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Method for determining intentional interference type in conditions of uncertainty of interference environment based on known models

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Abstract. The study aimed to theoretically substantiate a method for the identification of intentional interference types in an uncertain interference environment for software-defined radio systems by using known interference models and formalised analysis of the communication channel state vector. The methodological basis included window calculation of the matched feature vector, their normalisation, signature coding, metric and probabilistic comparison with a template library, threshold rejection of uncertain cases, and model-simulation verification in the streaming architecture of software-defined radio. As a result, a formalised feature space and signature profiles of five basic classes of interference were formed: impulse, broadband noise, harmonic, modulation, and low-visibility – as stable multi-parameter patterns of common signal indicator changes that ensure class separation in different signal-to-noise ratio modes, bit error probability variability, and spectral power density morphology, and are reproduced in repeated runs with unchanged parameters. The method is implemented in the form of a computational pipeline with a sequence of stages "state vector → event detection → segmentation → signature description → dimensionality reduction → comparison → decision", where resource-intensive operations are activated only in the presence of an event trigger, and the interfaces between the blocks record a transition from observations to a compact impact signature. The resulting classification rules with membership thresholds and a controlled rejection procedure have been formulated, which transfers new signatures to the accumulation mode and incremental supplementation of the database with subsequent confirmation of profile stability on repeated observations. Simulation testing on a series of parameterised scenarios showed the reproducibility of signature profiles and classification decisions under fixed settings. The practical significance of the study results is determined by the possibility of implementing the method by developers and integrators of embedded software-controlled radio systems and radio monitoring systems for streaming determination of the type of intentional interference based on signature profiles with threshold rejection of unknown cases and controlled replenishment of the signature library

Keywords: channel state vector; time-frequency descriptors; computational pipeline; signature coding; reject option

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INTRODUCTION

The research relevance is determined by the fact that Software-Defined Radio (SDR) in real conditions of radio-electronic warfare loses its operability not only due to background noise, but primarily due to specific scenarios of deliberate interference, which manifest themselves in various combinations of degradation of the Signal-to-Noise Ratio (SNR), Received Signal Strength Indicator (RSSI), Bit Error Rate (BER) and Power Spectral Density (PSD). Under such conditions, it is not enough to simply record the fact that interference is present – it is critical to algorithmically determine its type based on measured parameters and time-spectral characteristics. Interference classification is considered a computational data processing task with a procedure for rejecting undefined classes and the possibility of expanding signature descriptions, which is especially relevant for SDR platforms with limited computational resources and strict processing delay requirements.

In studies of interference immunity in mobile radio networks, S. Boholii *et al.* (2022) showed that adaptive beamforming provides a significant reduction in interference due to spatial signal selection. The results confirmed the effectiveness of spatial adaptation, but the classification interpretation of the interference type in algorithmic form was not considered. T. Hurskyi *et al.* (2025) provided a quantitative assessment of the effectiveness of radio-electronic suppression of control channels of First-Person View (FPV) unmanned platforms. The channel degradation indicators described the effects of the interference but did not form a procedure for computational recognition of the nature of the interference signal. A description of models and technical methods for generating radio interference was presented by V. Zylevich & S. Svakha (2025), which reveals the energy and spectral properties of various types of interference in telecommunications systems. This presentation provided the basis for parameterised modelling of interference and the formation of feature templates in simulation environments. The algorithmic logic of step-by-step situational control in conflict radio-electronic interaction was considered by V. Kantsedal & A. Mogyla (2025), where the response process is presented as a sequence of computational steps. However, the mechanism for rejecting unknown types of interference and forming new classes in the classification model is not formalised.

The problem of interference recognition in open-set conditions has been studied in detail by H. Han *et al.* (2022), who introduced an open-set formulation for the jamming pattern recognition problem. The paper proves that the threshold decision rule reduces the risk of misclassification of unknown interference patterns and increases the reliability of automatic analysis. A systemic risk approach to intentional electromagnetic interference was proposed by N. Davies *et al.* (2025), where interference is considered as a factor in the interaction of subsystems of complex radio-electronic complexes. This interpretation emphasised the feasibility of embedding interference-type determination algorithms into the computational architecture of radio systems as a separate analytical module. Methods for interference recognition based on multi-domain features were proposed by P. Wang *et al.* (2022), where the combination of several feature spaces increases the accuracy of classification in wireless networks. The results confirmed the effectiveness of the multidimensional representation of the channel state as an input vector for the recognition model.

Automatic classification of interference signals in cognitive radio systems of unmanned platforms was investigated by A. Krayani *et al.* (2022), where time-frequency representations were used as robust descriptors of the interference type. The suitability of compact time-spectral features for practical recognition algorithms was demonstrated. A spectrogram-oriented approach to detecting and classifying interference in Orthogonal Frequency Division Multiplexing (OFDM) systems for unmanned aerial vehicles is presented by Y. Li & M. Pawlak (2022), where machine learning (ML) is combined with specialised feature selection. The results showed that the alignment of the feature structure and the classification model determines the robustness of recognition at low SNR values. Practical methods for detecting and ML-classifying interference in satellite navigation signals were discussed by J. Rijnsdorp *et al.* (2023), where the emphasis is on the suitability of algorithms for implementation in receiving devices. This approach emphasised the importance of resource efficiency, controlled complexity, and scalability of classification solutions.

A synthesis of the above sources revealed a research niche: existing works either demonstrate ways to improve noise immunity or describe interference classification, but do not sufficiently combine these lines into a formalised method for determining the type of intentional interference in conditions of uncertainty of the interference environment as a software-implemented data processing system for SDR. There remains a need for a clearly defined data structure (channel state vector as a multidimensional feature space), a reproducible algorithmic pipeline (collection → pre-processing → feature extraction → classification → reject → signature database update), as well as explicitly stated complexity and resource constraints that ensure practical applicability for SDR platforms. These requirements set the framework for the further development of the proposed method and its simulation validation in a software environment, focused on application in further research and development of a knowledge base of task templates. The study aimed to theoretically justify a method for determining the type of intentional interference in conditions of uncertainty of the interference environment for software-defined radio systems based on the use of known interference

models and formalised analysis of the communication channel state vector.

MATERIALS AND METHODS

The research was conducted as theoretically and algorithmically oriented and aimed at constructing a reproducible computational scheme for determining the type of intentional radio interference in conditions of an uncertain interference environment for SDR. The material basis was formed by formalised parametric descriptions of the radio channel state, presented as time series of measured indicators and their derivatives in the form of feature vectors. The basic state vector included the signal-to-noise ratio (SNR), received signal strength indicator (RSSI), bit error rate (BER), spectral power density (PSD), as well as time statistics (mean values, variances, rates of change, stationarity indicators) and derived time-frequency descriptors formed from short-time transformations and local spectral estimates. All parameters were interpreted as a unified multidimensional feature space of the channel state, in which the type of interference is manifested not by a single indicator, but by a combination of coordinated changes in energy, error, and spectral-structural characteristics, which makes it possible to describe the impact and further classification. To ensure the reproducibility of algorithmic solutions and the possibility of re-testing in different configurations, feature formation was conducted in a fixed computing mode: with a given sampling frequency, sliding window length for SNR/BER/RSSI estimation, PSD estimation parameters (window type, overlap, frequency resolution) and rules for matching temporal and spectral features in a common vector. The rules for normalising features (scaling to comparable ranges and resistance to changes in absolute signal levels) were recorded separately, since it is normalisation that determines the correctness of similarity metrics for comparing signatures in the knowledge base.

In addition, a formalised taxonomy of types of intentional interference and corresponding signature manifestations in the multidimensional feature space of the channel state was used as the material basis for the study. Within the model corpus, impulse, broadband noise, harmonic, modulation, and structured low-probability of intercept/low probability of detection (LPI/LPD) influences were considered, for which coordinated profiles of changes in SNR, RSSI, BER and PSD, as well as time-spectral patterns in the form of local energy maxima, spectral peaks, sidebands and quasi-periodic structures were set for the LPI/LPD class of low-probability-of-intercept/low-probability-of-detection influences. For the reproducible formation of these profiles in the model body, controlled parameterised synthetic implementations of the useful signal and interference effects in the complex I/Q baseband were used. BPSK, QPSK, and 16-QAM with pulse shaping via RRC filtering, as well as OFDM with a cyclic prefix as a control case of a structured spectrum, were used as reference models of the useful signal to verify the robustness of the features to different "normal" spectral morphologies of transmission. Low-power interference (LPI/LPD) was generated in forms that minimize contrast at average SNR/RSSI, leaving reproducible local time-frequency invariants. These include noise-like DSSS signals based on pseudo-random sequences and FHSS influences, where a short time is spent at a frequency, resulting in short local energy maxima in the TF representation instead of stable peaks in the global PSD. Additionally, low-energy chirp/LFM components with a characteristic "sloped" trace in the spectrogram and burst signals with a low duty cycle provide episodic TF anomalies and increase non-stationarity without prolonged degradation of energy averages.

The parameters of the influences were set in a normalised form relative to the sampling frequency and the length of the analysis window (relative bandwidth, frequency sweep rate, dwell time at frequency, duty cycle), and the amplitude ratios were adjusted through SNR scenarios so that for LPI/LPD influences, the main class separation was provided by spectral, entropy, and time-frequency descriptors, rather than absolute power levels. The interference signature was interpreted as a reproducible vector representation of a channel state fragment formed from energy, statistical, and time-frequency descriptors, including estimates of spectral entropy, occupied bandwidth, pulse structure regularity, BER variability, and RSSI change rates. To ensure comparability of signatures between scenarios, coordinated signature coding was used with a reduction in the dimensionality of the feature space using autoencoder or perceptron transformations, which made it possible to obtain compact latent vectors suitable for metric comparison. Thus, the research materials included not only time series of channel parameters and synthetically generated signals/interference, but also formalised signature descriptions of typical interference effects and rules for their vector representation, which were used as a basic information set for further algorithmic classification and incremental expansion of the knowledge base.

The methodological part was based on a combination of system analysis, feature modelling and algorithmic signal classification and was implemented as a formalised computational pipeline: "channel state vector → interference event detection → signature coding → metric comparison → classification decision → rejection or database update". The channel state vector was defined as and was subject to normalisation and time smoothing in sliding windows to reduce the impact of random fluctuations and ensure the stability of subsequent estimates, with the specification of the feature composition being conducted in the form (1):

$$x(t) = [SNR(t), RSSI(t), BER(t), PSD(t), H(t), \sigma^2(t)] \in R^n, \quad (1)$$

where $H(t)$ – channel impulse response; $\sigma^2(t)$ – signal dispersion.

Detection of the interference event was implemented as a multi-criteria threshold procedure incorporating combined changes in SNR, BER, RSSI and spectral indicators, followed by signal segmentation using the adaptive window method with the selection of quasi-stationary fragments. For each fragment, a set of temporal, spectral, and time-frequency features was calculated, including energy distributions, spectral entropy, bandwidth estimates, peak structure parameters, and regularity indicators. Signature coding was implemented by converting the primary feature space into a compact vector representation using dimension reduction and machine learning methods implemented in scikit-learn to reduce the computational load and improve the stability of similarity metrics for SDR platforms with limited resources. Signature comparison was performed using cosine similarity and Euclidean distance, and the decision was made based on the maximum estimate of membership in known classes.

To account for the uncertainty of the interference environment, a rejection mechanism was used, whereby the input vector was classified as an unknown type of interference provided that the maximum estimate of membership in the set of known classes did not exceed the threshold value . In the case of rejection, a new signature record with metadata was formed, and the procedure for incremental replenishment of the knowledge base was initiated after confirmation of the stability of repeated observations. To ensure the scalability and consistency of the signature library in multi-node operating scenarios, the method provided for a two-level architecture of interaction between edge software-defined radio devices and the cloud environment, where local SDR platforms perform initial detection, segmentation, feature formation, and classification decisions in real time with minimal delay, while the cloud level is used as a centralised repository for the global signature database, a service for synchronising updates between devices, and a computing circuit for resource-intensive operations, including retraining dimensionality reduction models or classifiers on expanded datasets, as well as in-depth analysis of ambiguous or rejected cases that require more templates, repeated runs, and more complex validation procedures than are available on edge devices.

Algorithmic suitability was assessed by analysing computational complexity and resource requirements, in particular the complexity of matching a signature with a database of order , where – dimension of the feature vector and – number of templates in the database. MATLAB (Version R2024a), Python (Version 3.12) with NumPy, SciPy and scikit-learn libraries, as well as GNU Radio (Version 3.10.0.0) for SDR-oriented simulation scenarios were used as the modelling and software environment. MATLAB was used for controlled numerical experiments with signal/noise generation and verification of the correctness of feature calculations and threshold rules; Python was used for reproducible data processing implementations, batch data set formation, and parametric runs; NumPy and SciPy were used as tools for numerical calculations, transformations, and spectral estimates; scikit-learn was used for the implementation of classification procedures, threshold calibration, and verification of decision consistency; GNU Radio was used for modelling the SDR streaming architecture, where collection, pre-processing, feature formation, and classifier decisions are interpreted as a sequence of software blocks with delay and computational complexity constraints. Calibration of membership thresholds τ_sim, τ_dist and τ_prob was performed as a separate optimisation procedure on a validation subset of scenarios with known interference classes and a control set of "unknown" profiles.

The optimisation goal was to simultaneously maximise the proportion of correct classification of known classes (Accuracy_known) and minimise the proportion of false classification of unknown influences (False Acceptance Rate_unknown), which was formalised through a multi-criteria function of the form $J(\tau) = w_1 \cdot F1\_known - w_2 \cdot FAR\_unknown$, where F1_known is the F1 measure for known classes, FAR_unknown is the proportion of unknown signatures mistakenly assigned to existing templates, and w_1 and w_2 are the weighting coefficients for stable typing and protection against forced classification. For the cosine similarity metric scheme, the threshold τ_sim was determined by the maximum $J(\tau)$ in the search process within the permissible interval [0,1], for the Euclidean distance τ_dist – as the minimum distance value that ensures the specified True Positive Rate_known level with the restriction FAR_unknown $\leqslant \varepsilon$, and for the probabilistic classifier τ_prob – based on the analysis of ROC curves and the selection of the point that maximises the Jude index (TPR – FPR). Additionally, the stability of the optimal τ was verified for variations in SNR and window analysis parameters; the threshold was considered acceptable only if the decision was invariant within the acceptable range of scenarios. This procedure ensured a formally justified selection of thresholds that balances sensitivity to known classes and resistance to unknown signatures in conditions of uncertain interference. Within the framework of model-simulation validation, the delay, operational memory, and scalability of the signature database in streaming mode were quantitatively assessed, as these parameters determine the practical suitability of the conveyor for implementation on edge-SDR devices. The evaluation was performed for two reference computing profiles: "desktop-contour" for control reproducibility (x86-64 class CPU) and "edge-contour" for limited resources (ARM class), in a single streaming analysis configuration with a sliding window and a conditionally activated extended processing branch.

RESULTS

Formalisation of multidimensional feature space and normalised radio channel state vector

Formalisation of the feature space and channel state vector showed that heterogeneous radio channel

observation parameters can be reduced to a consistent multidimensional representation suitable for signature identification of intentional interference. As a result of computational processing, the energy, error, spectral, temporal, and time-frequency characteristics were reduced to a single normalised state vector x(t), formed in fixed sliding windows and with consistent scaling rules. The formation of x(t) was conducted following representation (1), where the components SNR(t), RSSI(t), BER(t), PSD(t), H(t) and $\sigma^2(t)$ after normalisation were used as the basic input for feature grouping and subsequent signature coding. This reduction eliminated the heterogeneity of the original scales and ensured the metric comparability of signatures between different interference scenarios. The generalised result of feature structuring and their role in signature description is presented in Table 1.

Table 1. Composition and grouping of features in the channel state vector for signature identification of interference

Group of characteristics	Indicators	Computational descriptors	Role in signature description
Energetic	SNR, RSSI	Average in window, local deviations, rate of change	Record signal energy degradation and abnormal level jumps
Error-based	BER	Moving average, variability, threshold exceedances	Reflect the impact of interference on reception integrity
Spectral	PSD	Bandwidth, spectral peaks, uneven distribution	Can distinguish between narrowband, broadband, and structural influences
Temporal	Time series of parameters	Dispersion, autocorrelation, stationarity	Detect impulsivity and non-stationary modes
Time-frequency	Local TF representations	Spectral entropy, local energy maxima	Hidden and subtle structural patterns are identified
Structural	Derived features	Regularity, quasi-periodicity, impulse indices	Forming invariant signatures of interference types

Notes: local TF representations are local time-frequency representations of a signal obtained in short sliding windows as a distribution of energy over time and frequency (e.g., based on short-time Fourier transform or wavelet transform) to highlight short-term and subtle spectral-structural patterns

Source: compiled by the authors using MATLAB R2024a and Python 3.12

Analysis of the generalised grouping in Table 1 showed that the key condition for reproducible signature identification is the functional structuring of heterogeneous channel parameters into coordinated feature blocks, rather than their simple enumeration. Energy features (SNR, RSSI) in this logic serve as a primary indicator of interference events, but do not in themselves provide reliable typification, since different classes of interference can produce similar levels of degradation. The bit error rate (BER) serves as a functional confirmation of the impact on reception and can be used for short-term peak disturbances to be distinguished from stationary changes in the channel. Spectral features (PSD and derivatives) form the basic morphological description of interference, capturing the differences between broadband noise effects, narrowband harmonic components, and more complex modulation structures. Time statistics and time-frequency descriptors enhance discrimination in scenarios with weak "visibility" in SNR/RSSI and enable the detection of structural patterns, in particular for LPI/LPD influences, where local TF features, entropy and regularity invariants become decisive.

The study also established that the correctness of metric signature comparison is determined not only by the composition of features, but also by fixed rules of normalisation and window matching, as they reduce sensitivity to scale and random fluctuations and ensure comparability between scenarios. As a result, formalisation of the feature space as a coordinated signature database has been recorded, in which each feature block has a functional role in the final decision. Energy features (SNR/RSSI and derivatives) provide primary detection of reception deterioration, false features (BER in windows, variability) reflect the impact on transmission quality and separate "noise" deterioration from structured interference, spectral features (PSD, bandwidth, peak structure, entropy) reproduce the morphology of interference in the frequency domain, and temporal and time-frequency descriptors (impulsiveness, regularity, non-stationarity) provide structural confirmation of the class. Normalisation and window matching are critical for correct metric comparison, as they translate signature similarity into dependence on the type of influence rather than absolute levels and random fluctuations. As a result, the formed space supported two key modes of the method: stable classification of known classes and justified rejection of undefined cases when the profile does not match any template.

Signature multiparametric profiles of the main types of intentional radio interference

Generalisation of the results of signature coding showed that for different classes of intentional interference in a multidimensional feature space, a reproducible profile of compatible changes in energy, error, spectral and time-structural indicators is formed. In contrast to isolated channel degradation indicators, it

is the stable combinations of features in sliding windows that ensure class separability and suitability for template matching. As a result of model-simulation runs and signature coding, a generalised set of profiles for five basic types of intentional interference has been formed, presented in Table 2.

Table 2. Generalised signature characteristics of impulse, broadband noise, harmonic, modulation and LPI/LPD interference

Type of interference	Energy indicators (SNR, RSSI)	BER profile	Spectral characteristics (PSD)	Time and TF indicators	Stable signature pattern
Impulse	Short deep SNR dips, sharp RSSI jumps	Peak BER bursts	Broadband energy emissions	Short pulses, high non-stationarity	Rare or serial energy peaks + BER bursts in narrow windows
Broadband noise	Sustained reduction in SNR	Consistently elevated BER	Uniformly increased PSD across the band	Temporal stationarity	Flat spectral profile + prolonged degradation
Harmonious	Moderate decrease in SNR with relatively stable RSSI	Moderate growth in BER	Narrow spectral peaks	Frequency	Dominant narrow line + regularity in time
Modulational	SNR fluctuations	Non-uniform BER	Sidebars, complex PSD structure	Quasi-periodic structures	Spectral component packets + unstable BER
LPI/LPD	Weak SNR/RSSI changes	Low or fluctuating BER	Weak local patterns	Hidden regularity	Low-energy TF patterns + entropy deviations

Source: compiled by the authors using GNU Radio 3.10.0.0 and Python 3.12

Analysis of the generalised profiles in Table 2 showed that the separation of types is ensured not by the extremity of individual parameters, but by the configuration of their joint behaviour. Pulse influences are reliably separated by short-duration energy and false peakiness, while broadband noise influences are separated by a combination of stationary spectral "flatness" and persistently elevated BER. Harmonic and modulation interference are separated primarily by spectral morphology: isolated narrow peaks versus a multi-component structure with sidebands. Insignificant LPI/LPD effects do not form distinct energy anomalies, but demonstrate reproducible time-frequency and entropy deviations, which makes their identification possible only in an extended feature space. The conducted signature typology formed a reproducible correspondence between "interference class → stable multi-parameter pattern", i.e., it transferred the description of interference from the level of general characteristics to the level of specific coordinated changes in the feature space suitable for template comparison.

Within this logic, each class is recorded not by a single marker, but by a configuration of interrelated manifestations in SNR, RSSI, BER, PSD and derived time-spectral descriptors, thereby reducing the risk of class substitution by random fluctuations of a single indicator. The profiles obtained can be interpreted as "signature trajectories" of the channel state: for impulse influences, eventfulness in time dominates with short local disturbances and a characteristic increase in BER instability; for broadband noise – relative stability in time with uniform PSD "filling" and systematic deterioration of error characteristics; for harmonic – narrowband peak structure in PSD and regularity of temporal manifestations with less pronounced changes in average RSSI; for modulation – a combination of sidebands and more complex spectral morphology with quasi-stable temporal fragments and wave-like BER behaviour; for LPI/LPD – low contrast of energy indicators with the simultaneous appearance of weak repetitive patterns in time-frequency indicators, which become key for classifying the impact as a structured, low-visibility class.

A significant result was that typology provides a "minimally sufficient" description of a class in terms of coordinated changes in different groups of characteristics: energy indicators provide the fact and direction of degradation, false indicators provide its practical consequences, spectral indicators provide the form of intervention, and time-frequency indicators provide structural organisation and repeatability. Thanks to this, signature templates become suitable for metric comparison both in the mode of stable classification of known classes and in the mode of incremental expansion of the database: when a new implementation demonstrates a repeatable coordinated profile that does not systematically coincide with existing templates, it can be defined as a candidate for a new signature without the need for complete retraining of the core. Thus, the former typology acts as an operational 'language' for the knowledge base: it provides comparable, reproducible, and scalable descriptions of interference that directly support template comparison, threshold rejection of undefined cases, and controlled replenishment of the signature library as new classes of influence appear.

Computational SDR pipeline for streaming processing and real-time decisions

Within the scope of the results obtained from algorithmic formalisation, the method for determining the type of interference is presented not as a set of separate procedures, but as a complete reproducible computational pipeline in which all processing stages are arranged in a sequential chain with fixed input and output data interfaces. This structuring shifts the signal analysis from the level of "individual operations" to the level of a flowchart decision-making scheme suitable for implementation in SDR-oriented systems under conditions of limited resources and delays. To capture the reproducible logic of data flow through the method rather than a descriptive list of operations, the algorithm was reduced to a structural block diagram with two fundamentally different modes of operation: routine monitoring without activating resource-intensive procedures and extended processing, which is triggered only after detecting a fault event according to agreed threshold criteria.

As a result of the architectural generalisation of the conveyor, the method was found to be suitable for two-level implementation with the distribution of calculations between the edge and cloud levels, where local SDR devices perform primary processing, signature encoding and classification in real time, while the cloud environment provides centralised storage of the global signature database, inter-device synchronisation of updates, and execution of resource-intensive procedures for retraining and analysis of undefined cases. This division made it possible to clearly show at which point the state vector S transitions from "present channel description" to "signature description of the impact", how the suspicious fragment is isolated and the descriptor is formed, and where exactly the decision is made between classification based on known patterns and initiation of incremental replenishment of the knowledge base in the case of an unknown signature. This coordinated sequence of blocks and branches, as well as the transition points between the "continue work" and "in-depth analysis → comparison → decision/update" modes, are shown in Figure 1.

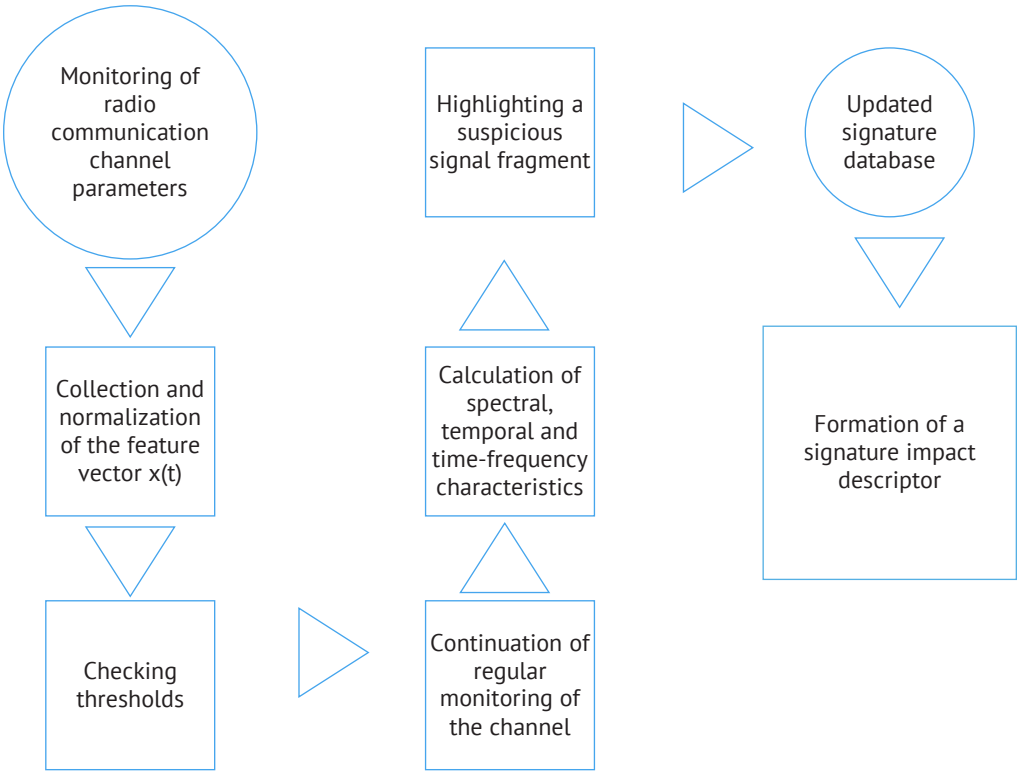

Figure 1. Block diagram of an algorithmic conveyor for determining the type of intentional interference
Source: compiled by the authors using scikit-learn and Python 3.12

Figure 1 shows that the input object of the conveyor is the channel state vector , formed in the communication parameter monitoring mode, after which the event detection threshold block is launched (control of critical deviations, in particular for BER). If the threshold conditions are not met, the system switches to the mode of continuing operation without activating extended processing, which, in the logic of the conveyor, means that there are no grounds for a signature description as a fault event. If the detection criteria are met, the pipeline moves to the advanced processing branch, where the suspicious fragment is selected, the spectral and temporal characteristics are calculated, and the interference descriptor is formed as a compact signature representation. The next central stage is a metric comparison of the formed signature

with the knowledge base templates: if there is a match, a classification decision is formed, and if there is no match, a mechanism for creating a new template and adding a new signature to the base is activated, which implements incremental knowledge expansion without complete retraining.

Thus, the key result of algorithmic formalisation is recorded: the method is presented as a reproducible pipeline with clearly defined mandatory blocks and unambiguous interfaces between them, which eliminates the variability of interpretation of "when exactly" and "which exactly" features are transferred to the signature, as well as at what point the basis for the classification decision arises. In this logic, the detection node acts as a flow control gateway: it filters background parameter fluctuations and initiates resource-intensive operations only when there is a consistent degradation of the channel across several indicators, i.e., it minimises unnecessary calculations and reduces the risk of "reclassifying" normal modes as interference. Segmentation and feature calculation form stable quasi-stationary fragments, within which the signature stage provides not just a description of the signal, but a compact and comparable vector representation of the impact: it unifies energy, error, spectral, and structural manifestations in a common space suitable for metric comparison. The final pair of nodes, "comparison → decision/update", sets the dual-loop behaviour of the system: for known classes, it supports fast pattern recognition based on maximum similarity, and for undefined cases, it introduces a formal rejection mechanism with a threshold S, which prevents forced assignment to the false class and transfers such observations to a controlled accumulation mode. This combination of "classification + reject option + incremental replenishment" renders the conveyor suitable for operation in conditions of incomplete a priori information: the system not only recognises what is already described in the database, but also has a formalised way of expanding the signature database without destroying the decision-making logic and without the need to completely reconfigure each stage.

Results of classification and rejection of unknown signature profiles

Within the framework of generalising the results of algorithmic implementation, formalised decision-making rules have been established that distinguish between assigning a signature to a known class and controlled rejection of undefined cases. The classification node of the method is presented as a threshold-metric procedure, in which the decision is based not only on the maximum similarity to the template, but also on checking the sufficiency of this similarity relative to the established membership threshold. This approach makes it possible to avoid the forced assignment of any observation to an existing class and to introduce a separate mode for processing new or atypical signatures. The generalised resulting rules for comparing metrics, threshold criteria and decision types are given in Table 3.

Table 3. Resultant classification rules and signature rejection thresholds (reject option)

Metric/assessment of belonging	Settlement terms	Threshold criterion	Type of solution	System operation	Status of entry in the signature database
Cosine similarity	$\max_i \cos(x, s_i)$	$\geqslant \tau\_sim$	Known class	Assigning a class with the maximum similarity value	Existing template is used
Cosine similarity	$\max_i \cos(x, s_i)$	$< \tau\_sim$	Rejection	The signature is marked as unknown	Temporary candidate record
Euclidean distance	$\min_i d(x, s_i)$	$\leqslant \tau\_dist$	Known class	Assignment of nearest class	Existing template is used
Euclidean distance	$\min_i d(x, s_i)$	$> \tau\_dist$	Rejection	Switching to accumulation mode	Temporary candidate record
Probabilistic estimation of the classifier	$\max_k P(y_k \mid x)$	$\geqslant \tau\_prob$	Known class	Classification decision by argmax	Existing template is used
Probabilistic estimation of the classifier	$\max_k P(y_k \mid x)$	$< \tau\_prob$	Reject option	Refusal of compulsory classification	New template after confirmations
Agreed multimetric assessment	$(sim \geqslant \tau\_sim) \wedge (P \geqslant \tau\_prob)$	Both thresholds were met	Confirmed class	Decisions with increased confidence	Updating template statistics
Agreed multimetric assessment	Thresholds are not aligned	Partial fulfilment	Undefined case	Re-examination/ additional signs	Deferred candidate

Source: compiled by the authors using scikit-learn and MATLAB R2024a

Analysis of the generalised rules in Table 3 showed that the effective decision-making logic in the method reduces to a formalised division of two modes: rapid typing according to known patterns and controlled "non-decision-making" in cases where the signature does not have sufficient similarity to any of the

existing classes. For the metric approach, this is implemented symmetrically: for cosine similarity, "membership" is determined by exceeding the threshold τ_sim for the maximum similarity, while for Euclidean distance, it is determined by not exceeding τ_dist for the minimum distance; in both cases, the decision about the known class is the result of not a single comparison, but competition with the entire set of templates, which makes the classification dependent on the relative position of the signature in the feature space. At the same time, the reject option mechanism introduces a fundamentally different condition: if none of the templates meets the specified proximity criterion, the signature is not "forcibly" assigned to the nearest class, but is transferred to the rejection mode, i.e., it becomes an object for accumulation and further incremental replenishment of the knowledge base. This branch minimises the risk of misclassification in conditions of uncertain interference, when the input influence may be new or combined and formally closer to one of the classes only due to random fluctuations in features.

The threshold mechanism can be implemented not only through "geometric" metrics (cos, d), but also through a probabilistic interpretation of the classifier output, where the criterion becomes the maximum a posteriori estimate $\max_k P(y_k|x)$ relative to τ_prob. This unified reject option for different types of models: regardless of whether the decision is obtained as a comparison with benchmarks or as the output of a multi-class classifier, rejection is formed according to the same logic of "insufficient confidence → unknown type". Another crucial result is the introduction of a consistent rule for multimetric verification: class confirmation is considered most robust when both the similarity threshold and the probability threshold are met simultaneously, rather than just one of them. Instead, partial fulfilment of thresholds (e.g., high similarity without sufficient P or vice versa) is interpreted as an uncertain case and transferred to a re-verification mode or descriptor completion mode, which reduces the sensitivity of the system to "borderline" signatures between classes. As a result, the resulting decision-making logic is recorded as a two-level procedure "maximum similarity → threshold verification → class or rejection", which simultaneously ensures stable recognition of known types of interference and a formalised mechanism for working with new signatures. This scheme increases the system's resistance to uncertainty in the interference environment and supports the controlled expansion of the signature database without compromising the reproducibility of the algorithmic pipeline.

Model-simulation validation of the method in streaming SDR scenarios

In the note on the reproducibility test results of the proposed method, its algorithmic pipeline was integrated into a stream-oriented SDR signal processing architecture and tested in a series of controlled parameterised simulation scenarios. Validation was performed not at the level of individual features or an isolated classifier, but at the level of the complete working chain "signal generation → channel → noise superimposition → feature coding → signature comparison → decision", which corresponds to the logic of the computational pipeline adopted in the methodology. This approach verified not only the correctness of classification decisions but also the consistency of interfaces between blocks, stability of operation in streaming mode, and repeatability of results at fixed scenario parameters. A generalised structural diagram of the simulation test is shown in Figure 2.

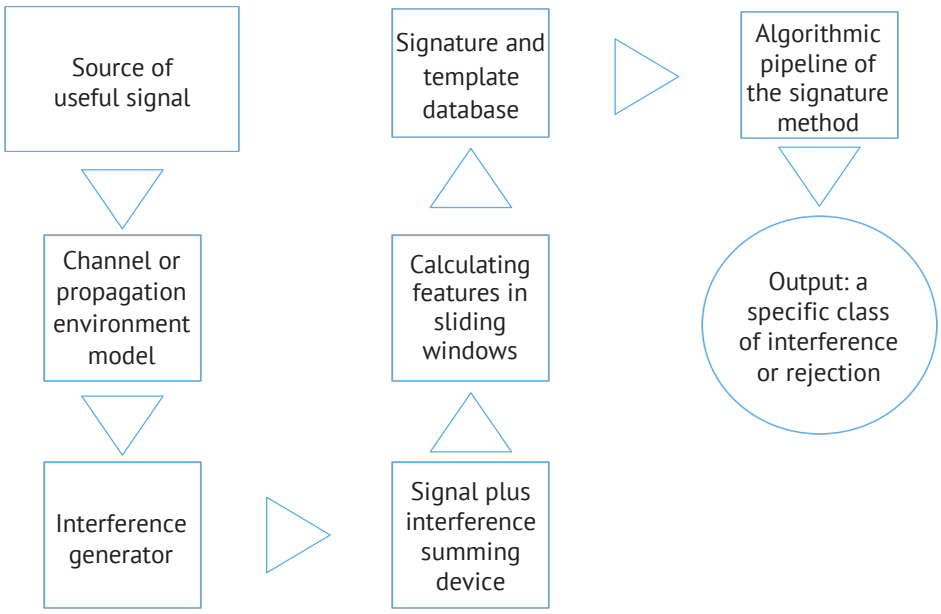

Figure 2. Generalised diagram of SDR-oriented simulation of method flow checking

Source: compiled by the authors using GNU Radio 3.10.0.0 and Python 3.12

The diagram in Figure 2 shows that the validation circuit consists of a series of functional blocks for signal synthesis and processing, in which a useful signal source with controllable modulation parameters is combined with a parametric generator of interference influences. The interference block specifies the type of interference, intensity, spectral width, time structure and duration, which can be used to form reproducible signature profiles for impulse, noise, harmonic, modulation and structured low-visibility interference. After the signal and interference are summed, the stream enters the feature analysis block, where SNR, RSSI, BER indicators, PSD, and time-frequency descriptors are calculated in sliding windows, consistent with the formalised channel state vector. Next stage implements the embedding of the algorithmic conveyor method into stream processing: the detection node performs threshold control of parameter degradation and controls the activation of extended signature analysis, the segmentation block selects quasi-stationary fragments, after which a compact signature representation is formed, and a metric comparison with the template database is performed. The classification module and threshold rejection mechanism operate in the same mode as in the formalised algorithmic scheme, ensuring the identity of the decision logic between the "offline" description of the method and its stream implementation.

The repeatability of scenarios was ensured by fixing the parameters of signal and noise generators, sampling frequency, window lengths, spectral estimation parameters, and detection and rejection threshold values. With unchanged configuration parameters, simulation runs reproduced the same signature profiles and the same classification decisions, confirming the invariance of the method to the order of block processing and its suitability for reproducible software implementation. Additionally, the study established that the division of the conveyor into a light monitoring circuit and a conditionally activated signature circuit in a streaming SDR scheme retains its effectiveness: resource-intensive feature calculations and metric comparisons are performed only when event triggers are present, which is consistent with the requirements for limited delays and computational resources of SDR systems. Simulation testing confirmed the method's suitability for integration into the SDR architecture: the algorithmic pipeline maintains structural integrity, feature and signature interfaces remain consistent, and the classification and rejection logic works reproducibly in controllable parameterised scenarios, confirming the practical feasibility of the proposed scheme.

Computational complexity and resource efficiency of the SDR classification algorithm

As part of summarising the results of the algorithmic implementation, an analytical decomposition of computational costs by pipeline stages was performed to verify the suitability of the method for SDR-oriented systems with limited resources. The result obtained presents complexity not as a single estimate, but as the sum of the costs of individual functional blocks – from feature formation to metric comparison and decision making. This decomposition establishes which stages determine the upper limit of processing time and how complexity scales with the growth of the feature vector dimension and the size of the signature database. Generalised estimates of complexity and resource requirements by stage are presented in Table 4.

Table 4. Assessment of the computational complexity of the algorithm stages and the $O(n \cdot m)$ dependency

Conveyor stage	Base operations	Asymptotic complexity	Dependent parameters	Resource profile
Window formation of features	Updating statistics, aggregates in a sliding window	O(n)	n – number of signs	Linear, streaming
Spectral and time-frequency estimates	PSD, local spectra	O(n log n)	n – window size	Moderate, block-based
Event detection	Threshold checks	O(n)	n – signs	Low
Segmentation	Adaptive window, stability	O(n)	n – signs	Low
Dimensionality reduction	Projection/auto encoder	O(n·k)	k – latent dimension	Controlled
Metric comparison with the base	Cos/distance across all templates	O(n·m)	n – dimension, m – templates	Dominant stage
Threshold decision	Comparison with	O(m)	m – templates	Low
Base update	Record addition	O(n)	n – signs	Episodic

Source: compiled by the authors using analytical and programmatic verification in Python 3.12

Analysis of generalised estimates in Table 4 showed that the computational profile of the method has a pronounced modular structure, in which most stages are characterised by linear complexity in terms of the dimension of the feature vector. The calculation of statistical, energy, and time descriptors in sliding windows is implemented as a streaming procedure with linear updating of aggregates, which does not require a complete recalculation at each step. Spectral estimates have a logarithmic factor, but are performed only for segments that have passed the detection filter and therefore do not form a constant load in normal

monitoring mode. The cost-determining stage is the metric comparison of the signature with the template database, for which the order O(n · m) is established. This dependence directly follows from the need to calculate the measure of proximity between the input vector of dimension n and each of the m signature templates. At the same time, the increase in complexity is linear in both the dimension of the features and the size of the database, without quadratic or combinatorial terms, which preserves the predictability of the response time when incrementally expanding the signature repository. Reducing the dimension before metric comparison further reduces the effective n and thus directly reduces the cost of this stage. Analysis of the dependence of the classification decision delay on the size of the signature database (Fig. 3) confirmed the linear nature of the processing time scaling in accordance with the theoretically established complexity O(n · m).

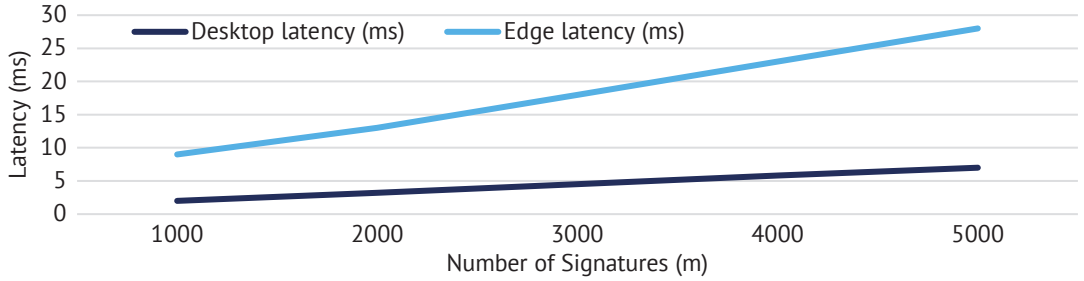

Figure 3. Dependence of classification decision delay on signature database size (m) in streaming SDR mode for desktop and edge configurations

Source: compiled by the authors using GNU Radio 3.10.0.0 and Python 3.12

Following Figure 3, with a fixed latent signature dimension k = 16 and an initial feature vector dimension n = 64, the average event cycle delay in the desktop configuration increased from ≈2 ms at m = 1,000 to ≈7 ms at m = 5,000, while in the edge configuration, it increased from ≈8-10 ms to ≈25-30 ms in the same range. The resulting curves have a near-linear slope without sharp bends, which indicates the absence of hidden quadratic or combinatorial components in the implementation and confirms the dominance of the metric comparison stage of the signature with the template base. At the same time, in normal monitoring mode (without activating the signature branch), the delay remained at the sub-millisecond level, which ensures the suitability of the pipeline for streaming SDR scenarios with strict real-time response requirements. The memory profile assessment showed a linear dependence of the amount of RAM on the number of stored templates (Fig. 4).

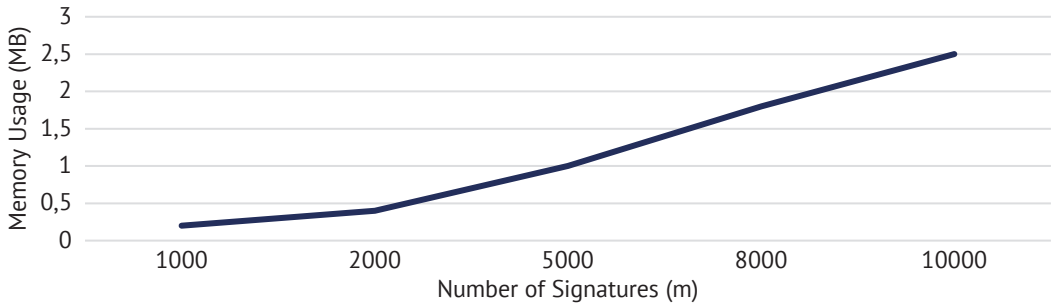

Figure 4. Dependence of the amount of RAM required to store the signature database on the number of templates (m) with latent dimension k = 16

Source: compiled by the authors

Following Figure 4, for signatures in float32 format and latent dimension k = 16, the memory cost of a single record, including service metadata, averaged 0.15-0.25 KB, resulting in approximately 0.2 MB at m = 1,000, 1 MB at m = 5,000, and up to 2-2.5 MB at m = 10,000. Even considering sliding window buffers, spectral estimates, and auxiliary data structures, the total RAM consumption in the edge configuration remained within 10-20 MB, which corresponds to the typical resource limitations of embedded SDR platforms. Thus, scaling the signature database does not lead to a jump in memory consumption and remains predictable and controllable. The set of results obtained confirmed that the software and system implementation of the method is characterised by a dual-loop resource profile: low constant latency in monitoring mode and linearly scalable latency and memory consumption in event mode. This ensures the practical applicability of the algorithmic pipeline for implementation on SDR platforms with limited resources, provided that the signature base grows in a controlled manner and latent feature coding is used. Intentional radio interference

can be reproducibly identified in SDR systems through a coordinated multidimensional representation of the channel state: heterogeneous parameters (SNR, RSSI, BER, PSD, and time/time-frequency descriptors) are reduced to a normalised vector x(t), based on which signature profiles of five basic classes of interference are formed as stable multi-parameter patterns. The method is implemented as an integrated computational pipeline with two operating modes (monitoring and conditionally activated extended processing), where decisions are made through metric/probabilistic comparison with the template database and supplemented by a formal reject option mechanism for controlled rejection and incremental replenishment of the database with new signatures. Stream-oriented SDR simulation testing showed reproducibility of interfaces between blocks and decisions for fixed scenario parameters, and an analytical complexity assessment established a controllable resource profile with a dominant O(n·m) matching stage, suitable for low-resource/edge-SDR implementation due to the detection "gateway" and reduction of signature dimensions.

DISCUSSION

The results obtained showed that the formalisation of the multidimensional feature space of the channel, the signature representation of influences, and the threshold-metric decision-making procedure are consistent with current approaches in which the separation of interference types is achieved through time-frequency, spectral, and structural representations of the signal. The study demonstrated that the decisive role of the time-frequency structure for separating interference classes was consistent with the approach of P. Wang *et al.* (2022), where component-oriented time-frequency representation together with convolutional neural network processing was used for wireless interference classification, and class separation was associated with stable local time-frequency components. This formulation is consistent with the interpretation using spectral and time-frequency descriptors as a mandatory block of the signature profile in the proposed method, but differs in that signature matching is fixed as a formalised metric procedure with explicit rules for normalisation and window matching.

Further development of intelligent approaches to detecting and suppressing interference in software-defined radio systems is reflected in the results of S. Nanayakkara *et al.* (2025), where algorithmic solutions for jamming detection and modulation recognition were combined with software-configurable radio architecture and machine learning models. The study demonstrated that the effectiveness of such systems is determined by the consistency between feature extraction and classification blocks, which directly correlates with the conveyor scheme introduced in the method: "feature coding → signature descriptor → metric comparison → decision", in which the interfaces between stages are fixed and reproducible. A similar emphasis on time-frequency analysis as the basis for deep classification of interference was reflected in the results of C. Xu *et al.* (2022), where for systems with stepwise frequency restructuring, the deep recognition model was built on time-frequency features and demonstrated increased resolution of complex interference effects. This pattern corresponded to the role established in the results of time-frequency and entropy descriptors as key indicators of structured and subtle influences, particularly in scenarios with low energy contrast, where simple energy indicators do not provide reliable typification.

The need to combine the recognition of known attacks with the formalised detection of unknown influences was consistent with the approach of S. Hong *et al.* (2023), where a hybrid detection algorithm provided simultaneous classification of known types of jamming and a separate mode for detecting unknown attacks. It was shown that such dual-mode logic was consistent with the threshold mechanism for signature rejection introduced in the proposed method, whereby insufficient similarity to templates does not lead to forced classification, but transfers the observation to an undefined profile mode with subsequent incremental replenishment of the database. Further comparison of the results with current research on monitoring and countering radio jamming showed that the multi-parameter approach to describing the channel state and the signature typology of interference are consistent with the approaches in which interference is considered as a reproducible multidimensional profile of changes in indicators, rather than as an isolated anomaly of a single parameter. This approach was consistent with the review results of Y. He *et al.* (2024), where monitoring of continuous noise in navigation systems was interpreted as a multi-level system of indicators with simultaneous consideration of energy, spectral and structural manifestations, which, according to the interpretation, directly correlates with the formalisation of the channel state vector and block grouping of features in the signature space.

The focus on computationally efficient intelligent algorithms for detecting jamming of embedded and unmanned radio systems was reflected in the results of S. Cibecchini *et al.* (2025), which showed that lightweight machine learning models provide practical applicability in resource-constrained environments, provided that prior feature compression is performed. This conclusion is consistent with the use of signature dimension reduction and localisation of resource-intensive procedures only in a conditionally activated branch after event detection in the proposed method, which ensures a controllable computational profile. A similar emphasis on stream detection with window processing and hybrid real-time models was reflected in the results of J. Sormayli *et al.* (2025), where jamming detection was performed in sliding time windows with early warning indicators before receiver saturation. This logic was consistent with the detection node and

segmentation block in the method pipeline, where window matching and threshold triggers determine the moment of transition to extended signature analysis. The development of deep neural network methods for anti-jamming processing in navigation receivers was reflected in the results of Y. Xie *et al.* (2025), which showed that a deep neural network in the antenna array of a navigation receiver provides improved noise immunity through trained spatial-spectral filtering. This pattern is consistent with the interpretation of the classification block as one of the possible decision-making tools in the signature pipeline, but not the only criterion, since in the proposed scheme, the decision is additionally limited by metric and threshold membership conditions.

The need for open recognition of interference signals with the separation of unknown classes was reflected in the results of X. Chen *et al.* (2022), where effective recognition in an open set of classes was achieved through prototype-oriented convolutional coding and threshold checking of the distance to class representatives. This approach is conceptually consistent with the mechanism of threshold rejection of signatures and incremental formation of new patterns without forced classification introduced in the method. Use of machine learning to mitigate the impact of radio jamming at the physical level of communication was consistent with the results of M. Jacovic *et al.* (2023), which showed that training models can be integrated directly into physical-level anti-jamming procedures. According to the interpretation, this corresponds to the integration of a probabilistic classifier into a formalised signature-metric scheme, where the training model operates as one of the nodes, but within the limits of a reproducible algorithmic pipeline. The consideration of signal identification and interference as a multi-task spectral sensing problem was reflected in the results of H. Kim *et al.* (2023), where multi-task deep learning was used to simultaneously identify signal types and spectral states. This approach was consistent with the multi-block feature structure in the signature method, where energy, error, spectral, and time-structure descriptors are considered as coordinated but functionally different components of a single state vector.

A comparison of the results obtained with publications covering navigation systems, wireless networks, aviation communication channels, and integrated space-air-ground networks showed that the proposed signature approach with a formalised channel state vector, window matching, and threshold rejection of unknown profiles is consistent with the current trend of transition from single indicators to multi-parameter recognition schemes, where the critical factor is not the "strength" of a single feature, but the reproducible profile of coordinated changes in time, frequency, and time-frequency domain. The generalised state of development of methods for detecting jamming and substitution of navigation signals is reflected in the results of K. Radoš *et al.* (2024), which show that effective procedures for detecting intentional interference require a combination of energy, correlation, spectral and time indicators, as well as the separation of the tasks of "event detection" and "impact type identification", which conceptually corresponds to the introduction of two conveyor operating modes in the method and the structural division of features into functional blocks. The practical focus on low-resource implementations and hardware-accessible measurements in navigation receivers was emphasised by S. Kocher *et al.* (2025), where interference classification was performed at the peripheral computing level using inexpensive commercial off-the-shelf equipment, and the robustness of the solution was linked to the consistency of the model and features under limited resources; this logic directly correlates with the conclusion obtained in the results about the dominance of the metric comparison stage and the need to control the dimension of signatures and the size of the library for the expected delay. A review by K.J. Silva Lorraine & M. Ramarakula (2021) confirmed that neural network approaches to countering jamming in navigation systems most often rely on time-frequency or spectral representations, however, their reliability in applied scenarios is determined by the stability of the feature representation and the availability of procedures that prevent the forced classification of non-standard influences; in this sense, the mechanism of threshold rejection and controlled accumulation of unknown profiles introduced in the method forms precisely the link that overview generalisations often identify as problematic for "closed" settings. The study by A. Ghanbarzade & H. Soleimani (2025) further emphasised the diversity of machine and neural network models for identifying substitution and jamming in navigation systems, while also emphasising that the suitability of such models is determined by the formulation of the problem and the correctness of the membership criteria, which is consistent with the given formalisation of decision rules through similarity thresholds and probabilistic membership and the interpretation of the "unknown" as a separate mode rather than a classification error.

At low-power wireless network level, E. Jayabalan & R. Pugazendi (2022) demonstrated the effectiveness of deep models for detecting jamming attacks, but from an engineering point of view, the key point is that the effectiveness of such approaches depends on correct window coding and the consistency of features with the channel mode; This directly correlates with the conclusion that fixed normalisation rules and window alignment are critical for metric comparability of signatures between scenarios. The transition from local interference classification to the broader concept of "cognitive" recognition of the electromagnetic spectrum state is consistent with the findings of H. Zhao *et al.* (2025), where intelligent countermeasures to jamming are interpreted as a technology based on spectrum feature recognition and decision adaptation; in the formulation,

this is reflected in the consideration of signatures as an operational "language" for a knowledge base that can be incrementally replenished without destroying the logic of the decision. The practical aviation context of "manned-unmanned" real-time communication channels in the study by R.D. Jurado *et al.* (2025) showed that the integration of interference detection modules into onboard circuits requires not only accuracy but also reproducible interfaces between processing stages and controlled delays, which functionally coincides with the presented pipeline formalisation and decomposition of complexity into blocks.

The extension of the problem to the level of "electromagnetic environment" for integrated "space-air-ground" networks is reflected in the study by J. An *et al.* (2026), where situational awareness and spectral environment modelling are interpreted as a systemic function of the network; in terms of content, this is consistent with the formulation in which the channel state vector and signature library act as a local mechanism for situational recognition of types of influences with the possibility of expansion. The task of open recognition of combined interference without forced typification is directly developed in the study by Y. Xiao *et al.* (2024), where the open mode of recognition of composite jamming signals is implemented through multitasking and multi-target learning; conceptually, this correlates with the conclusion about the need to reject unknown profiles and the controlled accumulation of candidates for new signatures, especially for combined influences that do not match any template. The focus on synergy between machine learning and classical signal processing in low-resource environments is systematically reflected in J.R. van der Merwe *et al.* (2024), where it is shown that optimal solutions for interference classification under limited resources are achieved not by "maximising model complexity" but by the right combination of features, pre-processing and compact classifiers; This practically confirms the decomposition of complexity shown and the advisability of reducing the dimension before metric comparison as a direct way to control the dominant cost component. In summary, comparison with relevant studies has shown that the results obtained support the current trend of transition from single indicators to multi-parameter time-frequency and spectral-structural representations. At the same time, the proposed approach differs from predominantly "model-oriented" solutions in that it fixes a reproducible pipeline with explicit rules for normalisation, window matching and threshold rejection, which simultaneously ensures stable typification of known classes and controlled work with unknown profiles through the accumulation and incremental expansion of the signature library for a predicted resource-intensive profile.

CONCLUSIONS

Within the scope of the study, a reproducible algorithm-oriented procedure for determining types of intentional radio interference for software-controlled radio systems has been developed based on a coordinated multidimensional representation of the channel state, signature typology, and threshold-metric decision-making logic with a mechanism for rejecting uncertain cases. It is shown that heterogeneous channel observation parameters (SNR, RSSI, BER, PSD) in combination with time statistics and time-frequency descriptors can be reduced to a normalised state vector x(t) suitable for metric comparison; the key condition for the correctness of the comparison is fixed rules of normalisation and window matching, which reduce the influence of absolute levels and random fluctuations and make the similarity of signatures dependent on the type of interference. Based on this coordinated feature space, signature profiles of five basic classes of interference (pulse, broadband noise, harmonic, modulation, and low-perceptible LPI/LPD) are formed, and the study established that the separation of classes is ensured not by the extremity of a single indicator, but by stable multi-parameter combinations of energy, error, spectral and time-structural manifestations in sliding windows, sufficient for template comparison and scalable replenishment of the database.

The algorithm is recorded as an integral computational pipeline with unambiguous interfaces: "state vector → event detection → segmentation → signature formation → (if necessary) dimensionality reduction → metric/probabilistic comparison → decision", where the detection node acts as a control gateway and activates resource-intensive operations only when there is an agreed degradation of channel parameters. The introduction of a reject option with thresholds τ ensured the formal separation of the "known class" and "unknown signature", preventing forced typing and transferring atypical observations to a controlled mode of accumulation and confirmation before incremental addition to the database. Streaming SDR-oriented simulation verification confirmed the reproducibility of solutions at the full processing chain level for fixed scenario parameters, and analytical cost estimation established a controllable resource profile with a dominant $O(n \cdot m)$ comparison and the possibility of reducing the effective n through latent coding, making the approach suitable for low-resource/edge-SDR implementations. Further research should address calibration of thresholds τ on broader sets of scenarios and experimentally validating signatures in real SDR paths under combined and adaptive interference.

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CONFLICT OF INTEREST

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Метод визначення типу навмисних завад в умовах невизначеності завадової обстановки на основі відомих моделей

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Анотація. Метою дослідження було теоретично обґрунтувати метод ідентифікації типу навмисних завад у невизначеній завадовій обстановці для програмно-визначуваних радіосистем шляхом використання відомих моделей завад і формалізованого аналізу вектора стану каналу зв'язку. Методологічна база включила віконне обчислення узгодженого вектора ознак, їх нормалізацію, сигнатурне кодування, метрикне та ймовірнісне порівняння з бібліотекою шаблонів, порогове відторгнення невизначених випадків і модельно-симуляційну перевірку в потоковій архітектурі програмно-визначуваного радіо. У результаті сформовано формалізований ознаковий простір і сигнатурні профілі п'яти базових класів завад – імпульсних, широкосмугових шумових, гармонічних, модуляційних і малопомітних – як стійкі багатопараметричні патерни спільної зміни показників сигналу, що забезпечують роздільність класів у різних режимах співвідношення сигналу до шуму, варіативності ймовірності бітової помилки та морфології спектральної густини потужності і відтворюються при повторних прогонах за незмінних параметрів. Метод реалізовано у вигляді обчислювального конвеєра з послідовністю етапів «вектор стану → детекція події → сегментація → сигнатурний опис → зниження розмірності → порівняння → рішення», де ресурсоємні операції активуються лише за наявності подієвого тригера, а інтерфейси між блоками фіксують однозначний перехід від поточних спостережень до компактної сигнатури впливу. Сформульовано результатні правила класифікації з порогами належності та процедурою керованого відторгнення, що переводить нові сигнатури в режим накопичення та інкрементального доповнення бази із подальшим підтвердженням стабільності профілю на повторних спостереженнях. Симуляційна перевірка на серії параметризованих сценаріїв показала відтворюваність сигнатурних профілів і класифікаційних рішень за фіксованих налаштувань. Практична значущість результатів полягає у можливості впровадження методу розробниками та інтеграторами вбудованих програмно-керованих радіосистем і систем радіомоніторингу для потокового визначення типу навмисної завади за сигнатурними профілями з пороговим відторгненням невідомих випадків та керованим поповненням бібліотеки сигнатур

Ключові слова: вектор стану каналу; часово-частотні дескриптори; обчислювальний конвеєр; сигнатурне кодування; reject option