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LEARNING TO DETECT LPI RADAR SIGNALS: A STUDY OF STRUCTURE IN FREQUENCY MODULATED NOISE WAVEFORMS

НАВЧАННЯ ВИЯВЛЕННЮ СИГНАЛІВ LPI-РАДАРА: ДОСЛІДЖЕННЯ СТРУКТУРИ У ЧАСТОТНО-МОДУЛЬОВАНИХ ШУМОВИХ СИГНАЛАХ.

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Annotation. *This paper investigates the detectability of a structured noise radar waveform using a shallow convolutional neural network (CNN). The waveform under study is generated by frequency modulation of a constant-envelope carrier with low-bandwidth Gaussian noise, following the approach introduced in paper [1]. Designed to achieve perfect peak-to-average power ratio (PAPR) and spectrum shape similar to Gaussian, such signals are well-suited for low-probability-of-intercept (LPI) radar systems. A key question addressed in this work is whether these waveforms possess latent structure that can be exploited by data-driven detectors lacking knowledge of the exact transmitted realization.*

To explore this, a neural network was trained on spectrogram representations of received signals embedded in additive white Gaussian noise. The neural network's detection capability was evaluated against a classical power detector and an ideal coherent detector using matched filtering.

Results show that the neural network underperformed the power detector, indicating that it was unable to extract additional structure from the waveform. In contrast, a control experiment with randomized linear frequency modulated (LFM) signals demonstrated that the same or similar network could outperform the power detector, confirming its capacity to learn structure when present.

These findings suggest that, under the tested conditions, the considered modulated noise waveform does not offer detectable structure accessible to shallow neural architectures, supporting its suitability for LPI applications.

Keywords: *noise waveform, noise radar, LPI radar, neural network, non-cooperative detection.*

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Introduction.

Noise radar systems that transmit waveforms resembling thermal noise offer advantages for low-probability-of-intercept (LPI) sensing [2, 3]. Besides, noise waveform signals allow specific regimes of operation of long range-Doppler radars [4]. Unlike conventional radar signals, noise radar waveforms are typically unpredictable, having no deterministic structure known to a non-cooperative receiver. As a result, classical matched filtering is not applicable in interception scenarios, and detection often relies on suboptimal power or energy detectors [5, 6].

However, not all noise radar signals are fully unstructured. In this work, we focus on a specific class of noise waveforms introduced in [1], where a constant-envelope carrier is frequency-modulated by a low-frequency, low-bandwidth white Gaussian noise signal. These waveforms maintain a perfect peak-to-average power ratio (PAPR) and exhibit low spectral occupancy, yet may embed nontrivial temporal or spectral features arising from the modulation process.

The central question addressed in this study is whether such structure (if present) can be learned and exploited by a data-driven detector. Rather than assuming the waveform to be entirely random from an interceptor's point of view, we use a neural network as a probing tool: if trained detection performance exceeds that of a classical power detector, this would suggest the presence of latent features not captured by second-order statistics. Conversely, parity in performance would support the hypothesis that the waveform provides no such structure to a non-cooperative observer.

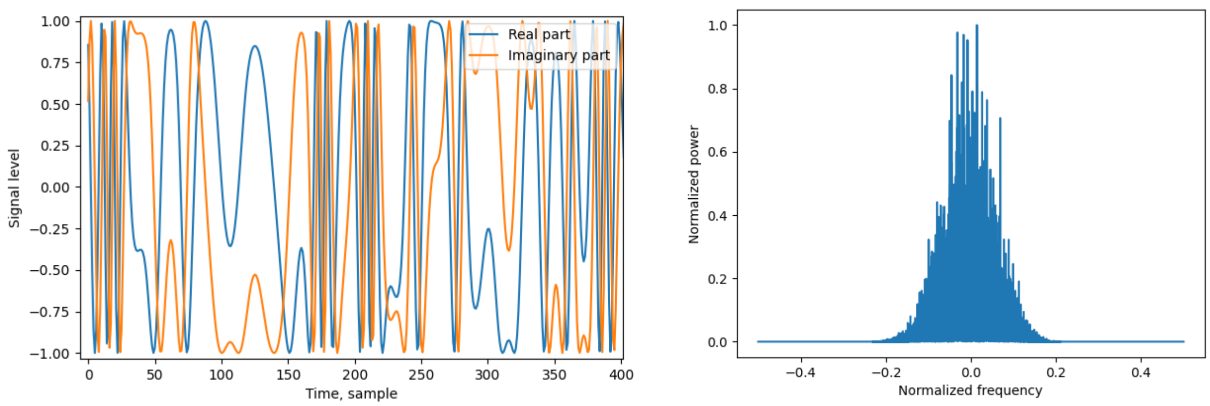

Figure 1 – Time realization and power spectrum of noise waveform generated with frequency modulation

Authors' development

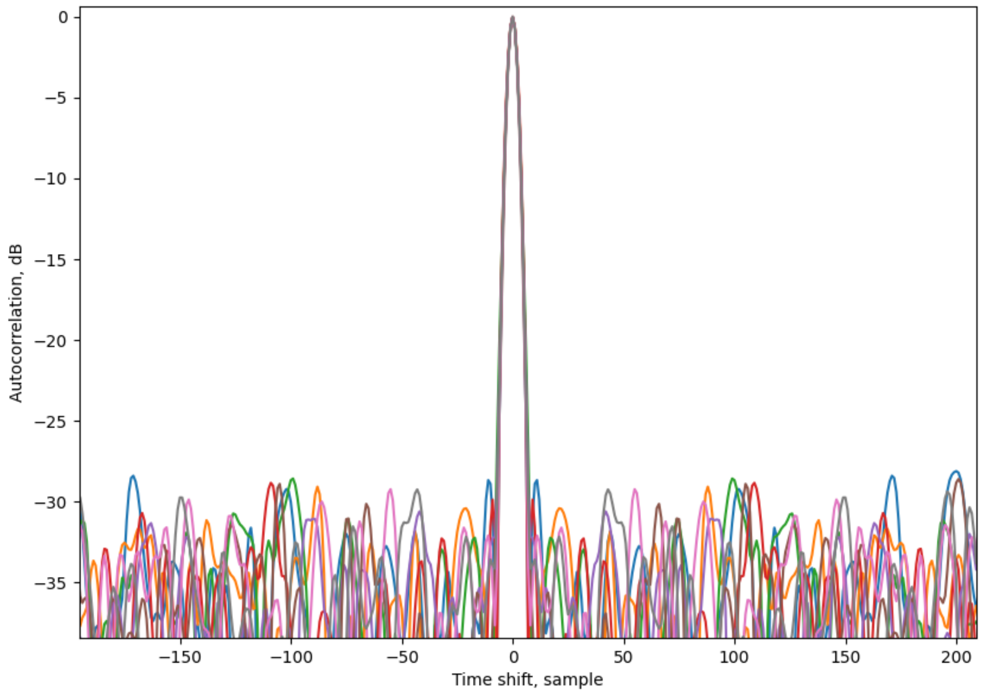

Figure 2 – Autocorrelation estimation of the investigated signal, plots of 8 realizations.

Authors' development

Through a controlled numerical experiment, this work aims to assess the detectability and implicit structure of these modulated noise radar signals, and to evaluate the practical capabilities and limitations of neural networks in passive detection tasks.

Neural Network Design.

To explore whether structural features in the noise waveform can be learned and exploited for detection, we implemented a relatively shallow convolutional neural network (CNN) operating on complex-valued spectrogram inputs. The choice of spectrograms was motivated by the visible time-frequency patterns observed in the signal, which are not apparent in the time or frequency domain alone.

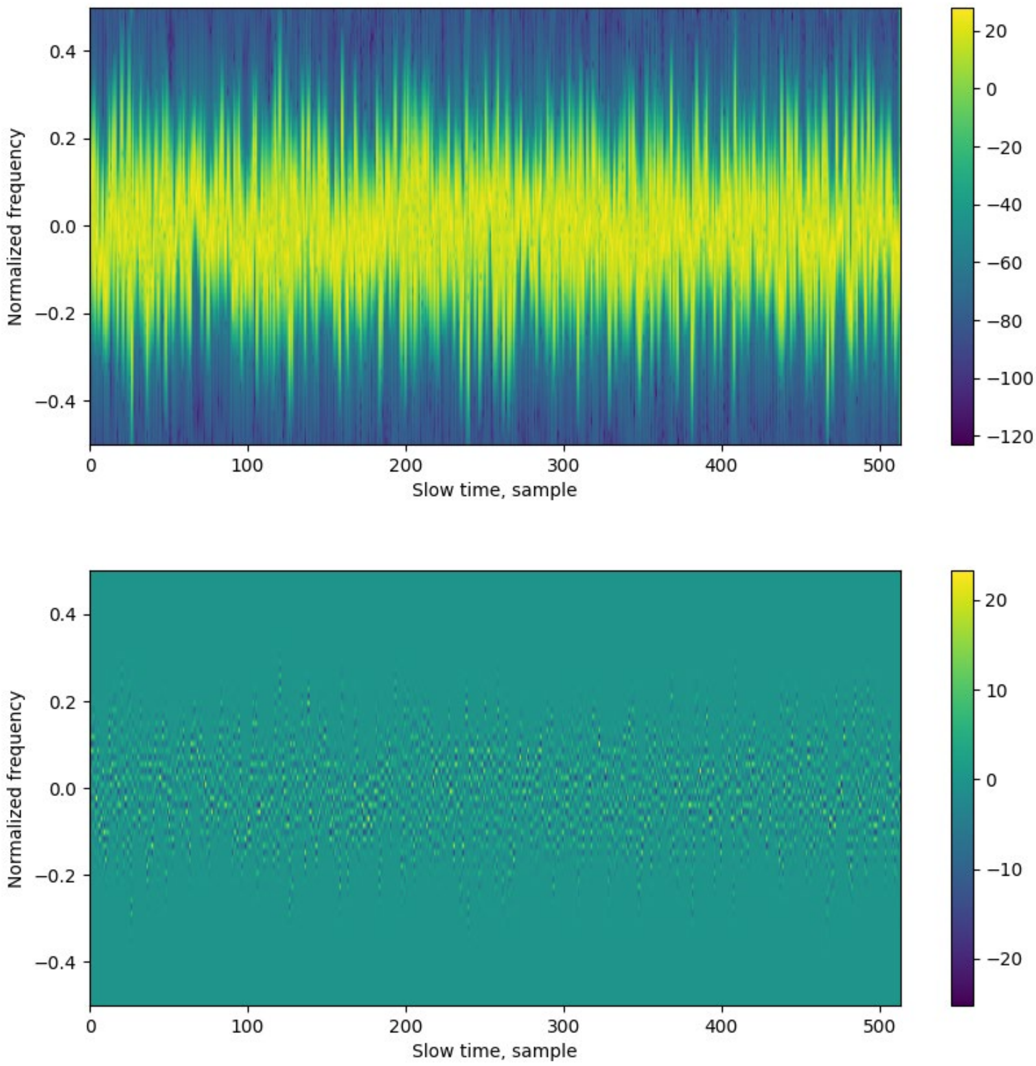

Figure 3 – Spectrogram of the investigated signal: (top) power, dB (bottom) real part

Authors' development

The network receives complex spectrograms as two-channel real-valued inputs: one for the real part and one for the imaginary part. To enhance the network's ability to separate meaningful structure from energy, a third input channel is added internally to represent the spectrogram's power (magnitude squared), allowing the network to incorporate energy-based information explicitly rather than having to extract it from phase relationships.

The architecture consists of:

- Four convolutional layers, grouped into two blocks with max-pooling applied after each block;
- A temporal average pooling operation along the time axis, compressing time

variation and promoting translation invariance;

- A flattening layer, followed by two fully connected (dense) layers;
- A final sigmoid activation layer to output a probability for binary classification (signal-present vs. noise-only).

All convolutional and dense layers use the ReLU activation function, except for the output layer. The total number of parameters remains modest, allowing efficient training while maintaining the capacity to learn structure if it exists in the data.

This design prioritizes generalization, interpretability, and the ability to extract potentially subtle and localized time-frequency features that might indicate the presence of the structured noise waveform.

Training Procedure.

The neural network was trained as a binary classifier to distinguish between noise-only and signal-present spectrograms. The training objective was to evaluate whether the network could detect structured features in the signal at increasingly lower SNR levels.

The loss function used was binary cross-entropy, and training proceeded in a staged fashion. Initially, all training examples were generated with an input SNR of 0 dB, a regime where signal detection is relatively easy. As soon as the network achieved at least 99% accuracy on a sliding evaluation batch of 512 samples, the SNR was reduced by 0.3 dB, thereby making the detection task progressively more difficult. Learning rate progression has been used with its gradual decreasing throughout the training.

If the network failed to improve its detection threshold (i.e., did not reach a lower SNR) for 300 consecutive batches, the SNR was temporarily increased by 1 dB to reintroduce an easier training regime and allow the network to continue making progress. This adaptive loop was repeated over a total of 50,000 batches, with each batch containing a 50-50% mix of signal-present and noise-only examples.

Typical progress of the training is shown in figure 4. The model achieves the best SNR with 99% accuracy at training iteration around 30000 and then oscillates around it. It means that the choice of the total iteration number of 50000 is reasonable.

Throughout training, configurations corresponding to the lowest SNR level at which the network achieved 99% detection accuracy were saved as checkpoints. These checkpoints were later evaluated on independent test sets to determine their generalization performance and to assess whether the network had learned features indicative of signal structure beyond simple energy cues.

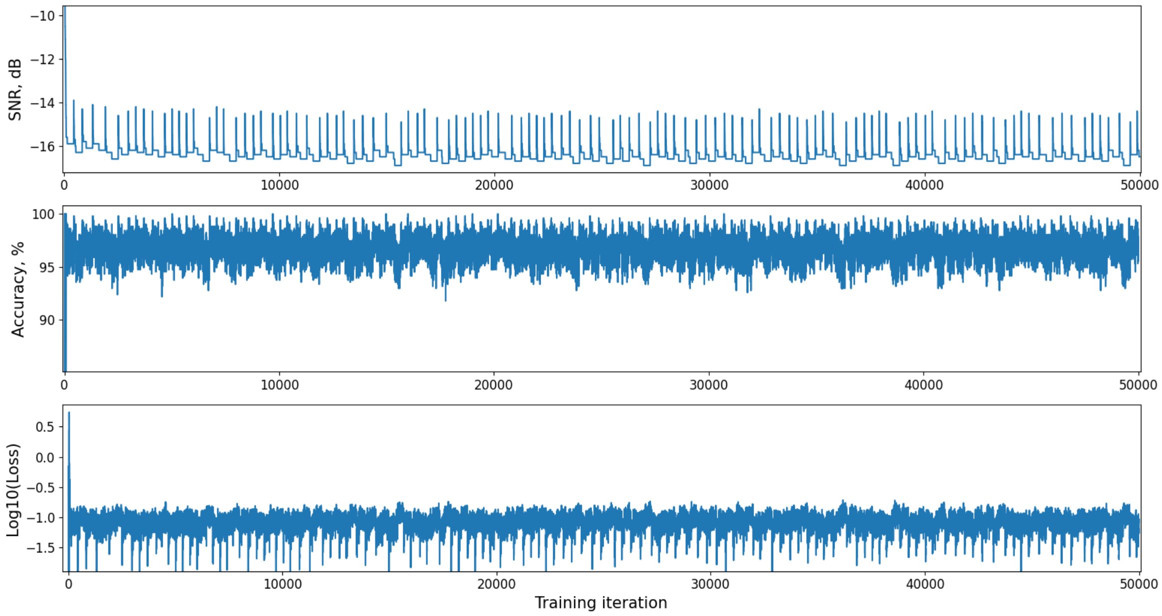

Figure 4 – Typical training progress curves: SNR of the input signals, accuracy of the algorithm, loss.

Authors' development

Results.

The detection performance of the neural network-based detector was evaluated against two benchmarks: a classical power detector and a coherent matched filter that assumes full knowledge of the signal realization. For all detectors, the false alarm probability was fixed at 10^{-5}, and performance was assessed by measuring the detection probability as a function of signal-to-noise ratio (SNR). This approach allows for a direct comparison of detection curves across methods, highlighting the relative sensitivity of each detector under equal false alarm constraints. One value characteristic to finally compare the methods is SNR difference for a given probability of detection which we set at 0.8. The typical set of detection curves for the methods is shown in fig.5. The detection curves for the approaches have quite similar shape. the neural network detector curve does not show any unexpected behavior.

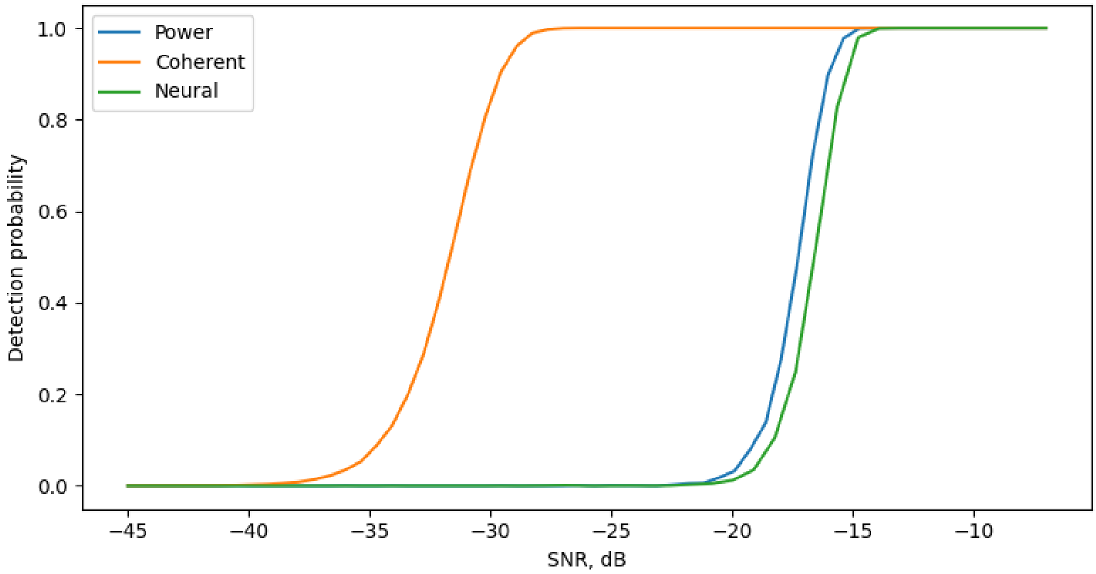

Figure 5 – Detection performance comparison for the noise waveform.

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For the modulated noise waveform, the neural network's detection threshold was found to be approximately 0.6 dB worse than that of the power detector. This indicates that on one hand the network learned the constructive representation which allows reasonable detection performance and, on another hand, that it did not discover any additional structure beyond the second-order statistics already exploited by the energy-based method. As expected, a coherent detector with access to the exact signal realization achieved significantly better detection performance, consistently detecting the signal at substantially lower SNR levels. This highlights the inherent gap between cooperative (matched) and non-cooperative detection in the context of noise radar waveforms.

To validate the capacity of the neural network to learn structured signals in low-SNR regimes, the same architecture was trained on linear frequency modulated (LFM) signals with randomized start times and frequency spans. It is worth noting that it is not uncommon to add random modulation to LFM signals to obtain LPI signals [7]. In this case, the neural network achieved detection performance that was approximately

1 dB better than the power detector, demonstrating its ability to exploit deterministic or semi-deterministic time-frequency structure.

These results support the interpretation that the modulated noise waveform under study does not contain readily exploitable structure for passive detection using shallow convolutional networks. At the same time, they confirm that the chosen network architecture and training regime are capable of learning from structured signals when such structure is present.

Conclusions.

This work investigated whether a neural network could detect latent structure in a specific noise radar waveform constructed via frequency modulation of a constant-envelope carrier with low-bandwidth Gaussian noise. The motivation was to assess whether such waveforms, while designed to appear noise-like and difficult to intercept, might contain subtle features that could be exploited by machine learning-based detection methods.

A shallow convolutional neural network was trained using a progressive difficulty strategy to detect the presence of this waveform in additive white Gaussian noise, without access to the signal realization reflecting a non-cooperative interception scenario. Its performance was compared to that of a classical power detector and a coherent matched filter.

The results showed that the neural network achieved detection performance approximately 1 dB worse than the power detector for the modulated noise waveform. This suggests that the network did not uncover any structural features beyond what is already captured by second-order energy statistics. In contrast, a control experiment with randomized linear frequency modulated (LFM) signals demonstrated that the same neural network architecture could outperform the power detector by approximately 1 dB, indicating its ability to learn and exploit structure when present.

These findings support the conclusion that, under the conditions studied, the specific noise waveform used does not offer exploitable structure for non-cooperative detection using shallow convolutional networks. While not ruling out the possibility that deeper architectures or alternative learning strategies could reveal hidden features, the results provide evidence that such waveforms are indeed effective for low-probability-of-intercept applications and remain difficult to detect without prior knowledge.

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Анотація. *У статті досліджується можливість виявлення структурованого шумового радіолокаційного сигналу за допомогою неглибокої згорткової нейронної мережі. Розглянутий сигнал генерується шляхом частотної модуляції носія з постійною огинаючою низькочастотним гаусовим шумом обмеженої смуги, відповідно до підходу, описаного в роботі [1]. Такі сигнали мають ідеальне відношення пікової потужності до середньої і схожість спектру на Гаусів, що робить їх придатними для використання в радіолокаційних системах з низькою ймовірністю перехоплення.*

Ключовим питанням цієї роботи є наявність прихованої структури в таких сигналах, яку можна було б використати за допомогою методів машинного навчання у випадку, коли реалізація переданого сигналу є невідомою.

Для перевірки цього припущення нейронну мережу було навчено на спектрограмах прийнятих сигналів, занурених у додатковий білий гаусовий шум. Ефективність виявлення за допомогою нейромережі порівнювалася з класичним детектором потужності та з ідеальним когерентним детектором, що використовує фільтрацію за зразком.

Результати показали, що нейромережа поступається детектору потужності, що свідчить про її неспроможність витягнути додаткову структуру із сигналу. Натомість контрольний експеримент із випадковими лінійно-частотно модульованими сигналами продемонстрував, що та ж мережа здатна покращити показники детектора потужності, підтверджуючи її здатність до виявлення структурованих сигналів.

Ці висновки свідчать про те, що в умовах дослідження розглянутий шумовий сигнал не містить структури, доступної для не глибоких нейронних мереж, що підтверджує його придатність для LPI-застосувань.

Ключові слова: *шумовий сигнал, шумова радіолокація, радар із низькою ймовірністю перехоплення, нейронна мережа, не кооперативне виявлення.*