

# APPLICATION OF DIFFUSION MODELS FOR RADAR SIGNAL SYNTHESIS AND IMPROVEMENT OF OBJECT DETECTION QUALITY

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**Аннотация** Освещены вопросы повышения эффективности обнаружения малоразмерных воздушных объектов на основе применения диффузионных моделей для синтеза и восстановления радиолокационных сигналов, формируемых мобильными радиолокационными станциями. Предлагаемый подход основан на использовании генеративных моделей типа DDPM и score-based моделей для расширения обучающих выборок, подавления шумов и улучшения информативности радиолокационных портретов объектов. Результатом работы является разработка методики и программно-аппаратного модуля в составе малогабаритного интеллектуального радиолокационного комплекса, обеспечивающего повышение вероятности обнаружения и точности классификации малоразмерных целей. Проведена оценка реализуемости предложенного подхода на современной элементной базе и определены его основные характеристики. Предложен метод обнаружения и распознавания воздушных объектов, основанный на совместном применении диффузионных моделей и алгоритмов глубокого обучения, обеспечивающий устойчивость к шумам и дефициту обучающих данных.

**Ключевые слова:** радиолокационная станция, DDPM, генеративные модели, синтез радиолокационных сигналов, обнаружение воздушных объектов, малоразмерные цели.

**Abstract:** This paper addresses the problem of improving the efficiency of detecting small-sized aerial objects through the application of diffusion models for the synthesis and reconstruction of radar signals generated by mobile radar systems. The proposed approach is based on the use of generative models, including DDPM and score-based models, to expand training datasets, suppress noise, and enhance the informativeness of radar signatures of objects. The result of the study is the development of a methodology and a hardware-software module as part of a compact intelligent radar system, providing increased detection probability and improved classification accuracy of small-sized targets. The feasibility of implementing the proposed approach using modern electronic components has been evaluated, and its key characteristics have been determined. A method for detection and

recognition of aerial objects is proposed, based on the combined use of diffusion models and deep learning algorithms, ensuring robustness to noise and limited training data.

**Keywords:** radar system, DDPM, generative models, radar signal synthesis, aerial object detection, small-sized targets.

## **Introduction**

The use of radar systems for airspace surveillance has become widespread over the course of their development and is actively applied in both military and civilian domains. Under modern conditions, radar systems serve as a key tool for preventing man-made disasters by enabling timely detection and monitoring of aerial objects of various origins [1; 2]. The main advantages of radar technology include wide-area coverage, up to full 360-degree scanning capability, long detection ranges achieved through control of energy and frequency parameters, as well as all-weather and round-the-clock operation. At the same time, modern radar systems are characterized by several limitations, including high implementation complexity, significant size and weight, and increased requirements for operator qualification [3–5].

The current stage of radar system development is associated with the integration of intelligent signal processing methods aimed at automating decision-making and reducing the impact of the human factor. One of the most promising directions is the use of generative deep learning models, particularly diffusion models, which enable the synthesis of radar signals, reconstruction of noisy data, and expansion of training datasets. This leads to improved informativeness of radar signatures and enhances the quality of subsequent detection and classification of objects [6]. In classical radar, three levels of information processing are distinguished: primary, secondary, and tertiary. At the primary processing stage, the task is to detect useful signals against a background of noise and interference. The integration of diffusion models improves filtering and signal reconstruction efficiency through stochastic reverse processes (denoising), thereby reducing false alarm probability and increasing system sensitivity.

Secondary processing is aimed at determining the coordinates of detected objects (range, azimuth, elevation angle), where modern algorithms provide high-precision automation of this stage. The use of synthetically generated data obtained through diffusion-based approaches enhances the robustness of algorithms to variations in observation conditions. At the tertiary processing stage, the task of object recognition and classification is addressed. Traditionally, this requires highly qualified operators; however, the application of deep learning methods combined with diffusion models enables the formation of more informative radar representations and the automation of the identification process for man-made objects. As a result, classification accuracy is improved and operator workload is reduced, which is critically important for modern intelligent radar systems.

## Methods

The solution to the problem of classifying aerial objects in radar systems is based on the analysis of trajectory and signal features, including velocity, direction of motion, trajectory shape, and parameters of the reflected signal. The most informative representation is the spectral domain, which makes it possible to identify characteristic structural features, including the presence of side components that distinguish objects of natural and man-made origin [8–10]. To automate the recognition process, an approach is employed in which the input to the model is a digitized spectrum of the reflected signal, represented as a two-dimensional image of fixed size. This representation enables the application of deep learning methods designed for image processing. To improve training efficiency and compensate for the lack of data, a diffusion model is used, implementing a generative process for synthesizing spectral signatures.

$$q(x_t | x_{t-1}) = \mathcal{N}(x_t; \sqrt{1 - \beta_t} x_{t-1}, \beta_t I)$$

where  $x_0$  denotes the original data,  $x_t$  represents the noisy data at step  $t$ ,  $t$  is the diffusion step index,  $\beta_t$  is the noise coefficient,  $\mathcal{N}(\cdot)$  denotes the normal (Gaussian) distribution, and  $I$  is the identity matrix.

$$p_\theta(x_{t-1} | x_t)$$

where  $p_\theta$  is a parameterized neural network that implements the reconstruction process.

The model is trained by sequentially adding noise to the original data and recovering the initial distribution using a reverse denoising procedure. This approach enables the generation of new samples that preserve the statistical properties of real radar signals. The generated spectral representations are used to augment the training dataset and improve the robustness of the classifier to variations in observation conditions and noise interference. Representing data as images with dimensions equivalent to the original spectral signatures ensures compatibility with neural network architectures and enables efficient integration of generative and discriminative processing stages.

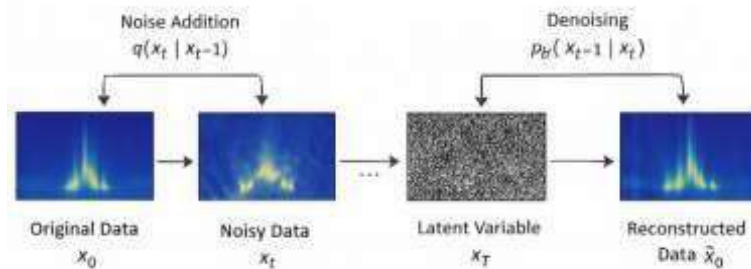


Figure 1. The diffusion model process.

The generation of spectral signatures of radar signals is implemented using a diffusion model architecturally adapted for processing two-dimensional spectral representations. At the initial stage, the input data undergo symmetric reflection at the boundaries, which allows accounting for edge pixel

information and reduces distortions during subsequent convolution operations. In the core part of the model, a sequence of convolutional layers is applied to extract features from the spectral image. Convolution kernels of fixed size are used to capture local frequency and amplitude characteristics of the signal. Inter-layer normalization is performed using instance normalization, which stabilizes the distribution of activations and enables independent channel calibration. The ReLU activation function is employed to highlight significant positive components of the spectral representation. During the denoising process, characteristic of diffusion models, operations functionally analogous to transposed convolutions are used to gradually restore the spatial resolution of the spectral image. At the final stage, the hyperbolic tangent activation function is applied, ensuring normalization of output values within the range  $[-1, 1]$ , which соответствует требованиям к представлению спектральных данных. The quality assessment of generated spectral signatures is performed using a discriminative model that compares synthetic and real data. This model consists of a sequence of convolutional layers with the LeakyReLU activation function, which preserves information about weak negative variations and обеспечивает более стабильное обучение. Both real spectral images and those synthesized by the diffusion model are used as input, forming the basis for evaluating their statistical consistency.

The proposed architecture enables the generation of spectral data that closely matches the distribution of real radar signals and can be effectively used to augment training datasets and improve the performance of subsequent detection and classification tasks for aerial objects.

## Results

To stabilize training and improve the quality of synthesized spectral representations, InstanceNorm2D normalization is applied within the model architecture. This approach ensures independent channel calibration based on the estimation of mean and standard deviation within each data instance. As a result, generation stability is enhanced and the statistical consistency between synthetic and real spectra is improved.

The developed architecture includes a sequence of convolutional layers that extract features from spectral signatures using varying parameters. At the final stage, an output layer is employed to estimate the correspondence between the generated spectrum and the real data distribution. The input data are represented as multi-channel spectral images, while the model output is interpreted as the probability of belonging to the real distribution of radar signals.

Simulation results demonstrate that the diffusion model is capable of generating spectral signatures that are statistically consistent with real data. The synthesized spectra reproduce key characteristics of reflected signals, including the structure of side components, confirming the adequacy of the proposed approach for augmenting training datasets.

The use of generated data enables the formation of a representative dataset for training classification models for aerial object recognition. This leads to improved accuracy of automated classification and reduces dependence on subjective factors associated with operator-based analysis.

The integration of the proposed approach into the hardware-software architecture of a mobile intelligent radar system enables real-time visualization of recognition results, including the display of coordinate and classification attributes of detected objects. The obtained results demonstrate correct classification of targets as man-made objects based on the analysis of spectral characteristics.

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