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PROACTIVE GNSS INTERFERENCE MITIGATION AGAINST JAMMING AND SPOOFING USING COMPACT NEURAL MODELS

Introduction

Global Navigation Satellite Systems (GNSS) represent a critical technological foundation for positioning, navigation, and time synchronization in transportation, energy, telecommunication, and autonomous systems. However, due to the extremely low power of received satellite signals, GNSS receivers remain highly vulnerable to intentional radio-frequency interference, particularly jamming and spoofing. Recent studies indicate a growing number of interference incidents and emphasize the necessity of improving detection and mitigation mechanisms [10].

Traditional interference mitigation techniques are primarily based on spatial-temporal signal processing methods, such as adaptive beamforming and space-time filtering. These approaches generally follow a reactive control principle, where system parameters are adjusted only after signal degradation has been detected. Under rapidly changing radio-electronic conditions, such a strategy may result in partial loss of useful information and degradation of positioning accuracy.

In recent years, machine learning methods have been actively investigated for GNSS interference detection and classification. Deep neural architecttures capable of modeling temporal dependencies have shown promising results. Temporal Convolutional Networks (TCN) demonstrate competitive performance in sequence modeling and time-series prediction tasks [2]. Transformer-based architectures, introduced in [1], significantly improved the modeling of long-range dependencies through the attention mechanism. Their adaptation to time-series forecasting has been further developed in recent works [4–7], where efficient long-horizon prediction capabilities were demonstrated.

At the same time, the deployment of deep learning models in GNSS receivers is constrained by computational complexity and energy efficiency requirements. The survey of efficient transformer architecttures [3] and neural network compression techniques [8] highlights the feasibility of designing compact models suitable for resource-limited platforms. Lightweight neural architectures such as MobileNets [9] illustrate the possibility of balancing inference speed and accuracy, which is particularly relevant for real-time signal processing tasks.

Despite the significant progress in neural-based interference detection, most existing solutions focus on post-event classification rather than predictive control. The problem of proactive interference mitigation, based on forecasting the future state of the signal and enabling early adaptation of filtering parameters, remains insufficiently explored. In particular, there is a lack of integrated approaches combining compact neural architectures with predictive modeling of both jamming and spoofing under practical resource constraints.

Therefore, this work proposes a proactive GNSS interference mitigation approach based on compact neural models designed for forecasting interference probability and type, followed by adaptive adjustment of mitigation parameters. The proposed method aims to reduce signal degradation losses and improve the robustness of GNSS receivers against intentional radio-frequency threats.

Analysis of Existing Approaches

GNSS interference mitigation has been extensively studied in the context of signal processing and radio-frequency security. Recent surveys emphasize the increasing complexity of jamming and spoofing attacks and the necessity of advanced detection and mitigation strategies [10]. Conventional approaches are primarily based on spatial filtering, adaptive antenna arrays, and space-time processing techniques. While such methods are effective under stationary interference conditions, they are inherently reactive and require observable signal degradation before mitigation mechanisms are activated.

To overcome the limitations of purely signal-processing-based techniques, machine learning models have been introduced for interference detection and classification. Deep neural networks have demonstrated strong capability in extracting hidden temporal and spectral patterns from GNSS signal features. Temporal Convolutional Networks (TCN),

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evaluated in [2], have shown competitive performance compared to recurrent architectures in sequence modeling tasks due to their ability to capture long-range temporal dependencies while maintaining parallel computation efficiency.

Transformer architectures, introduced in [1], significantly advanced sequence modeling through the attention mechanism, enabling improved representtation of global dependencies. Subsequent research extended transformers to time-series forecasting problems. Informer [6] and Autoformer [7] proposed efficient transformer variants tailored for long-sequence time-series prediction. Temporal Fusion Transformers [5] further introduced interpretable multi-horizon forecasting mechanisms, which are particularly relevant for predictive interference mitigation scenarios. A comprehensive survey of transformer applications in time-series analysis is presented in [4], highlighting their effectiveness in modeling complex temporal dynamics.

However, the deployment of transformer-based models in real-time GNSS systems is constrained by computational complexity. Efficient transformer architectures have been systematically analyzed in [3], where optimization techniques for reducing memory consumption and inference latency are discussed. Model compression strategies such as pruning and quantization [8] enable further reduction of computational overhead while preserving predictive performance. Lightweight neural network designs, including MobileNets [9], demonstrate that compact architectures can achieve acceptable accuracy under strict resource limitations.

Despite the availability of efficient neural architecttures, most existing GNSS-related machine learning solutions focus on interference detection and classification rather than proactive mitigation. The majority of approaches perform binary or multi-class classifycation after interference has already affected the signal. Predictive modeling aimed at forecasting interference evolution and enabling early adaptation of mitigation parameters remains insufficiently addressed.

Therefore, there is a research gap at the intersection of GNSS interference mitigation, compact neural architectures, and proactive control. Integrating lightweight temporal models with predictive signal analysis provides a promising direction for reducing latency in mitigation response and improving system robustness against both jamming and spoofing threats.

Problem Formalization

The operation of a GNSS receiver under interference conditions can be represented as a dynamic observation process in which multiple signal characteristics are measured over time. Let the receiver observe at time $\boldsymbol{t}$a feature vector representing the current signal state:

$$x_t \in \mathbb{R}^d \tag{1}$$

where d – denotes the dimensionality of the feature space. The feature vector may include signal-to-noise ratio (SNR), spectral characteristics, carrier phase variations, and other indicators commonly used in GNSS interference analysis [1], [10].

Since interference phenomena such as jamming and spoofing typically evolve over time rather than appearing instantaneously, it is necessary to consider the temporal structure of observations. Instead of analyzing a single observation vector (1), the receiver forms a time window consisting of the last k observations:

$$X_t = [x_{t-k+1}, x_{t-k+2}, \dots, x_t] \in \mathbb{R}^{k\times d} \tag{2}$$

The matrix X_t thus represents a short-term temporal context describing the evolution of signal parameters within the observation interval. This formulation allows the problem to be treated as a time-series modeling task, which is particularly suitable for neural architectures designed to capture temporal dependencies [2], [4].

In conventional interference mitigation systems, adaptive filtering mechanisms are activated only after the interference has already affected the signal quality. In such reactive schemes, the control parameters depend solely on the current observation:

$$w_t = f(x_t) \tag{3}$$

where w_t – denotes the vector of mitigation parameters (e.g., antenna weights or filtering coefficients), and $f(\cdot)$represents the control rule.

However, this reactive principle introduces an inherent delay between the onset of interference and the system response. To reduce this delay, the proposed approach introduces a predictive component that estimates the future state of the signal environment. Instead of relying only on the current observation, the control parameters are computed based on the predicted interference state:

$$w_t = f(\hat{y}_{t+\Delta t}) \tag{4}$$

where $\hat{y}_{t+\Delta t}$ – denotes the predicted interference-related parameters at a future time $t + \Delta t$, and Δt is the prediction horizon.

To obtain the predicted interference state, a lightweight neural model is introduced. The prediction model is defined as a nonlinear mapping from the observation sequence (2) to the future interference state:

$$\hat{y}_{t+\Delta t} = F_\theta(X_t) \quad (5)$$

where $F_\theta(\cdot)$ – denotes the neural network parameterized by weights θ.

The predicted output vector is defined as:

$$\hat{y}_{t+\Delta t} = [p_{t+\Delta t}, c_{t+\Delta t}, \ell_{t+\Delta t}] \quad (6)$$

where $p_{t+\Delta t}$is the probability of interference occurrence, $c_{t+\Delta t}$is the interference class, and $\ell_{t+\Delta t}$ is the interference intensity.

The model is trained using a composite loss function:

$$\mathcal{L}(\theta) = \alpha\mathcal{L}_{int} + \beta\mathcal{L}_{class} + \gamma\mathcal{L}_{reg} \quad (7)$$

where $\mathcal{L}_{int}$ – is the binary cross-entropy loss for interference probability prediction, $\mathcal{L}_{class}$ is the categorical cross-entropy loss for classification, and $\mathcal{L}_{reg}$is the mean squared error for intensity estimation. The coefficients α, β, γ control the relative importance of each component.

Once the prediction model is trained, the mitigation mechanism is activated when the predicted interference probability exceeds a predefined threshold:

$$p_{t+\Delta t} \geq \tau \quad (8)$$

where τ – is the decision threshold.

The effectiveness of the proposed proactive mitigation approach is evaluated using the improvement in signal quality:

$$\Delta SNR = SNR_{out} - SNR_{in} \quad (9)$$

where SNR_{in} and SNR_{out} – denote the signal-to-noise ratio before and after mitigation, respectively.

To ensure real-time applicability, the inference time of the neural model must satisfy:
neural model must satisfy:

$$T_{\text{inf}} < \Delta t \quad (10)$$

where T_{inf} – is the model inference time.

Thus, the proposed formulation combines temporal signal modeling (2), predictive interference estimation (5)–(6), and proactive control (4), providing a unified mathematical framework for GNSS interference mitigation.

Architecture of the Proposed Model

The architecture of the proposed proactive GNSS interference mitigation model is illustrated in Fig. 1. The model follows a modular pipeline designed for real-time signal analysis, predictive modeling, and adaptive control. It integrates temporal processing of GNSS signal observations with a lightweight neural prediction mechanism to estimate future interference conditions. The architecture enables early identifycation of signal degradation patterns associated with jamming and spoofing. Based on the predicted interference parameters, the system performs proactive adaptation of receiver settings to mitigate potential performance loss. The modular structure ensures flexibility of implementation and allows efficient deployment on resource-constrained GNSS platforms. The overall design supports real-time operation while maintaining a balance between computational efficiency and prediction accuracy.

At the input stage, the receiver forms a sliding observation window X_t, defined in (2), which captures the temporal evolution of signal characteristics such as SNR, spectral features, and carrier phase variations.

The input sequence $X_t$is processed by the feature extraction module, which transforms raw observations into a compact latent representation. This stage captures temporal dependencies in signal dynamics and reduces sensitivity to noise.

The extracted features are then passed to the prediction module, implemented as a lightweight neural network $F_\theta(\cdot)$. The model estimates the future interference state:

$$\hat{y}_{t+\Delta t} = F_\theta(X_t),$$

as defined in (5). The predicted vector $\hat{y}_{t+\Delta t}$ includes the probability of interference occurrence, its class, and intensity, as specified in (6).

The decision module evaluates the predicted interference probability using a predefined threshold condition:

$$p_{t+\Delta t} \geq \tau,$$

as given in (8). If this condition is satisfied, the system activates the proactive mitigation mechanism.

The control module computes mitigation parameters based on the predicted interference state:

$$w_t = f(\hat{y}_{t+\Delta t}),$$

in accordance with (4). This enables the system to adapt its parameters in advance, reducing the delay inherent in reactive approaches.

Finally, the architecture satisfies real-time constraints by ensuring that the model inference time remains below the prediction horizon:

$$T_{\text{inf}} < \Delta t,$$

as defined in (10), which guarantees timely application of mitigation actions.

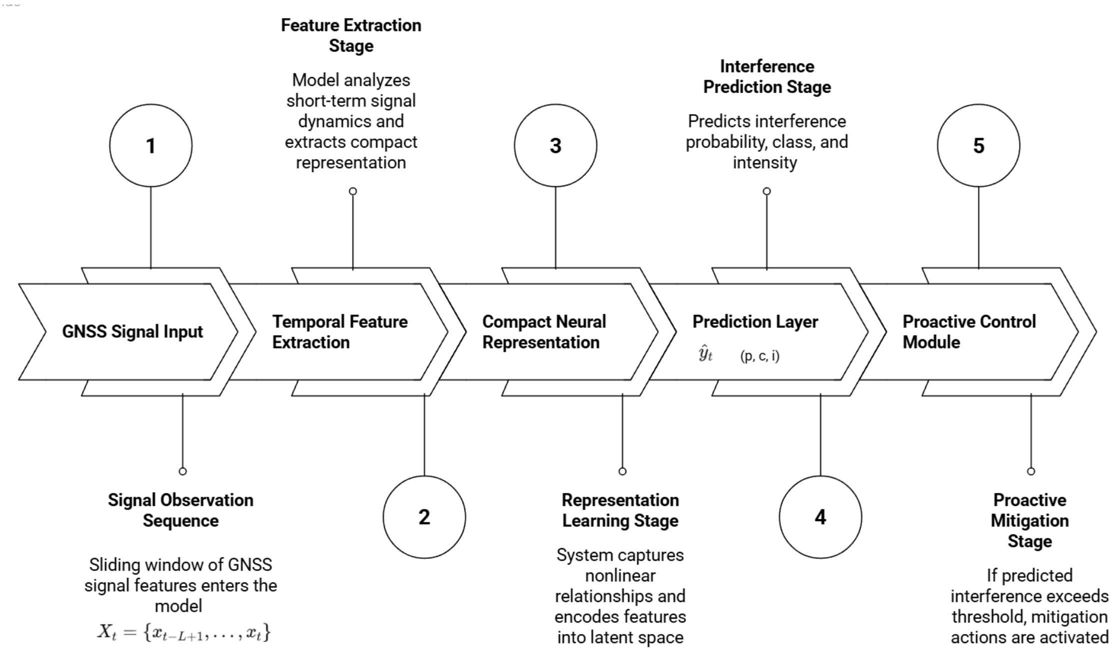

Fig. 1. Architecture of the proposed proactive GNSS interference mitigation model. The system processes temporal signal observations X_t, predicts interference parameters $\hat{y}_{t+\Delta t}$, and performs proactive mitigation based on adaptive control

Conclusions

This paper presents a proactive approach to GNSS interference mitigation based on compact neural models designed for real-time prediction of interference conditions. Unlike conventional reactive methods, the proposed approach enables early detection of signal degradation by forecasting interference probability, class, and intensity.

A unified mathematical framework has been developed, integrating temporal signal modeling, predictive estimation, and adaptive control. The formulation is based on the use of a sliding observation window and a nonlinear mapping that predicts future interference states, allowing mitigation parameters to be adjusted in advance.

The proposed architecture combines lightweight neural modeling with a decision mechanism based on a threshold condition, ensuring both prediction accuracy and computational efficiency. The inclusion of real-time constraints guarantees the applicability of the model in resource-limited GNSS receivers.

Overall, the results demonstrate that proactive interference mitigation can significantly improve system robustness under jamming and spoofing conditions. The proposed approach provides a scalable and efficient solution for enhancing the reliability of GNSS-based systems.

Future work will focus on experimental validation using real GNSS datasets, optimization of neural architectures for embedded platforms, and extension of the model to multi-sensor navigation systems.

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ПРОАКТИВНЕ УСУНЕННЯ ПЕРЕШКОД У GNSS ВІД ГЛУШІННЯ ТА ПІДРОБКИ ДАНИХ ЗА ДОПОМОГОЮ КОМПАКТНИХ НЕЙРОННИХ МОДЕЛЕЙ

У роботі запропоновано підхід до проактивного зниження впливу перешкод у глобальних навігаційних супутникових системах (GNSS), заснований на використанні компактних нейронних моделей. На відміну від традиційних реактивних методів, запропонований підхід забезпечує прогнозування стану сигналу та характеристик перешкод, зокрема ймовірності їх виникнення, типу (заглушення або спуфінг) та інтенсивності.

Розроблено формалізацію задачі у вигляді моделі часових рядів із використанням ковзного вікна спостережень, що дозволяє враховувати динаміку змін сигналу. Запропоновано архітектуру, яка поєднує модуль виділення ознак, нейронний блок прогнозування та механізм адаптивного керування параметрами приймача. Прийняття рішення про активацію механізму компенсації здійснюється на основі порогової умови для прогнозованої ймовірності перешкод.

Особливістю підходу є врахування обмежень реального часу та використання легковагових нейронних моделей, що забезпечує можливість застосування в ресурсно-обмежених GNSS-пристроях. Запропоноване рішення підвищує стійкість навігаційних систем до радіочастотних атак та дозволяє зменшити втрати точності позиціонування.

Ключові слова: інтерференційне придушення; цілісність сигналу; глушіння та спуфінг; темпоральне моделювання сигналів; предиктивна аналітика; компактні нейронні моделі; проактивне керування; GNSS

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This paper proposes a proactive approach to GNSS interference mitigation based on compact neural models designed for real-time prediction of interference conditions. Unlike conventional reactive methods, the proposed approach enables forecasting of signal degradation by estimating the probability of interference occurrence, its type (jamming or spoofing), and intensity.

The problem is formulated as a time-series modeling task using a sliding observation window, allowing the system to capture temporal dynamics of GNSS signal behavior. The proposed architecture integrates a feature extraction module, a lightweight neural prediction model, and an adaptive control mechanism for proactive adjustment of receiver parameters. The activation of mitigation is governed by a threshold condition applied to the predicted interference probability.

A key feature of the approach is its compliance with real-time constraints and suitability for resource-limited GNSS receivers due to the use of efficient neural architectures. The proposed method improves system robustness against radio-frequency interference and reduces positioning degradation under adverse conditions.

Keywords: interference mitigation; signal integrity; jamming and spoofing; temporal signal modeling; predictive analytics; compact neural models; proactive control, GNSS.

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