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Generating radar signals using one-dimensional GAN-based model for target classification in radar systems

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Abstract. Conventional radar systems are often unable to produce highly accurate results for target classification and identification via linear frequency modulation (LFM) signals. The potential of artificial intelligence, particularly deep learning, has been applied in various fields, which promotes utilizing them in the context of target classification in radar systems. However, to train deep learning models for this task, large datasets of LFM radar signals are required, which are practically difficult to obtain due to the time, effort, and involved high cost. Therefore, the presented work spots the light on utilizing the recent one-dimensional generative adversarial network (GAN) and Wasserstein GAN (WGAN) models to synthesize a large time-series LFM signal dataset from a reference smaller one. Moreover, the work fairly judges the generated LFM signals realistic via a decent qualitative and quantitative analysis, unlike other studies which rely solely on qualitative evaluation by human observers. The proposed study outcome reveals the WGAN's efficiency in synthesizing high-quality LFM signals while reducing the training time and resource requirements.

Keywords— radar target classification, linear frequency modulation signal, time-series signal, generative adversarial network, Wasserstein generative adversarial network

1. Introduction

Linear frequency modulation (LFM) signals are widely used in various applications, including radar systems, sonar, medical imaging, and communication systems [1]. These signals have the unique feature of a linear increase or decrease in frequency over a specific duration, which makes them particularly suitable for moving target applications [2]. The radar system works by emitting signals and detecting the reflected signals from targets to determine their position and velocity. However, traditional radar systems have limitations, such as limited accuracy and the inability to classify small or long-range targets. To overcome these limitations, researchers have started to explore the use of deep neural networks (DNNs) in radar systems [3]. However extensive amounts of data are needed when employing DNNs. Without access to massive amounts of data, these algorithms can not compete with radar systems.

The evolution of deep learning in the field of data generation has allowed for the creation of high-quality and diverse data. Deep learning models, such as GANs and variational autoencoders (VAEs), have been widely used for data generation in various domains, including image synthesis, text generation, speech synthesis, and music generation [4]. So it can be used to augment existing datasets [5], which can help improve the performance of deep learning models. This is particularly useful in scenarios where data collection is difficult or expensive.

For example, deep learning-based data generation has been used in the medical field, especially for rare diseases, where datasets are often limited due to the small number of patients affected by the condition,

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which can make it challenging to develop accurate diagnosis and treatment methods. Deep learning-based data generation can help generate synthetic medical images and data to augment small datasets, providing researchers with more diverse and comprehensive data to train machine learning models.

In our case, the accuracy and performance of radar systems in classification task heavily depend on the amount and quality of the data used for training. However, collecting large amounts of radar data can be time-consuming, costly, and challenging, especially in scenarios where the data is rare or difficult to obtain. Hence, the use of deep learning-based data generation techniques can be a game changer for radar systems, as they allow for the creation of synthetic radar signals that can augment existing datasets. By generating synthetic radar signals, deep learning models can be trained more efficiently, leading to better accuracy and performance in target classification and identification. This is particularly useful in military and surveillance applications where real radar data is scarce or difficult to obtain, enabling more accurate and reliable threat detection and decision-making.

The concept of deep learning for data generation involves training a model to learn the underlying distribution of a given dataset and then generating new data samples that resemble the original dataset. GANs use a generator network and a discriminator network to generate new samples that are similar to the original data, while VAEs use an encoder network and a decoder network to learn the latent space [6] of the original data and generate new samples from this latent space.

The unsupervised learning method of GANs is finding widespread use, particularly in the realms of picture generation and data augmentation, and has just recently entered the public consciousness [7]. One-dimensional GANs have just begun to emerge from their infancy and it uses for time-series signals [8]. In order to pave the way for future study into the application of GANs for this purpose, this paper presents the use of GANs-based in radar signal creation, especially LFM signal generation.

Although, the traditional GAN architecture has some limitations, including mode collapse, the difficulty of training, and generating signals that are not similar to real signals [9]. To overcome these limitations by using a variant of GANs known as the Wasserstein generative adversarial network (WGAN) [10]. In this paper, the WGAN architecture is proposed for the generation of LFM signals. The generator network has been trained to produce LFM signals that are similar to a set of reference signals and the discriminator network to distinguish the generated signals from the reference signals, while overcoming the limitations of traditional GANs. Our results show that a one-dimensional GAN-based approach can generate LFM signals that are highly similar to the reference signals while also being computationally efficient.

This paper is structured as follows: Section 2 presents a detailed exposition of the GAN-based approach for radar signals. The proposed method is then expounded in Section 3. The results are described in Section 4, while Section 5 contains a discussion of the results. Finally, conclusions are drawn in Section 6.

2. GANs for radar

GANs have gained significant attention in the field of signal processing, including the generation of radar signals. GANs are composed of two neural networks, a generator, and a discriminator, trained together to generate synthetic data that can be used for various applications, including data augmentation, anomaly detection, and waveform synthesis [11].

In the case of radar signal generation, GANs can be used to generate synthetic signals that mimic the properties of real-world radar signals. This can be achieved by training the generator to produce radar signals that are statistically similar to the signals collected from real radar systems.

One of advantage of using GANs for radar signal generation is that they can generate signals with specific properties that are not present in real-world data. For example, GANs can be trained to generate signals with specific noise levels, frequency ranges, or modulation types. This can be useful for testing the performance of radar systems under different conditions or for generating synthetic data for training machine learning algorithms in scenarios that are not easily replicable in real-world data.

We focus on one of the main advantages of using one-dimension GAN-based for radar time-series signal generation is that they can generate large quantities of data that can be used to train machine learning algorithms without the need for expensive and time-consuming data collection. This can be particularly useful in scenarios where data is limited or where collecting real-world data is difficult, such as in military or security applications. In the following two subsections, we will describe the main construction of GANs

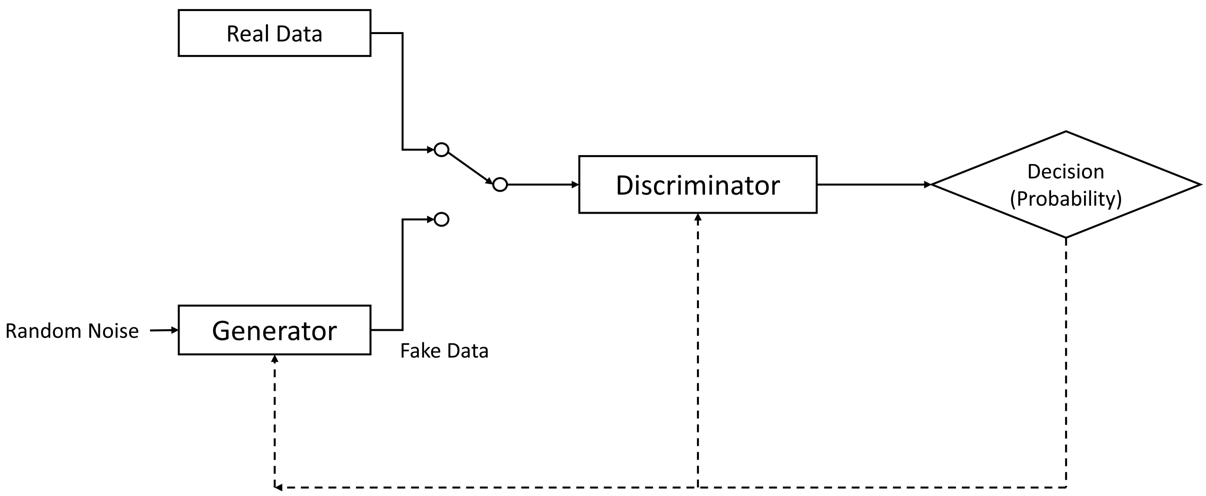


Figure 1. Basic GAN model architecture.

and WGANs.

2.1. The architecture of GAN

The architecture of GANs shown in figure 1 consists of two deep neural networks, each with its own objective. The generator takes random noise as input and generates fake data, while the discriminator takes both real and fake data as input and classifies them as real or fake. The objective of the generator is to produce data that is indistinguishable from real data, while the objective of the discriminator is to correctly classify the data as real or fake.

The training process of GANs is based on a minimax game between the generator and the discriminator. The generator tries to minimize the difference between the real and fake data distributions, while the discriminator tries to maximize the difference. This can be expressed as the following loss function [12]:

$$\min_G \max_D V(D,G) = \mathbb{E}_{x\sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z\sim p_z(z)}[\log(1 - D(G(z)))]. \tag{1}$$

Where G is the generator, D is the discriminator, Pdata(x) is the distribution of real data, P(z) is the distribution of noise, x is a real data point, and z is a noise sample. The first term in the loss function maximizes the log probability of the discriminator correctly classifying a real data point, while the second term maximizes the log probability of the discriminator incorrectly classifying a fake data point generated by the generator.

In the case of radar signal generation, the generator network takes random noise as input and produces a radar signal that should resemble the reference signal. The discriminator network evaluates whether the input signal is real or fake.

Although GANs have shown great potential in signal generation tasks, they also have some limitations:

- Mode collapse occurs when the generator of the GAN fails to learn the entire distribution of the data and instead generates a limited set of similar outputs, known as a mode collapse. In other words, the generator becomes over-reliant on a small subset of the training data, resulting in a lack of diversity in the generated signals. This limitation is a significant challenge for GANs, particularly in signal generation tasks where the output signals need to be diverse.

- Vanishing gradients is another limitation associated with GANs. It is a common issue in deep neural networks, including GANs, where the gradients can become very small during training, leading to slow convergence. In signal generation tasks, vanishing gradients can result in poor quality or even unusable generated signals. This limitation has been addressed in several ways, including the use of different optimization algorithms and normalization techniques.
- Unstable training is also a significant limitation of GANs. GANs have a non-convex optimization problem that can result in instability during training. In some cases, the discriminator can become too good at distinguishing between real and fake signals, which can cause the generator to generate low-quality signals. Additionally, the generator can produce signals that are too similar to the real signals, leading to the discriminator being unable to differentiate between the two. These issues can lead to an unstable feedback loop that hinders the training of the GAN.
- Requirement for a large amount of training data. This can be especially challenging in the case of signal generation, where obtaining sufficient real-world signal data can be difficult. Moreover, GANs are sensitive to the quality of the training data, and any noise or errors in the data can be amplified during the training process and affect the quality of the generated signals.

WGAN overcomes these limitations by using a different loss function, known as the Wasserstein distance, instead of the traditional cross-entropy loss.

2.2. The architecture of WGAN

The main idea behind WGANs is to replace the traditional discriminator in GANs with a critic network, which estimates the Wasserstein distance between the generated and real data distributions.

The Wasserstein distance is a measure of the distance between two probability distributions, and it has been shown to be more stable than the Jensen-Shannon divergence used in GANs [13]. The critic network is trained to minimize the Wasserstein distance, while the generator network is trained to maximize it. This leads to a more stable training process, as the critic provides a more informative and smoother feedback signal to the generator.

Additionally, WGAN introduces a constraint on the weights of the discriminator network, which helps to stabilize the training process. The constraint ensures that the discriminator network remains within the space of valid functions and that the generator network produces signals that are close to the real signals. This makes the WGAN architecture more robust and easier to train, resulting in generated signals that are closer to the real signals.

The mathematical expressions for the cost functions of the critic and generator in the WGAN architecture can be observed in Equations 2 and 3, respectively [14].

$$\nabla_w \frac{1}{m} \sum_{i=1}^{m} \left[f\left(x^{(i)}\right) - f\left(G\left(z^{(i)}\right)\right) \right] \tag{2}$$

$$\nabla_\theta \frac{1}{m} \sum_{i=1}^{m} f\left(G\left(z^{(i)}\right)\right) \tag{3}$$

The function f is a Lipschitz function. WGAN uses a clipping method to decrease the maximum weight value in f, in order to enforce the constraint, ∇_w is the gradient with respect to the weights w of the network, $x^{(i)}$ is the ith real sample in the batch, $z^{(i)}$ is the ith noise vector in the batch used to generate fake samples,m is the size of the batch used in training, and G is the generator network used to generate fake samples. figure 2 depicts the architecture of WGAN, where C represents the discriminator, and $C*$ is an approximate expression of the Wasserstein distance.

This is leads to some advantages as follows:

- Less prone to mode collapse, provide a more stable training process.
- Generate higher-quality signals with fewer samples. This is particularly useful in the case of radar signals, where the collection of real-world data is often limited or expensive. WGANs can learn the underlying distribution of the real signals from a few samples and generate a large number of realistic signals.

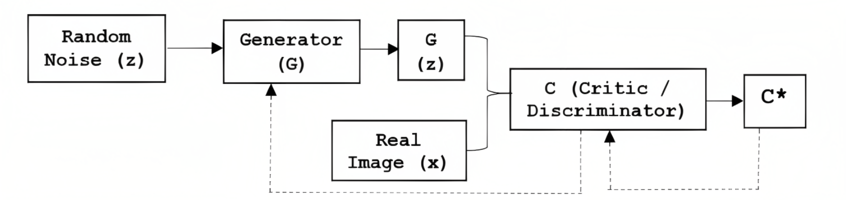


Figure 2. A diagram depicting the architecture of the WGAN.

- Generate diverse signals with different characteristics. This is useful for radar systems that need to detect various types of targets in different environments. WGANs can generate signals with different frequencies, modulation schemes, and noise levels, among other characteristics, which can be used to train radar systems to recognize a wide range of targets.

3. Methodology

This paper aims to utilize GAN-based approach in LFM signal generation by employing LFM signals from computer simulations to train a WGAN model. The success of this method will pave the way for future research on the application of GANs in radar systems. It is expected that the utilization of GANs in radar data augmentation will be an advantageous approach, particularly in scenarios where the collection of data is challenging, and expensive.

In our case, WGAN is preferred over basic GAN for signal generation tasks for several reasons stated in section 2.2. The proposed WGAN's block diagram is depicted in figure 3 in a highly abstracted form, z is a vector of random noise, typically drawn from a normal distribution with a mean and standard deviation of 0 and 1, respectively. The generator takes this noise vector as input and produces a generated signal, denoted as $G(z)$. x_t refers to the reference LFM signal in the training dataset. The discriminator (critic) is a neural network that receives a signal noted as x, which could be either a reference or a generated signal, and produces an output probability score that the image is real, denoted as D(X). With the use of weight clipping constraints on the discriminator (critic) network's weights. This constraint limits the magnitude of the critic network's weights to a fixed range, typically [-0.01, 0.01]. This helps to prevent the gradients from exploding or vanishing during training, which is a common problem in traditional GANs.

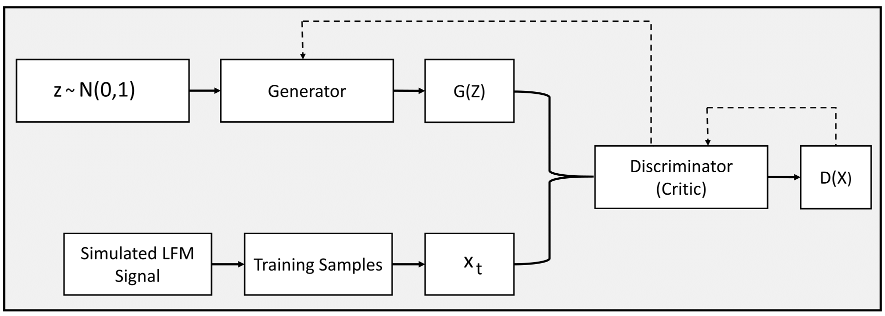


Figure 3. Abstracted form of WGAN block diagram for generating LFM radar signals.

The reference samples contained one thousand LFM signals with a fixed sampling frequency and random amplitude, as shown in Table 1.

Table 1. Parameters of reference signal generated with MATLAB

Parameter	Value	Unit
`Sampling frequency`	2^{24}	Hz
`Bandwidth`	2	MHz
`Pulse width`	100	μs
`Amplitude`	Random number [0.5-1]	Scaler

Figure 4 demonstrates the network architectures for the proposed WGAN for LFM signal, [15] demonstrates all terminologies. The proposed convolutional layers of the generator have stride = 2, kernel size = 4, and padding = 1, except for the first layer, which has kernel size = 114, stride = 1, and padding = 0. The discriminator contains a series of convolutional layers with kernel size = 4, stride = 2, and padding = 1, except for the last layer, kernel size = 114, stride = 1, and padding = 0. Thus, the 1824-element input sequence is converted to the probability D(x).

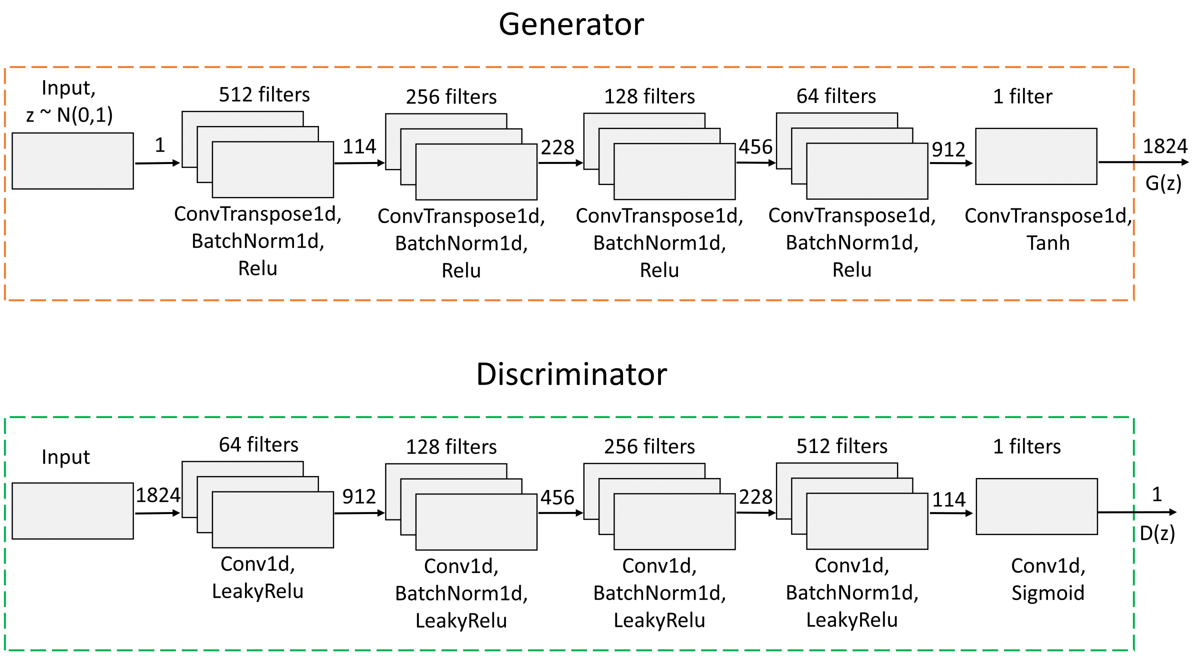


Figure 4. Architecture for the proposed WGAN.

The model is trained by reference LFM signals with a batch size of 8 and 64 epochs. The RMSprop optimizer was used to implement WGAN. RMSprop [16] is a gradient descent optimization algorithm that is commonly used in deep learning to update the weights of neural network models during training. It is a variation of the stochastic gradient descent (SGD) algorithm that adjusts the learning rate for each weight in the network based on the average of the squares of the gradients for that weight over a moving window of previous time steps.

We use the correlation function and the spectrogram of the instantaneous frequency of the signal to compare the generated signal with the reference signal.

The correlation function was used to measure the similarity between the WGAN-LFM signal and the reference LFM signal. When comparing two LFM signals, we can use the correlation function to determine the degree of similarity between the two signals. If the two signals are very similar, the correlation value will be high, while if the two signals are dissimilar, the correlation value will be low. By using this function, we can compare different aspects of the LFM signals, such as the duration, frequency sweep rate, and center frequency. This can be useful in applications where it is necessary to detect changes in LFM signals.

By using a spectrogram to compare two LFM signals, we can visualize the changes in frequency content over time for each signal and identify any similarities or differences [17]. This can be particularly useful in applications such as radar and sonar, where accurate detection and classification of signals are critical.

4. Simulation and Results

To evaluate the performance of the proposed WGAN for generating LFM signals, the two models GAN and WGAN had run on a Lenovo Ideapad 320 laptop running Windows 10. The machine was equipped with an Intel Core i5-7200U processor with two cores and a clock base speed of 2.71 GHz, 8 GB of DDR4 memory. All experiments were run using Python 3.10.4 with the PyTorch 1.12.0 deep learning framework. We utilized both quantitative and qualitative methods and compared the generated LFM signals with the reference signals Table 1.

For quantitative analysis, we compared reference LFM signals with generated LFM signals from GAN and WGAN, as shown in Table 2. With a fixed number of iterations for the two models, the average WGAN correlation equals 99.83%, which is significantly higher than GAN. In addition, it converges in an early number of iterations with higher accuracy compared to GAN, although WGAN consumes more time than GAN.

Table 2. Correlation analysis of generated signals.

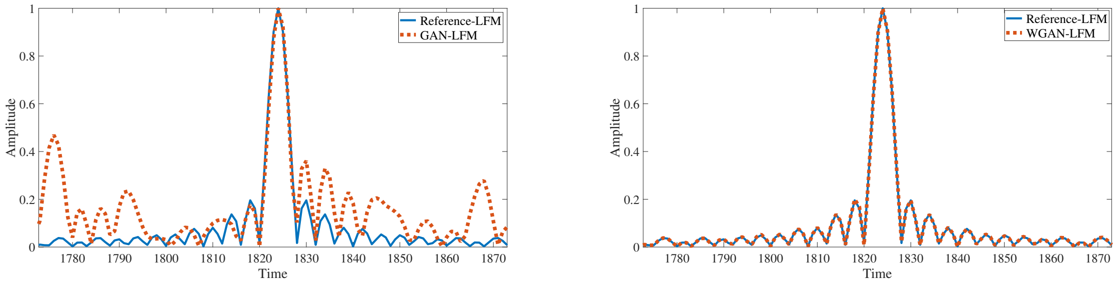
Model	GAN	WGAN
Correlation	44.86%	99.83%
Time Consumed	39 min	74 min

By using correlation analysis, it was observed that the frequency modulation rates of the LFM signals generated by the WGAN were highly similar to those of the reference signals. This indicates that WGAN is superior to traditional GAN for generating LFM signals that closely resemble the original signals as shown in figure 5.

Figure 6 is a qualitative analysis in which the spectrogram of the instantaneous frequency of the generated LFM signal was compared visually to those of the reference signal. The spectrogram function in MATLAB is a valuable tool for analyzing and visualizing the frequency content of radar signals over time. By using the spectrogram function, it is possible to identify frequency shifts or modulations in the radar signal, monitor changes in the environment, and compare different radar signals for analysis purposes.

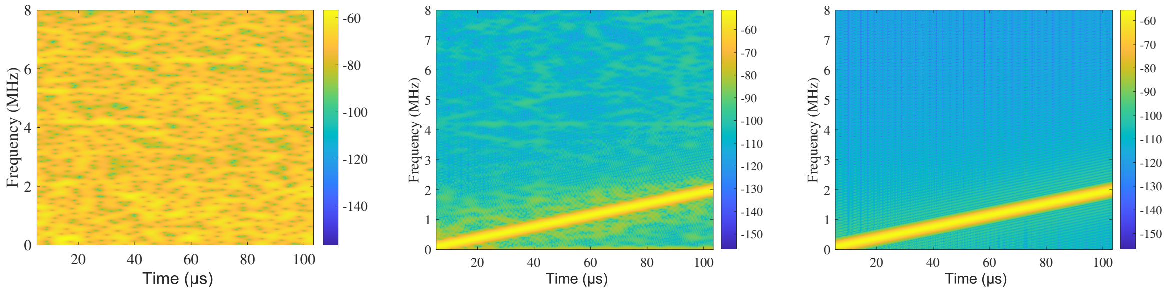
By comparing the results obtained from the spectrogram of generated LFM signal with reference signal, it was revealed that WGAN was able to accurately capture the frequency content of the reference signal. This further signifies the better performance of WGAN over traditional GAN in generating LFM signals with high accuracy and capturing their key features, as evidenced by the high degree of similarity observed between the spectrograms of WGAN signal and reference signal.

Figure 7 illustrates the LFM signal in the time domain, whereas the WGAN model has demonstrated efficiency and accuracy in following the reference LFM compared to the basic GAN model, which looks like a noise signal.



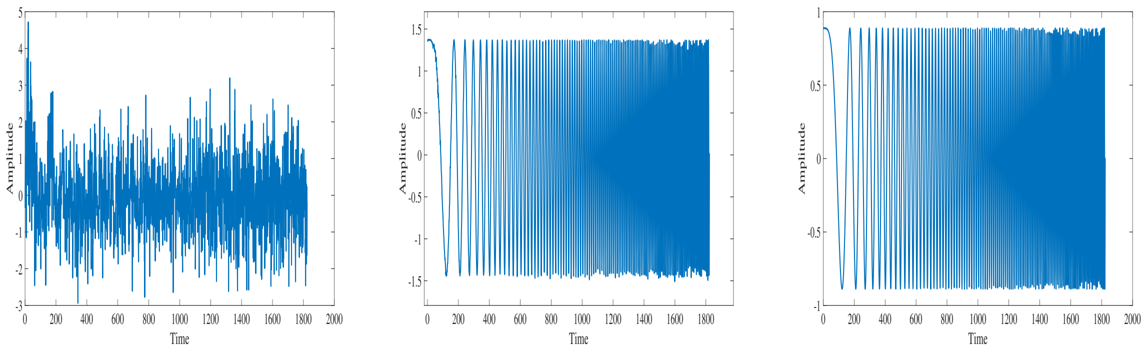
(a) (b)

Figure 5. Correlation analysis, solid line for the reference LFM signal, dashed line in (a) GAN LFM signal, and dashed line in (b) WGAN LFM signal.



(a) (b) (c)

Figure 6. Spectrograms of instantaneous frequencies of reference and generated LFM signals $B{=}2MHz$, $T{=}100\mu s$. (a) GAN LFM signal. (b) WGAN LFM signal. (c) reference signal.



(a) (b) (c)

Figure 7. LFM signal in time domain. (a) GAN LFM, (b) WGAN LFM, (c) reference LFM

5. Discussions

Our results demonstrate that the proposed approach can generate LFM signals that are highly similar to the reference signals, and it was evaluated in quantitative and qualitative analysis using metrics such as correlation analysis and the spectrogram of the instantaneous frequency of the signal. These results imply that the WGAN has the potential to be used for generating data sets for radar signals in various scenarios, particularly where collecting data can be difficult, time-consuming, or expensive. Which demonstrates the effectiveness of WGANs in generating signals that accurately capture the frequency content of original signals and could provide a practical alternative for signal generation in radar systems for target classification and identification tasks by generating synthetic radar signal data sets that can improve the performance of machine learning classifiers.

6. Conclusion

In this paper, LFM signals are generated using a WGAN. To the best of our knowledge, this is the first time a WGAN has been used to carry out this task. The generator network has trained using reference LFM signals from computer simulations to produce LFM signals that are similar to a set of reference signals while overcoming the limitations of traditional GANs. The proposed WGAN architecture used the Wasserstein distance as a loss function to measure the difference between the generated signals and the real signals, and it introduced a constraint on the weights of the discriminator network to stabilize the training process. We have provided a new and promising direction for the generation of LFM signals using deep learning techniques and shows the potential of WGANs for generating signals in general.

Our future developments include train a classification model and evaluate its performance and accuracy using the generated LFM signal datasets produced by WGAN. This development could involve different scenarios including background effects.

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