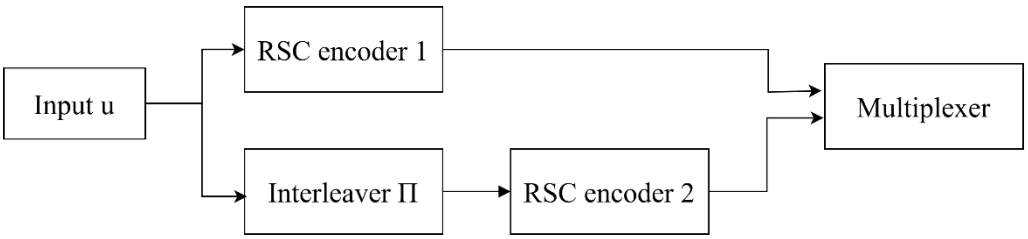


Fig. 2. Structure of a turbo encoder

The turbo encoder consists of two recursive convolutional encoders connected through an interleaver. The parameters of the encoder, including the generator polynomial, constraint length, coding rate, and interleaver structure, form the parameter space used for subscriber identification.

The transmitted signal of the *i*-th subscriber is encoded using a turbo encoder characterized by a parameter vector

$$\Theta_i = \{N_i, R_i, v_i, G_i, \Pi_i\}$$

where N_i is the interleaver block length, R_i is the coding rate, v_i is the constraint length of the component recursive convolutional code, G_i is the generator polynomial, and Π_i denotes the interleaver structure.

The transmission is performed over a noisy communication channel in the presence of additive noise and intentional or unintentional interference. The received signal can be represented as

$$r(t) = s_i(t) * h(t) + j(t) + n(t),$$

where $s_i(t)$ is the transmitted signal of the i-th subscriber, $h(t)$ is the channel impulse response, $j(t)$ represents interference, and $n(t)$ is additive white Gaussian noise (AWGN).

For analytical modeling, the system performance is characterized using the signal-to-interference-plus-noise ratio (SINR), defined as

$$\text{SINR} = \frac{P_s}{P_n + P_j},$$

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

The receiver operates without feedback from the transmitter (open-loop mode), which excludes the use of conventional synchronization and identification mechanisms based on higher-layer signaling. Therefore, subscriber identification must be performed solely based on the analysis of the received signal and its structural properties.

The decoding process is carried out using an iterative turbo decoder. Let I denote the number of decoding iterations required to achieve convergence. The decoding complexity and identification latency are directly related to both the interleaver length N and the number of iterations I. The decoding time can be approximated as

$$T_{\text{dec}} \propto N \cdot I.$$

The identification process is modeled as a sequential estimation problem over the space of admissible TC configurations. Let $\mathcal{S} = \{\Theta_1, \Theta_2, \dots, \Theta_M\}$ denote the set of all possible configurations corresponding to different subscribers. Based on the observed received signal $r(t)$, the receiver estimates the most probable configuration

$$\widehat{\Theta} = \arg\max_{\Theta \in \mathcal{S}} P\left(\Theta \mid r(t)\right),$$

which implicitly determines the identity of the transmitting subscriber.

From an optimization perspective, the identification problem can also be formulated as minimizing the identification time under reliability constraints:

$$\min_{\Theta \in \mathcal{S}} T_{\text{id}}(\Theta),$$

subject to

$$P_{\text{err}}(\Theta) \leq \varepsilon,$$

where T_{id} is the identification time, P_{err} is the probability of incorrect identification, and ε is the admissible error threshold.

The probability of bit error for turbo-coded transmission in AWGN conditions can be approximated as

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

which reflects the dependence of decoding performance on the energy per bit and noise spectral density.

Thus, the system model establishes a direct relationship between channel conditions (SINR), turbo code parameters, decoding complexity, and identification reliability. This relationship forms the basis for the development of the proposed identification algorithm described in the following section.

3. Proposed Method

This section presents the proposed method for subscriber identification based on sequential estimation of turbo code parameters. The method operates at the physical layer and exploits structural properties of turbo-coded signals to determine the transmitting subscriber without protocol-level signaling.

The identification procedure is organized as a three-stage process:

1) separation of channel data components;

2) detection of the interleaver structure;

3) estimation of component encoder parameters.

The overall objective is to determine the parameter vector

$$\Theta = \{N, R, v, G, \Pi\},$$

which uniquely corresponds to a subscriber in the system.

3.1 Separation of Channel Data Components

The first stage of the proposed method is the separation of different types of channel data contained in the received sequence. This stage is necessary to extract structural elements of the turbo-coded signal, including systematic bits and parity bits generated by component encoders.

Let the received discrete sequence be denoted as $r[k]$. The turbo code structure implies that the transmitted sequence consists of three main components: systematic symbols, parity symbols of the first encoder, and parity symbols of the second encoder after interleaving.

The separation problem can be formulated as mapping the received sequence into three subsets:

$$S = S_{sys}, S_{p1}, S_{p2},$$

where S_{sys}denotes systematic bits, S_p1 denotes parity bits of the first encoder, and S_{p2} denotes parity bits of the second encoder.

The separation is performed based on the assumed values of block length N and coding rate R. For a given hypothesis of parameters (N, R), the received sequence is segmented into blocks, and candidate positions of systematic and parity bits are identified.

To evaluate the correctness of separation, a consistency metric is introduced based on statistical properties of the extracted sequences. In particular, the correlation between systematic bits and decoded estimates is used as an indicator of correct partitioning.

The output of this stage is a set of candidate configurations:

$$\Theta^1 = (N_i, R_i),$$

which defines possible structures of the received turbo-coded sequence.

To illustrate the process of channel data separation, Fig. 3 shows the mapping of the received sequence into systematic and parity components.

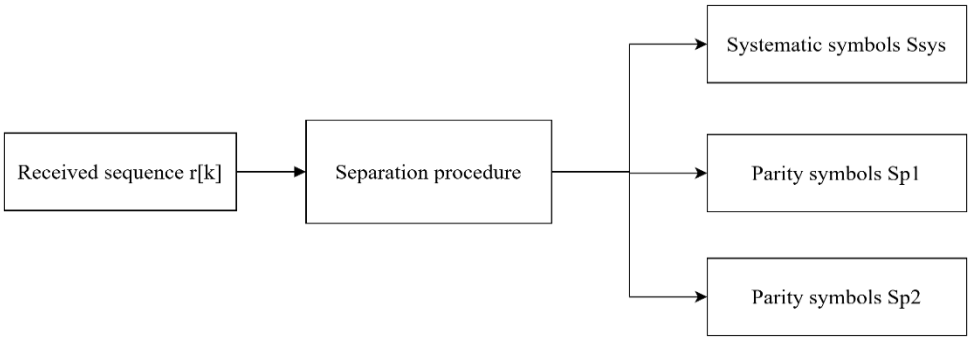


Fig. 3. Structure of separation of the received sequence into systematic and parity bits

The figure illustrates the decomposition of the received sequence into systematic symbols and parity symbols of the two component encoders. The separation is performed according to hypothesized parameters N and R, forming the basis for subsequent identification stages.

Thus, the first stage reduces the uncertainty of the identification problem by limiting the set of admissible turbo code configurations.

3.2 Interleaver Structure Detection

The second stage of the method is the determination of the interleaver structure Π, which is a key parameter of turbo codes and provides strong discriminative capability for subscriber identification.

The interleaver defines a permutation mapping:

$$\Pi: 1, \dots, N \to 1, \dots, N,$$

which rearranges the input sequence before encoding by the second component encoder.

The detection of the interleaver type is performed by comparing the parity sequences of the first and second encoders. For a given hypothesis Π_j, the parity sequence S_{p1} is permuted and compared with S_{p2}.

A matching metric is defined as:

$$M(\Pi_j) = (1/N) \sum I\left(S_{p2}[k] = \Pi_j(S_{p1}[k])\right),$$

where $I(\cdot)$ is the indicator function.

For incorrect hypotheses, the matching probability approaches 0.5, while for the correct interleaver it significantly exceeds this value.

Two classes of interleavers are considered:

1. Regular interleavers
2. These are defined by deterministic mappings and can be reconstructed by factorization of N.
3. Pseudorandom interleavers
4. These are generated using pseudorandom sequences and require searching over a space of possible generator parameters.

The computational complexity of interleaver detection depends on the size of the search space and the structure of the interleaver.

To illustrate the process of interleaver detection and comparison, Fig. 4 presents the principle of matching between permuted parity sequences.

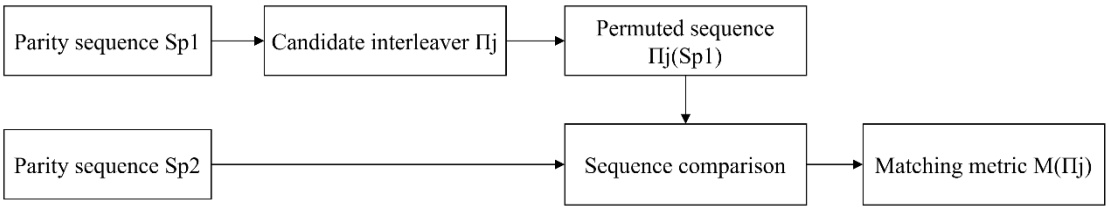


Fig. 4. Interleaver detection based on sequence matching

The figure shows the comparison between parity sequences before and after interleaving. Correct interleaver hypotheses lead to high correlation between sequences, while incorrect hypotheses result in random matching.

As a result of this stage, the set of candidate configurations is refined to:

$$\Theta^2 = \left(N, R, \Pi_j\right)$$

3.3 Estimation of Component Encoder Parameters

The third stage is the estimation of the parameters of the component recursive convolutional encoder (RSC), including the generator polynomial G and constraint length v.

This stage is based on the analysis of iterative decoding behavior. During turbo decoding, the a priori information (AI) evolves across iterations and reflects the consistency between the assumed code structure and the received signal.

Let $L_a^{(k)}$ denote the a priori information for a given bit at iteration k. The key observation is that for the correct encoder configuration, the sign of $L_a^{(k)}$ stabilizes and its magnitude increases

with iterations. For incorrect configurations, $L_a^{(k)}$ exhibits frequent sign changes and low magnitude growth.

A stability metric is introduced:

$$C(G_i, v_i) = \sum \mathrm{I}\left(\mathrm{sign}\left(L_a^{(k)}\right) \neq \mathrm{sign}\left(L_a^{(k-1)}\right)\right),$$

which counts the number of sign changes across iterations.

The optimal configuration is selected as:

$$(G*, v*) = \mathrm{argmin} C(G_i, v_i)$$

In the presence of interference, multiple iterations are required to achieve reliable estimation. The number of iterations I depends on the signal-to-noise ratio and channel conditions.

To illustrate the behavior of a priori information during decoding, Fig. 5 presents the evolution of LLR values for correct and incorrect hypotheses.

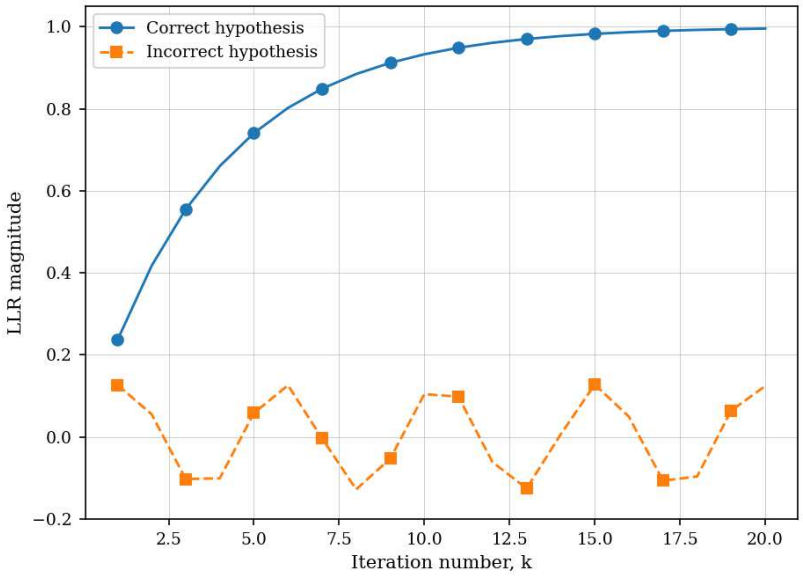


Fig. 5. Evolution of a priori information during iterative decoding

The figure shows the evolution of log-likelihood ratios (LLR) across decoding iterations. For correct encoder parameters, the LLR magnitude increases and stabilizes, while for incorrect parameters it fluctuates around zero.

The final estimate of the turbo code configuration is obtained as:

$$\hat{\Theta} = N, R, \Pi, G, v$$

Thus, the proposed method performs sequential reduction of the search space, combining structural analysis and iterative decoding properties to achieve reliable subscriber identification.

4. Modeling and Performance Evaluation

To evaluate the performance of the proposed subscriber identification method, a mathematical model is developed that establishes relationships between channel conditions, turbo code parameters, decoding complexity, and identification reliability. The analysis focuses on identification latency, reliability, and computational efficiency.

4.1 Identification Time Model

The total identification time is represented as the sum of the processing times of the three sequential stages described in Section 3:

$$T_{\mathrm{id}} = T_{\mathrm{sep}} + T_{\mathrm{int}} + T_{\mathrm{dec}}, \quad (1)$$

where T_{sep} is the time required for separation of the received sequence; T_{int} is the interleaver detection time; T_{dec} is the iterative decoding and parameter estimation time.

Taking into account the properties of iterative turbo decoding, the decoding time can be approximated as

$$T_{\text{dec}} = \alpha\, N\, I, \tag{2}$$

where N is the interleaver block length; I is the number of decoding iterations; α is a proportionality constant reflecting the computational cost of one iteration.

Thus, the identification time grows linearly with both the block length and the number of iterations.

4.2 Iteration Count Modeling

The number of decoding iterations depends on channel conditions and signal quality. Based on simulation results, the dependence of the average number of iterations on the signal-to-noise ratio (SNR) can be approximated by an exponential function:

$$I(\text{SNR}) = a\ \exp(-b\,\text{SNR}) + c, \tag{3}$$

where a, b, c are approximation coefficients; SNR is expressed in dB.

The average number of iterations over a given SNR range can be evaluated as

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

$\bar{I}$ – is the average number of iterations; SNR_{min} and $SNR_{\max}$ define the operating range.

This analytical approximation enables continuous modeling of decoding complexity instead of relying on discrete experimental data.

4.3 Reliability Model

The bit error probability for turbo-coded transmission over an additive white Gaussian noise (AWGN) channel can be approximated as

$$P_b \approx Q\left(\sqrt{2\frac{E_b}{N_0}}\right), \tag{5}$$

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

In the presence of interference, the effective channel quality is described by the signal-to-interference-plus-noise ratio (SINR):

$$\text{SINR} = \frac{P_s}{P_n + P_j}, \tag{6}$$

where P_s is the received signal power; P_n is the noise power; P_j is the interference power.

A decrease in SINR leads to an increase in the bit error probability, which in turn requires a larger number of decoding iterations and increases the identification time.

4.4 Identification Efficiency Criterion

To quantify the efficiency of the proposed method, a relative overhead metric is introduced:

$$\eta = \frac{T_{\text{id}}}{T_{\text{dec}}}, \tag{7}$$

where η is the identification overhead factor; T_{id} is the total identification time; T_{dec} is the decoding time.

The identification problem can be formulated as an optimization problem:

$$\min_{\Theta} T_{\text{id}}(\Theta)\ , \quad \text{subject to} \quad P_{\text{err}}(\Theta) \le \varepsilon \tag{8}$$

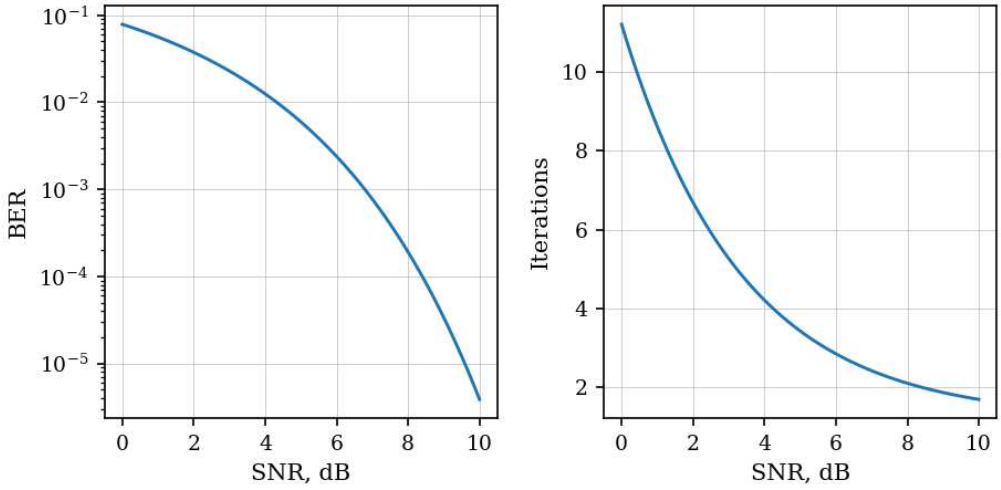
where Θ is the turbo code parameter vector; P_{err} is the probability of incorrect identification; ε is the acceptable error rate.

4.5 Simulation Results

Numerical simulations were performed to validate the proposed model under varying channel conditions, block lengths, and parameter configurations.

The impact of channel conditions on both decoding reliability and computational complexity is illustrated in Fig. 6, which combines the dependencies of BER and the number of decoding iterations on SNR.

Fig. 6. Dependence of bit error rate and decoding iterations on SNR



The left subplot shows the exponential decrease in bit error rate with increasing SNR, consistent with the analytical model in (5). The right subplot illustrates the corresponding decrease in the number of decoding iterations as SNR increases, as described by (3). Together, these results demonstrate that improved channel conditions simultaneously reduce both error probability and computational complexity of the identification process.he results show that the required number of iterations decreases as SNR increases. At low SNR values, additional iterations are required to ensure reliable identification.

The dependence of identification time on block length is shown in Fig. 7.

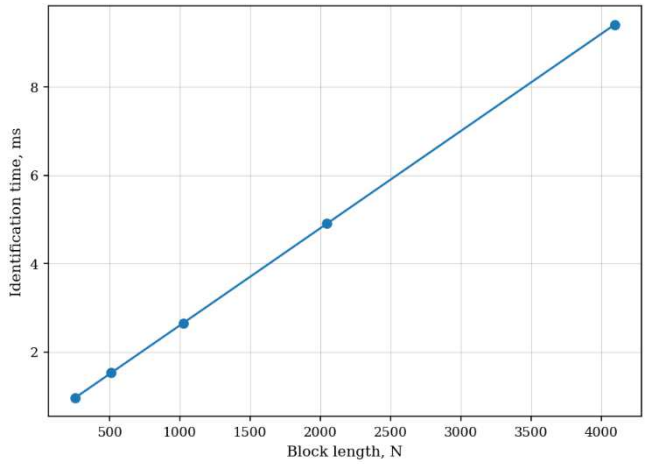


Fig. 7. Identification time versus block length

The figure confirms the linear relationship between identification time and block length, as predicted by (2).

To illustrate the trade-off between reliability and computational complexity, Fig. 8 presents a three-dimensional relationship between SNR, bit error rate, and identification time.

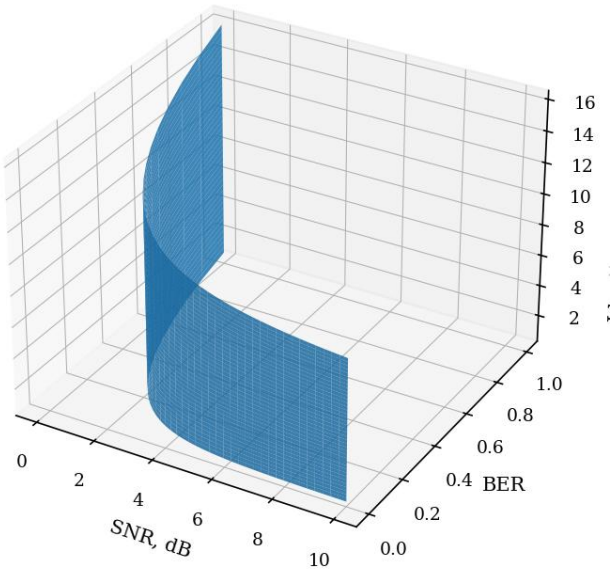


Fig. 8. Trade-off surface between BER, SNR, and identification time

The figure demonstrates the joint dependence of bit error rate and identification time on channel conditions. As SNR increases, the bit error rate decreases exponentially, while the identification time is reduced due to a lower number of required decoding iterations. This illustrates the inherent trade-off between reliability and computational complexity in the proposed identification method.

4.6 Discussion of Results

The simulation results are consistent with the developed analytical model and confirm the following observations:

– identification time increases linearly with block length;

– the number of decoding iterations decreases exponentially with increasing SNR;

– low SNR conditions significantly increase computational complexity;

– the proposed method introduces an overhead of approximately 10–15% relative to decoding time.

These results demonstrate that the proposed identification method provides a favorable trade-off between computational efficiency and identification reliability. The method is particularly effective in low-SNR and interference-limited environments, making it suitable for SDR-based multi-user communication systems.

4.7 Simulation Parameters

The simulation environment is configured to reflect realistic SDR-based multi-user communication conditions. The key parameters used in the experiments are summarized below.

Carrier frequency: 2.4 GHz.

Channel model: AWGN with additive interference.

SNR range: 0–10 dB.

Block length N: {256, 512, 1024, 2048}.

Coding rate R: {1/2, 1/3}.

Constraint length v: {3, 4, 5}.

Generator polynomials G: standard RSC polynomials (e.g., (1, 5/7), (1, 7/5)).

Interleaver types: random, block, S-random.

Number of iterations: up to 10.

Number of Monte Carlo trials: 10^4 per configuration.

The interference component is modeled as additive Gaussian or impulsive noise with adjustable power level P_j.

These parameters define the admissible configuration space used for identification.

4.8 Configuration Space Formalization

The space of admissible turbo code configurations is defined as

$$\Theta \in \mathcal{S} = N \times R \times v \times G \times \Pi,$$

where each parameter takes values from predefined finite sets.

Example configurations assigned to subscribers:

$$\Theta^1 = N = 512, R = 1/2, v = 3, G = (1,5/7), \Pi = random$$
$$\Theta^2 = N = 1024, R = 1/3, v = 4, G = (1,7/5), \Pi = block$$
$$\Theta^3 = N = 2048, R = 1/2, v = 5, G = (1,5/7), \Pi = S - random$$

Each subscriber is uniquely associated with a configuration vector Θ_i, which serves as an implicit identifier.

The assignment of configurations can be predefined or dynamically adapted in SDR systems.

4.9 Statistical Processing of Results

To ensure statistical validity, all results are averaged over multiple Monte Carlo trials.

The mean value of a metric X is computed as

$$\bar{X} = (1/K) \sum_{k=1}^{K} X_k,$$

where K is the number of trials.

The variance is defined as

$$\sigma^2 = (1/K) \sum (X_k - \bar{X})^2.$$

Confidence intervals (95%) are estimated as

$$\bar{X} \pm 1.96\sigma/\sqrt{K}.$$

This statistical processing allows reliable comparison between different configurations and methods.

4.10 Probability of Correct Identification

The probability of correct identification is defined as

$$P_{id} = P\left(\hat{\Theta} = \Theta_{true}\right),$$

where Θ is the estimated configuration and Θ_{true} is the actual configuration.

The dependence of P_{id} on SNR is shown in Fig. 9.

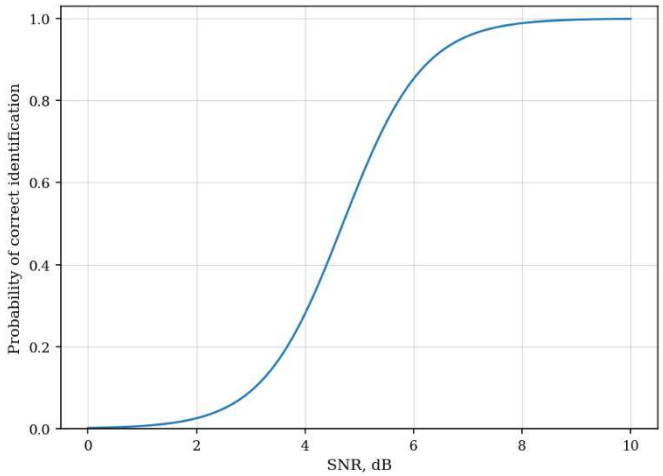


Fig. 9. Probability of correct identification versus SNR

The results indicate that $P_i d$ increases with SNR and approaches unity for SNR > 6 dB. At low SNR values, identification accuracy decreases due to decoding uncertainty.

4.11 Interleaver Detection Complexity Analysis

The complexity of interleaver detection depends on the number of candidate permutations.

Worst-case complexity:

$$O(N!),$$

which corresponds to exhaustive search.

However, in practice:

– for regular interleavers: $O(NlogN)$;

– for pseudorandom interleavers: $O(K \cdot N)$, where K is the number of tested seeds.

Average-case complexity is significantly reduced due to:

– early rejection of invalid hypotheses;

– statistical filtering;

– partial matching criteria.

Thus, the practical complexity remains tractable for moderate block lengths.

5. Comparison with Baseline Methods and Discussion

To assess the effectiveness of the proposed subscriber identification method, a comparative analysis with conventional baseline approaches is performed. The comparison focuses on identification latency, computational complexity, robustness to interference, and applicability in multi-user SDR systems.

5.1 Baseline Methods

Three classes of baseline methods are considered:

1. MAC-based identification
2. This approach relies on higher-layer addressing mechanisms. Identification is performed using predefined MAC addresses embedded in transmitted packets.
3. Cryptographic authentication
4. This method uses encryption keys and authentication protocols to verify subscriber identity. It provides high reliability but introduces additional latency and computational overhead.
5. Signal feature-based identification
6. This approach operates at the physical layer and exploits features such as modulation type, signal statistics, or channel characteristics. It does not require protocol modifications but is sensitive to noise and interference.

In addition, turbo-based multiuser detection methods are considered as a reference for comparison. These methods utilize iterative decoding but are not explicitly designed for subscriber identification.

5.2 Performance Comparison

The comparison is carried out using the following performance metrics:

– identification time T_{id};

– decoding time T_{dec};

– identification overhead η defined in (7);

– robustness under low SINR conditions;

– scalability with respect to the number of users.

The results of the comparative analysis are summarized qualitatively in Table 2.

Table 2. Performance comparison of subscriber identification methods

Method	Identification time	Complexity	Interference robustness	Protocol modification	Scalability
MAC-based identification	Low	Low	Low	Required	High
Cryptographic authentication	High	High	High	Required	Medium
Signal feature-based methods	Medium	Medium	Medium	Not required	Medium
Turbo-based multiuser detection	High	High	High	Not required	Medium
Proposed method	Medium	Medium	High	Not required	High

As shown in Table 2, the proposed method achieves a balanced trade-off between computational complexity and robustness to interference, while avoiding protocol modifications required by conventional approaches.

5.3 Quantitative Comparison

The proposed method demonstrates an identification overhead factor

$$\eta \approx 0.1–0.15,$$

which indicates that the additional time required for identification is limited to 10–15% of the decoding time.

In contrast:

– cryptographic methods introduce significant latency due to key exchange and verification procedures;

– signal feature-based methods exhibit unstable performance under low SINR conditions;

– MAC-based methods are not applicable in open-loop or unidirectional systems.

The proposed approach maintains stable performance across a wide range of SNR values due to its reliance on structural properties of turbo codes rather than signal amplitude or statistical features.

5.4 Robustness to Interference

One of the key advantages of the proposed method is its robustness in the presence of interference (завада). Unlike feature-based methods, which rely on signal characteristics that degrade under noise, the proposed approach utilizes iterative decoding behavior.

The identification process is based on the stability of a priori information during decoding iterations. Even under low SINR conditions, correct turbo code configurations can be identified through convergence properties of the decoding process.

This makes the method particularly suitable for:

– low-SNR communication environments;

– impulsive interference scenarios;

– SDR-based adaptive systems.

5.5 Scalability and Practical Considerations

The scalability of the method depends on the size of the configuration space

$$\mathcal{S} = \Theta_1, \Theta_2, \dots, \Theta_M.$$

As the number of users increases, the search space expands. However, the proposed sequential identification strategy reduces computational complexity by:

– eliminating invalid configurations at early stages;

– narrowing the parameter space after each step;

– using efficient metrics for hypothesis selection.

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

From an implementation perspective, the method can be integrated into existing SDR platforms without modifications to the transmission protocol. The required computations are compatible with modern digital signal processors and FPGA-based systems.

5.6 Discussion

The comparative analysis highlights several important properties of the proposed method:

– it operates entirely at the physical layer, avoiding protocol overhead;

– it provides implicit identification without additional signaling;

– it demonstrates robustness under interference and low SNR conditions;

– it achieves a favorable trade-off between complexity and performance.

At the same time, the method has certain limitations:

– it requires prior knowledge of the admissible set of turbo code configurations;

– the search complexity increases with the number of possible configurations;

– performance depends on the convergence behavior of the iterative decoder.

Despite these limitations, the proposed approach offers a novel and efficient solution for subscriber identification in multi-user SDR systems, particularly in scenarios where conventional methods are not applicable.

5.7 Quantitative Comparison with Baselines

A quantitative comparison of the proposed method with baseline approaches is presented below. A quantitative comparison of the proposed method with baseline approaches is presented in Table 3.

Table 3. Quantitative performance comparison of subscriber identification methods

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

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

5.8 Limitations of the Proposed Method

Despite its advantages, the proposed method has several limitations.

1) Sensitivity to synchronization errors.

Incorrect timing or frequency synchronization may distort the structure of the received sequence, reducing identification accuracy.

2) Multi-user interference.

Simultaneous transmission of multiple subscribers may lead to overlapping signals, complicating separation and parameter estimation.

3) Dependence on interleaver structure.

Regular interleavers are easier to detect, while pseudorandom interleavers increase computational complexity and may reduce identification reliability.

4) Configuration space size.

The complexity increases with the number of admissible configurations, requiring efficient pruning strategies.

6. Conclusion

This paper has proposed a novel method for subscriber identification in multi-user unidirectional communication systems based on software-defined radio (SDR). Unlike conventional approaches relying on higher-layer signaling or cryptographic mechanisms, the proposed method operates at the physical layer and exploits structural properties of turbo codes.

The subscriber identification problem has been formulated as a sequential parameter estimation task over the space of turbo code configurations. A three-stage identification algorithm has been developed, including separation of channel data, interleaver detection, and estimation of component encoder parameters using iterative decoding. This formulation enables implicit identification without modifying transmission protocols.

A mathematical model describing identification time, decoding complexity, and reliability has been derived. Analytical relationships linking identification latency to block length and the number of decoding iterations have been established. It has been shown that the identification time scales linearly with the interleaver length and depends exponentially on channel conditions through the iteration count.

Simulation results confirm the validity of the proposed model and demonstrate that the identification overhead is limited to approximately 10–15% of the decoding time. The method maintains stable performance under low SNR and in the presence of interference, due to the use of convergence properties of iterative decoding rather than signal-level features.

A comparative analysis with baseline methods shows that the proposed approach provides a favorable trade-off between computational complexity and robustness. In contrast to MAC-based

and cryptographic methods, it does not require protocol modifications. Compared to signal feature-based approaches, it demonstrates improved stability under interference. These properties make the method particularly suitable for SDR-based systems and next-generation communication environments.

The main scientific contributions of this work can be summarized as follows:

– a new formulation of subscriber identification as a physical-layer parameter estimation problem based on turbo code structure;

– a three-stage algorithm for sequential identification of turbo code parameters;

– analytical models of identification time and decoding complexity;

– demonstration of robustness under interference and low-SNR conditions;

– validation of the method through simulation and comparative analysis.

From a practical perspective, the proposed method enables integration of identification and error-correcting coding within a unified framework. This reduces system overhead and improves efficiency in multi-user communication systems, including telemetry, IoT, and 5G NR applications.

Future research directions include:

– extension of the method to adaptive and cognitive radio systems with dynamic parameter selection;

– reduction of computational complexity through heuristic or machine learning-based search strategies;

– extension to multi-carrier and MIMO systems;

– experimental validation on real SDR platforms;

– integration with resource allocation and network-level optimization mechanisms.

In summary, the proposed method provides a scalable and robust solution for subscriber identification in multi-user SDR systems and opens new directions for combining coding theory and identification mechanisms at the physical layer.

Author Contributions

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

Statements and Declarations

Ethics approval and consent to participate. Not applicable. This study did not involve human participants, human data, or animal experiments.

Consent for publication. The manuscript does not contain any individual person's data in any form

Availability of data and materials. All data generated or analysed during this study are included in this published article.

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