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Abstract. For deception jamming countermeasures of multistatic radar systems, existing intelligent anti-jamming methods require sufficient training samples and a large amount of labelled data, but it is difficult to obtain abundant labelled radar echo data in realistic operational environments. A deception jamming discrimination method based on semi-supervised learning with generative adversarial networks is proposed to specifically handle the situation of inadequate labelled samples. In this way, a small amount of labelled data and a large amount of unlabelled data obtained from radar stations, together with pseudo-labelled data generated by the generator are used to train the discriminator to improve the performance of jamming discrimination and the robustness of the discrimination network by exploiting the game between the generator and the discriminator. Simulation results show that, the proposed method can achieve the same performance using less than 10% of the labelled data of existing algorithms. It reduces data requirements and enhances operational capabilities, which is better suited to real-world battlefield environments.

Keywords: Multistatic radar systems, semi-supervised learning, anti-jamming method, signal processing.

1 Introduction

The electromagnetic environment of modern warfare is becoming more and more complex [1]-[2]. The information collected by the multistatic radar system is shared and fused in the fusion centre, which pushes for better identification and suppression of the interference and greatly improve the system's systematic capability [3]-[4].

Existing intelligent anti-jamming methods have exploited deep neural networks to multistatic radar jamming countermeasures, Liu proposed an anti-jamming method based on convolutional neural network, which effectively reduces the impact of noise and pulse number. At the same time, the influence of radar distribution on jamming discrimination under non-ideal conditions is mitigated [5]. Luo proposed a semi-supervised deception jamming discrimination method based on convolutional deep belief network, which lowers data requirements and enhances operational capability [6]. All these methods use various deep neural networks to address the technical bot-

tlenecks of the traditional echo signal processing process, such as insufficient feature extraction, single discrimination method, and information loss in the conversion process, in order to achieve effective discrimination of false targets.

However, the existing methods have common flaws that they all rely highly on big data volume and the performance is poor under non-ideal conditions. However, in the reality, it is difficult to collect the labelled data of the target and the interference discrimination cannot perform well when the SNR or sampling volume is low. To address the above issues, this paper focuses on constructing an end-to-end generative adversarial network and introduces a semi-supervised neural network training model from the perspective of learning the feature representation of the true distribution of the echo data. In this paper, a small amount of labelled data, a large amount of unlabelled data, and a large amount of pseudo-labelled data generated by the generator are used to train the discriminator. We borrow the idea from min-max game to help discriminate between the generator and the discriminator, the advantage of which is better performance of deceptive interference discrimination and robustness of the discrimination network, as well as less dependence of the network on the amount of data and improved effectiveness of small sample interference discrimination.

2 Signal Model

2.1 The Construction of A Multistatic Radar System Model

A multistatic radar system is composed with M transmitters and N receivers, and the transmitting signals of each transmitter are orthogonal to each other, as shown in Fig.1. Supposing that the transmitting signal of the m-th transmitting station is $S_m(t,q)$, $m=1,\ldots,M$, where t denotes the fast time domain, $0 \le t \le T$ (T stands for the length of time for a pulse repetition interval (PRI)), while q denotes the slow time domain, $q=1,2,\cdots,Q$ (Q equals the quantity of pulse repetition interval). Owing to the orthogonality of transmit signal, the target signal of a total of MN transmit-receive channel can be obtained by a matched filter set consisting of each transmit signal, where the channel consisting of the m-th transmitter to the n-th receiver ($n=1,\ldots,N$) is labelled as Channel-mn, the target echo signal of which is defined as $r_{mn}(t,q)$.

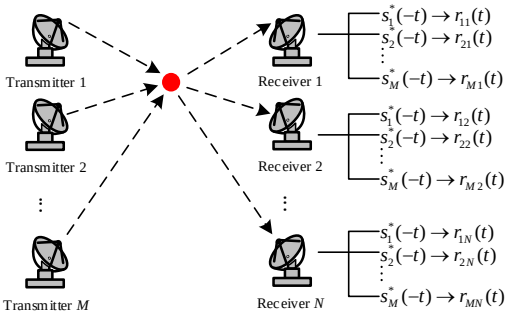


Fig. 1. Target detection channels of the multistatic radar system

Before the joint process of echo signals from each radar station in a multistatic radar, time and phase should be synchronized. The method of time synchronization is based on the unified time with reference to the multistatic radar, while phase synchronization is based on grid search to capture the target echoes from different radar stations in the same spatial resolution cell (SRC) for correlation identification.

Assuming that the target is equipped with a self-defense jammer, the received signal at each receiver $r_n(t,q)$ is the superposition of the real target signal $S_m(t,q)$, the jamming signal $J_m(t,q)$ and the noise signal $N_m(t,q)$:

$$r_n(t,q)=\sum_{m=1}^{M} r_{mn}(t,q)=\sum_{m=1}^{M}\left[S_m(t,q)+J_m(t,q)+N_m(t,q)\right] \tag{1}$$

Assuming that the real target obeys Swerlling-II undulation, assume α_n^q is the complex amplitude of the real target echo in the *q*-th PRI of the *n*-th receiver station, where α_n^q is a Gaussian distribution random variable with mean 0 and variance σ_n^2. For jamming signal, complex amplitudes in different pulse repetition intervals obey the same distribution and are independent of each other. Determined by the modulation method of the jammer, path attenuation and other factors, assume β_n^q is the complex amplitude of the false target captured by the *n*-th receiver. The noise signal is mutually independent complex Gaussian white signal $N_n(t,q)\sim CN\left(0,\sigma_{nk}^2\right)$, where σ_{nk}^2 denotes the variance of *n*-th echo's noise power.

2.2 Generation of Echo Data

After pulse compression of the echo by each receiver, considering the amount of sample data obtained by a single sampling of one PRI is too low to accurately describe the target characteristics, the slow time domain is detected to get multiple consecutive PRIs in the corresponding distance unit of the target, and use them as the signal vector of each radar station.

For unknown target echo, the sample data of real target is a complex Gaussian random vector with complex amplitudes component independent of each other, $\boldsymbol{\xi}^n=\left[\alpha_n^1,\alpha_n^2,\ldots,\alpha_n^q,\ldots,\alpha_n^Q\right]^{\mathrm{T}}$, where $\boldsymbol{\xi}^n\sim CN\left(0,\sigma_k^2\boldsymbol{I}_{Q\times Q}\right)$ and $[\bullet]^{\mathrm{T}}$ denotes matrix transposition operation. The sample data of the active false target is an unknown random vector $\boldsymbol{\xi}^n=\left[\beta_n^1,\beta_n^2,\ldots,\beta_n^q,\ldots,\beta_n^Q\right]^{\mathrm{T}}$, which is related to the amplitude modulation parameters of the interfering signal. With the noise existing, what can be obtained from the received signal is slow time complex envelope sequences mixed with noise sequence, where $\boldsymbol{N}^n\sim CN\left(0,\sigma_{nk}^2\boldsymbol{I}_{Q\times Q}\right)$ is noise signal sequence.

Finally, the slow time complex envelope sequences detected by receivers are sent into the multi-hidden layer network model to obtain the fusion centre's multidimensional and essential feature differences among different receivers for discrimination between true and false targets.

3 The Discrimination Network Based on SGAN

The training process of existing intelligent jamming adversarial methods relies on a large amount of labelled data. However, in real battlefield environments, the labelled data available for network training is limited. Therefore, this paper considers the construction of a semi-supervised generative adversarial network for jamming discrimination to improve battlefield operational performance.

In this paper, a SGAN model is constructed to obtain the multidimensional features of the received signals thus completing the discrimination of false targets. In semi-supervised GAN, we propagate data positively from the input layer to the output layer, and adjust the network structure parameters according to the error between the output and the input by a certain cost function, so that the output signal gradually approaches the label signal.

The input data of SGAN is made up with a combination of labelled real echoes and unlabelled generated data. For true target echoes, the data from different radar stations are linked horizontally after pre-processing (slow time complex envelope sampling) to build a data block and use it as a labelled input. The number of receiving stations N is set to be 4. Considering each input data block consists of $N*Q$ complex amplitude data, to facilitate the training of the network under different PRI conditions, the data block is then repeatedly expanded to a 40*40 data block, which is sent for supervised training.

The SGAN network uses a large amount of unsupervised data generated by the generator to enhance the discriminator's performance, in order to meet the output dimension matching the real echoes of a 40*40 block of data. Deconvolution is an inverse process of convolution (conv), thus scaling up the input dimension, where the input data of the generator is 5*5 noisy data passing through 3 inverse convolution layers, as is shown in Table I and Fig. 2. The output dimension is a simulated target echo signal of 40*40. The generator generates echo data that is highly similar to the real data and uses the unlabelled data to assist in the training of the discriminator. At the same time, the discriminator improves the imitation capability of the generator, which in turn improves the SGAN echo discrimination performance.

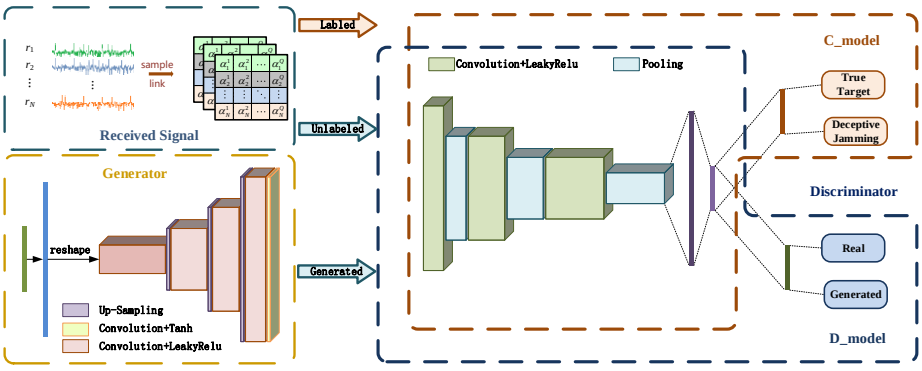


Fig. 2. Jamming Discrimination Network based on SGAN in Fusion Center

Table 1. The structure of SGAN

	Type	Number	Filter	Step
Generator	Conv 1	256	3*3	2
	Conv 2	128	3*3	2
	Conv 3	64	3*3	2
	Type	Number	Filter	Step
Discriminator	Deconv 1	64	4*4	2
	Deconv 2	128	4*4	2
	Deconv 3	256	4*4	2
	fc 1	Number	6400	
	fc 2	Number	2	
	C_Model	Activation Function	softmax	
	D_Model	Activation Function	sigmoid	

For the discriminator, two output layers are included, one for the unsupervised task and the other for the supervised task. They share the same feature extraction layer. The feature extraction layers constructed in this paper are 3 convolutional layers, the output of each convolutional layer containing a pooling operation with a step size of 2. The results of the convolutional part are passed into two fully connected layers and all outputs are normalized by batch processing. Ultimately, after 5 layers of operations, multidimensional essential features are extracted from the constructed block of data for echo discrimination. There are always two output predictions for each input data. One is a real/generated prediction, constructed as a C_model together with a feature extraction layer to predict whether the input data is true or false. A sigmoid activation function is used in the output layer and optimized using a binary cross entropy loss function. An output for supervised category prediction is constructed together with a feature extraction layer as D_model to predict the category of a given model. A softmax activation function is used in the output layer as well using the categorical cross entropy loss function for optimization. Although C_model and D_model have different output layers, they share all the feature extraction layers. This means that updates to one of the networks will affect both models[7]-[8].

During training, the discriminator is trained on the network parameters by the unlabelled data generated by the generator together with the labelled data captured by the radar. The echo data are all simulated, set to a target noise ratio TNR range of -3 to 18 dB (TNR for real targets is the signal noise ratio SNR and TNR for fake targets is the interference noise ratio JNR) and PRI range of 4 to 24. Each TNR and PRI generates a large amount of training data for each of the target and interference respectively according to the same other parameters. 10% of the data is used for C_model network training, and the remaining 90% of the unlabelled data is used for D_model network training along with the pseudo-echo data generated by generators.

During testing, each TNR and PRI generates 1000 sets of training samples for each of the target and interference respectively according to the same other parameters. The test samples are fed into the trained SGAN model using a multi-dimensional essential feature vector for interference discrimination.

4 Simulation

4.1 Simulation Analysis

All methods are tested on the same computer, Intel(R) Xeon(R) Gold 5218 CPU @ 2.30GHz 64-core, GeForce RTX 2080 TI. In contrast with the experiments in the references, the results and analysis are as follows.

Table 2. Discrimination probability of different algorithms

Methods	Traditional method	DNN	CNN	CDBN	SGAN
Discrimination probability	75.4%	98.9%	99.2%	91.3%	99.1%

When PRI is set to be 12 and SNR is set to be 6, the simulation result is listed in Table II. The jamming discrimination effect based on SGAN with 10% labelled date, it is significantly better than the discrimination method using only single feature of manually extracted (the Traditional method [9]), indicating that SGAN network can extract the multi-dimensional essential features of signal data and jointly apply to the discrimination of real and false targets. Meanwhile, compared to DNNs [10] and CNNs [5] using 20,000 labelled data for training, SGAN's interference discrimination accuracy remains essentially the same, but with a 90% reduction in the number of labels required. Meanwhile, in contrast to semi-supervised CDBN's [6] 91.3% discrimination accuracy with the same labelled data, the SGAN interference discrimination algorithm's discrimination performance improves a lot.

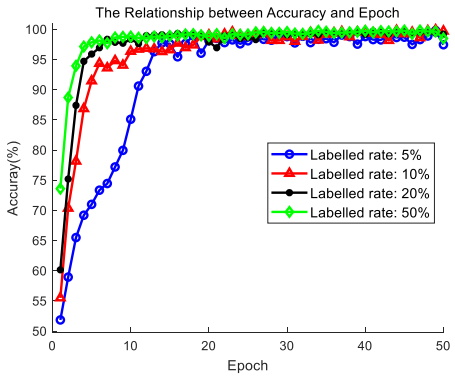


Fig. 3. Acc curves with different labeled data volumes

With the same parameter settings as above, Fig. 3 demonstrates the relationship between accuracy and epoch. SGAN algorithm improves the discrimination probability for different ratios of labeled data rapidly, as epoch increases eventually reaching over an accuracy higher than 98%. These experiments demonstrate the effectiveness of the proposed SGAN interference discrimination network. However, the increase in la-

belled rate leads to a faster increase in discrimination probability and ultimately a steadier result. A 5% label rate is less stable after multiple training rounds due to the small number of available labels. A label rate of 10% is able to guarantee a stable discrimination probability of greater than 99%, so this paper suggests using more than 10% of labels for the training of semi-supervised GAN interference discrimination networks to reduce the data dependency of the intelligent algorithm while ensuring the discrimination performance.

4.2 Simulation Results with Different PRI

Other parameters consistent with section 4.1, by varying SNR and PRI, the simulation validates the effect of the number of pulses on the false target identification performance. The range of TNR is set between -3dB and 18dB, and obtaining the target identification probability through the constructed SGAN model at different number of pulses, where the number of PRI Q varies from 4 to 20 with a stride of 4.

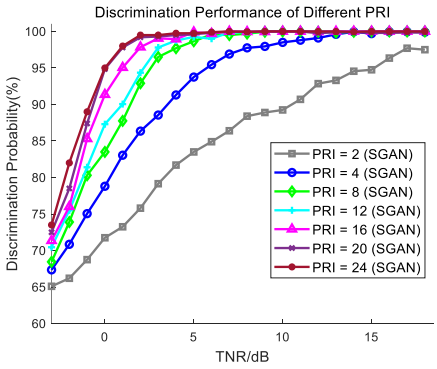
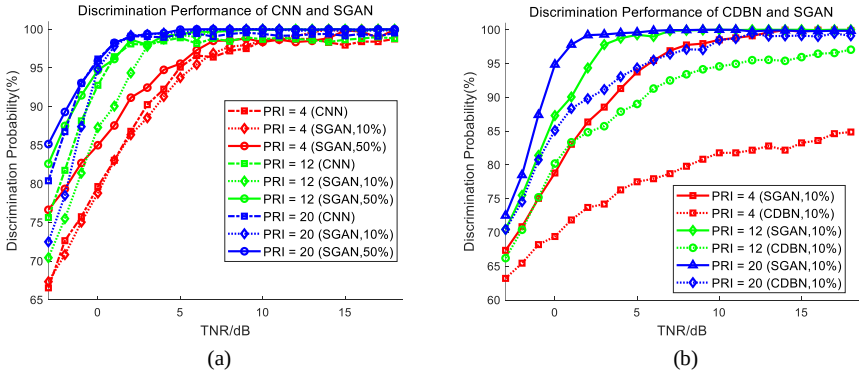


Fig. 4. The effect of the different TNR and PRI



(a) (b)

Fig. 5. The comparison of CNN, CDBN and SGAN. (a) The comparison of jamming discrimination effects between CNN and SGAN. (b) The comparison of jamming discrimination effects between CDBN and SGAN

As shown in Fig. 4, as the number of pulses PRI increases, the discrimination probability improves significantly for that the more samples used for interference discrimination in each group, the more information the deep neural network can use for reference, effectively improving the discrimination performance. When the amount of information satisfies the discrimination requirements, the discrimination probability tends to smooth out and no longer varies with PRI.

At the same time, as the TNR increases, the discrimination probability increases significantly, because the increase of TNR will reduce the influence of noise on the echo signal. The network can more easily obtain the essential characteristics of the real target or active deceptive interference, thus improving the performance of discrimination. Comparing with the literature [9], the above experiments demonstrate that the SGAN interference discrimination algorithm is able to guarantee interference discrimination performance under different PRI conditions.

4.3 The Comparison of Different Discrimination Methods

Compared with CNN jamming discrimination methods under the same condition, Fig. 5(a) simulation results reveals that the algorithm in this paper with 10% labelled data is slightly worse than CNN at low TNR. However, when TNR is greater than 0dB, the discrimination probability of the two methods converges and are greater than 99% eventually. Also, when the proportion of labelled data is increased to 50%, the SGAN discrimination network can significantly outperform the fully supervised CNN discrimination network. The above comparison experiments are sufficient to demonstrate that the SGAN network is superior to existing CNN interference discrimination algorithms.

As shown in Fig. 5(b), the algorithm is able to guarantee a significant improvement in discrimination performance with the same label rate compared to the same semi-supervised CDBN interference discrimination algorithm. This experiment demonstrates that the SGAN network is a robust interference discrimination method that outperforms the CDBN semi-supervised interference discrimination network in different environments.

5 Conclusion

A semi-supervised GAN method for jamming discrimination of multi-base radar systems is put forward in this paper, specifically addressing the drawbacks of insufficient labelled samples on deceptive jamming discrimination network. The network uses a small amount of labelled data, a large amount of unlabelled data obtained from reality and pseudo-labelled data generated by generators to train the discriminator. The pseudo-labelled data reduces the dependence of the interference discrimination network on the amount of data, thus improving the robustness and universality of the discrimination performance under small sample conditions. Simulation results show that the method can achieve the same performance as CNN with 10% of the labelled data, much better than the performance of CDBN network with the same rate, compared with existing artificial intelligence interference identification methods that require

tens of thousands of labelled data for network training. At the same time, this method significantly outperforms the original CNN interference discrimination method at 50% of the labelled data. The experiments demonstrate that this method lowers down data requirements, enhances the practicality of network construction, and is more suitable for real-world battlefield environments.

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References

1. H. Griffiths.: Multistatic, MIMO and networked radar: The future of radar sensors?. In: The 7th European Radar Conference, pp. 81-84 (2010).
2. H. Godrich, A. M. Haimovich and R. S. Blum.: Target Localization Accuracy Gain in MIMO Radar-Based Systems. IEEE Transactions on Information Theory, 56(6), 2783-2803 (2010).
3. Y. Gao, H. Li and B. Himed.: Knowledge-Aided Range-Spread Target Detection for Distributed MIMO Radar in Nonhomogeneous Environments. IEEE Transactions on Signal Processing, 65(3), 617-627 (2017).
4. A. Abdalla, Z. Yuan and B. Tang.: ECCM schemes in netted radar system based on temporal pulse diversity. Journal of Systems Engineering and Electronics, 27(5), 1001-1009 (2016).
5. J. Liu, M. Gong, M. Zhang, H. Li and S. Zhao.: An anti-jamming method in multistatic radar system based on convolutional neural network. IET Signal Process, 1-12 (2021).
6. H. Luo, J. Liu, S. Wu, Z. Nie, H. Li and J. Wu.: A Semi-Supervised Deception Jamming Discrimination Method. In: 2021 IEEE 7th International Conference on Cloud Computing and Intelligent Systems (CCIS), pp. 428-432. (2021).
7. Prabhat, Nishant and D. Kumar Vishwakarma.: Comparative Analysis of Deep Convolutional Generative Adversarial Network and Conditional Generative Adversarial Network using Hand Written Digits. In 2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS), pp. 1072-1075. (2020).
8. I. J. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville and Y. Bengio.: Generative adversarial nets. Advances in Neural Information Processing Systems 27 (NIPS 2014), pp.2672-2680. (2014).
9. S. Zhao, L. Zhang, Y. Zhou, N. Liu and J. Liu.: Discrimination of active false targets in multistatic radar using spatial scattering properties. IET Radar Sonar & Navigation, 10(5), 817-826 (2016).
10. J. Liu, M. Gong, M. Zhang, T. Zhan, H. Li and M. Zhang.: Method for discrimination of false targets in multistation radar systems based on the deep neural network. Journal of Xidian University, 48(2), 133-138 (2021).