Super Resolution of Wind Data Using Generative Adversarial Networks

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***Abstract*—This report presents an innovative approach for enhancing the resolution of low-resolution (LR) wind velocity data, using Generative Adversarial Network (GAN). GANs are proved to be better performers in enhancing the resolution of images when compared to other deep learning models based on CNN. Our implementation employs a GAN based on a customized version of the SRGAN i.e., PhIREGAN network designed for wind data. Moreover, we have modified the training approach by integrating *The Kolmogorov Law of Turbulence* into loss function. The outcomes from our modified training approach has shown significant improvement, particularly in terms of Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Metric (SSIM) and Energy Spectral characteristics.**

***Index Terms*—Generative Adversarial Network(GAN), The Kolmogorov Law of Turbulence,Physics Informed Resolution Enhancing GAN (PhIREGAN), Super Resolution Generative Adversarial Network(SRGAN).**

I. INTRODUCTION

Accurate High Resolution (HR) data is essential for optimal resource planning. The data produced by the Global Climate Model(GCM)[1] has the resolution of around 1^o or close to 100km. Such a low resolution is not sufficient to accurately assess renewable energy resources, which typically require resolution finer than 10 km, preferably 2 km. As a result, there is a great need for physically accurate methods to improve the resolution of GCM output for studying the impact of energy on different climatic conditions.
In order to decrease the cost of generating HR data, various Machine Learning (ML) techniques have been implemented as part of GCMs. The deep learning model, PhIREGAN (Physics Informed Resolution Enhancing GAN)[1] is used for generating HR data, which is said to learn the spatial characteristics in the data and produce outputs that are realistic to the actual data. In this paper, we present a method of generating HR climate data by enhancing wind GCM outputs using the modified version of PhIREGAN. The proposed method produces high-quality images using adversarial training that learns and preserves physically relevant characteristics.

A. Contributions of the work:

→We modified the training approach of existing PhIREGAN model by integrating Kolomogorov law of turbulence into our loss function.
→This modified training approach enhanced the SSIM, PSNR and Energy spectrum performance compared to existing PhIREGAN model.

II. PROPOSED METHODS

A. Architecture

The architecture of PhIREGAN is similar to the state-of-art SRGAN[4] with several modifications. The Generator network is a deep fully convolutional neural network with 16 residual blocks along with skip connections. All kernels of convolutional layers are 3×3 and are followed by ReLU activation functions. Through experimentation, it was discovered that removing batch normalization layers from the SRGAN architecture was necessary. These layers were found to obstruct the network's capacity to effectively transfer data. The GAN structure in Fig.1, which consists of a generator and a discriminator, is implemented.
The discriminator network consists of eight convolutional layers, each followed by leaky rectified linear unit (ReLU) activations with a negative slope (alpha) of 0.2. After the convolutional layers, the tensor is flattened, and two fully connected layers follow, with the first having 1024 units and the second producing a single output for binary classification. The activation functions used throughout the network are leaky ReLUs. The Generator network is trained against the Discriminator network and vice-versa, iteratively, and as the training progresses, more realistic images are produced by generator, while the discriminator improves in differentiating between real and fake data. This adversarial approach is similar to minmax optimization problem,

$$\min_G \max_D E[\log(D(y))] + E[\log(1 - D(G(x)))]...[1]$$

B. Loss Functions

1) Generator Loss: The loss function of the generator is designed considering three aspects: first, the adversarial process between the generator and discriminator, second, the features contained in the SR image, and third, the Kolmogorov loss. Generator Loss function is as follows:

$$G_{Loss} = L_{Adv} + (\alpha)L_{Content} + (\beta)L_{Kol}$$

where L_{Adv} represents the adversarial loss[1] between the generator and discriminator , α = 0.01 and β = 0.1. It is defined as:

$$L_{Adv} = E[\log(1 - D(G(x)))] \sim -\log(D(y))$$

The content loss[1] is a way of measuring how closely the generated high-resolution image matches the actual high-resolution image. It is done by calculating the average squared difference between corresponding pixels in the two images and is given by:

$$L_{Content} = ||y - G(x)||_2^2$$

Kolmogorov loss:
Kolmogorov -5/3 law : The 5/3's law states that, in some inertial range [k1,k2], the energy density of the flow E(k) behaves like $Ck^{-5/3}$,where k denotes the current wave number.[3]

$$E \propto k^{-5/3}$$

$$E = Ck^{-5/3}$$

$$\log(E) = \log(C) - \frac{5}{3}\log(k)$$

$$\frac{dE}{dk} = -\frac{5}{3}\frac{E}{k}$$

Energy Spectrum (E) is obtained by taking fourier transform of image and squaring the fourier amplitudes. Wave numbers (k) represent spatial frequencies, with each point in the frequency domain corresponding to a unique wave number. Then we perform categorizing or binning fourier amplitudes into intervals corresponding to different wave number ranges. The mean amplitude in each bin represents average energy at the wave number. The Kolmogorov loss is a way of measuring how well the generated image is able to capture the spectral characteristics of the actual ground truth data. It is calculated as:

$$L_k = 1/N * \sum_{i=1}^{N}(\frac{dE_{HR}}{dK_i} - \frac{dE_{SR}}{dK_i})^2$$

2) Discriminator Loss: It is given by:

$$L_D(x, y) = -\log(D(y)) - \log(D(G(x)))...[1]$$

III. Data Set

Wind data for ML training is derived from NREL's wtk-us.h5 dataset using HSDS. It includes wind speed and direction at 100 meters above the US. High resolution (HR) grids are extracted per time step, and low resolution (LR) grids are created by subsampling HR data. LR and HR wind components are organized into smaller grids, generating PNG images for training. Data is then converted into tensorflow TFRecord format for efficient processing during training.[1][2]

IV. Experiments and Results

A. Training:

We used two-step training, LR to MR and then MR to HR. In first step, We train a network to get 2x resolution enhancements of LR data i.e., from 10x10 to 20x20 pixel resolution. Then we use another network to increase resolution from 20x20 to 100x100 [1]. As SR involves adding huge number of pixels to LR image, it is difficult for single network to reduce difficulty involved in obtaining gain of 10x super resolution while learning complex underlying distributions and physical characteristics. So we split the training part into two steps. Networks are trained using adversarial approach (GAN approach). We used modified form of loss functions from PhIREGAN model training process where we added new loss component call Kolmogorov loss to make images more consistent with Kolmogorov law of Turbulence[3]. We trained model iteratively for 10240 images while optimizing the loss value and using the hyper-parameters as mentioned in table 4.

B. Evaluation Metrics

1) Structure Similarity: SSIM, determines how structurally similar the SR and HR images. It depicts distortion as a combination of three distinct elements, brightness, contrast, and structure.[2] The SSIM is defined as:

$$SSIM(X, F) = \frac{2\mu_X\mu_F}{\mu_X^2 + \mu_F^2} \cdot \frac{2\sigma_X\sigma_F}{\sigma_X^2 + \sigma_F^2} \cdot \frac{\sigma_{XF}}{\sigma_X\sigma_F}$$

where μ and σ represent the mean and standard variance of the image patch. σ_{XF} displays the usual covariance correlation between the SR and HR image. As SSIM approaches 1, the picture quality gets better.
2) Peak Signal-to-Noise Ratio: Peak signal-to-noise ratio (PSNR) is the ratio between the maximum possible power of an image and the power of corrupting noise that affects the quality.[2] PSNR is defined as follows:

$$PSNR = 10\log_{10}\left(\frac{L^2}{MSE}\right) = 20\log_{10}\left(\frac{L}{\sqrt{MSE}}\right)$$

Here, L is the number of maximum possible intensity levels (minimum intensity level suppose to be 0) in an image.[1]

MSE is the mean squared error and it is defined as:

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}(O(i, j) - D(i, j))^2$$

where, O,D represents the matrix data of Ground truth, generated images respectively. Here m ,i ,n and j represents the numbers of rows of pixels, the index of that row of the image, the number of columns of pixels and the index of that column of the image respectively. The larger the value of PSNR, the more closer the SR image to the Ground truth image. The PSNR range between 25 and 30 is said to be fair.

C. Results

MODEL	PSNR ↑	SSIM ↑
PhIREGAN	28.66	0.32
modified PhIREGAN	**29.19**	**0.34**

TABLE I
Summary of average metric values

From table 1 ,2 and 3 it is clear that our training approach has outperformed the existing PhIREGAN in terms of both PSNR and SSIM. Also from figure 5 we can observe that, compared to existing PhIREGAN model, our model closely matches the actual spectral characteristics .

V. CONCLUSION

GAN models, such as PhIREGAN, are best suited for enhancing the resolution of wind data. Adversarial training helps the models learn complex high-frequency patterns in images and also understand physical characteristics. We implemented the PhIREGAN model on the WIND dataset and modified its training process by adding a Kolmogorov loss term to the loss functions. This improved the model's ability to learn energy spectrum features of wind data, resulting in more realistic SR images that follow the laws of wind flow. Additionally, we observed an improvement in the performance of our model when evaluated using metrics such as SSIM as shown in table 2 and PSNR as shown in table 3. Perfomance of this model can be further improved by training on more number of images and increasing number of epochs.

REFERENCES

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VI. APPENDIX

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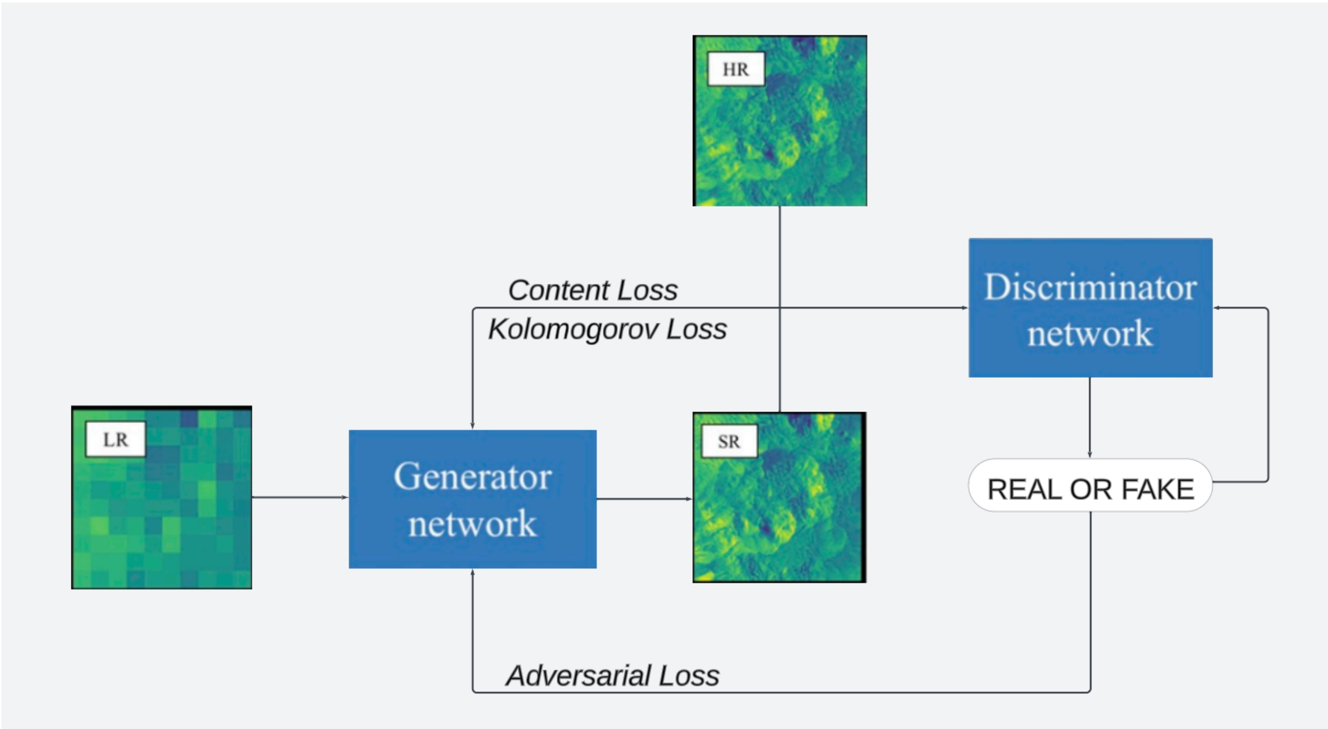

Fig. 1. Schematic of GANs for Super Resolution

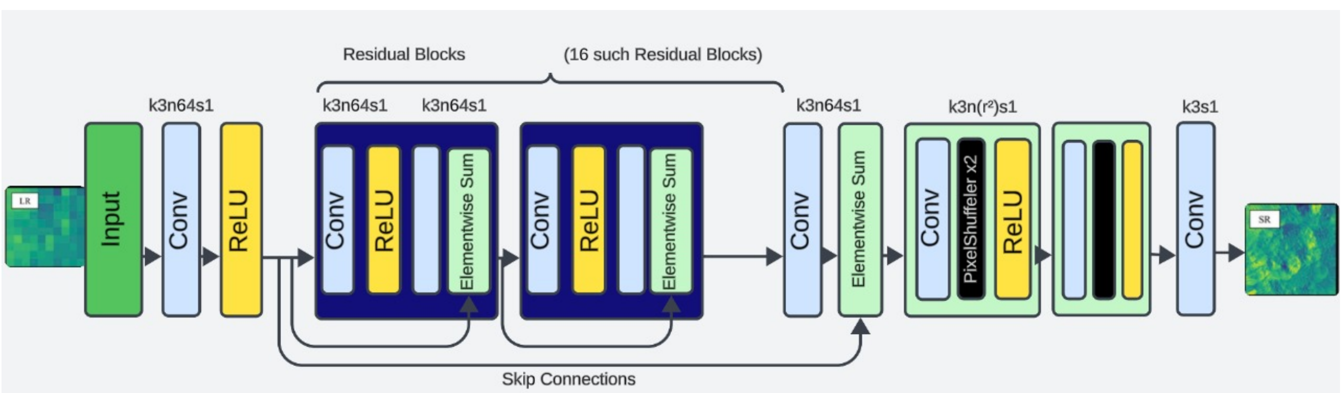

Fig. 2. Architecture of the generator.

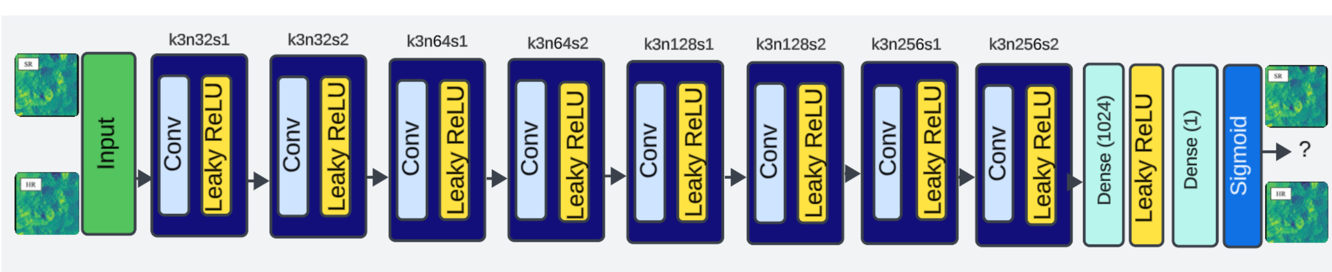

Fig. 3. Architecture of the discriminator.

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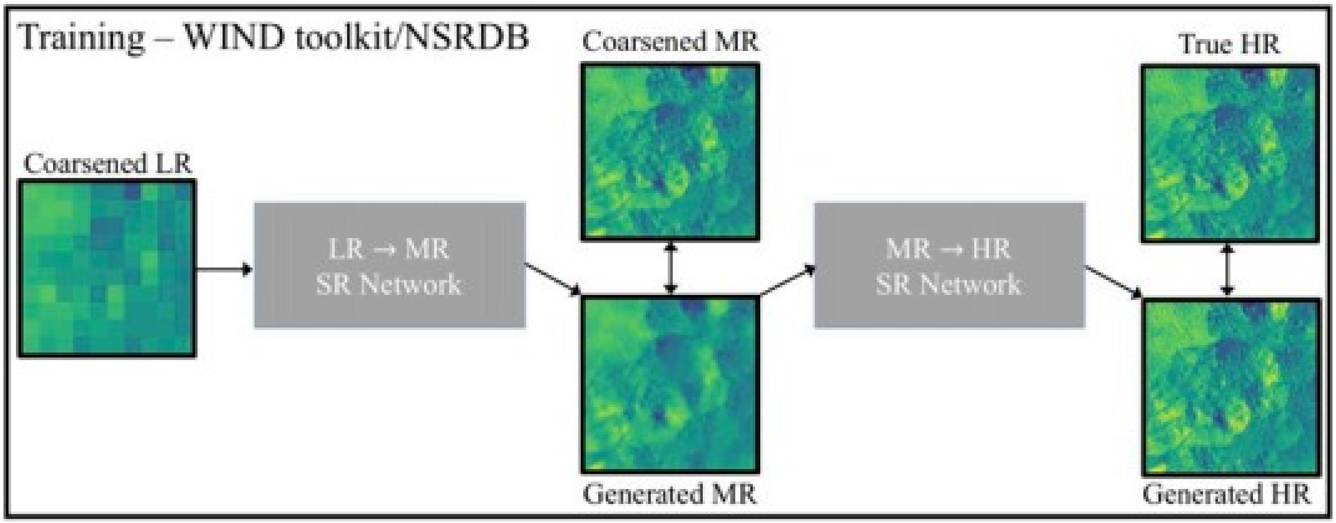

Fig. 4. Two step Training Process

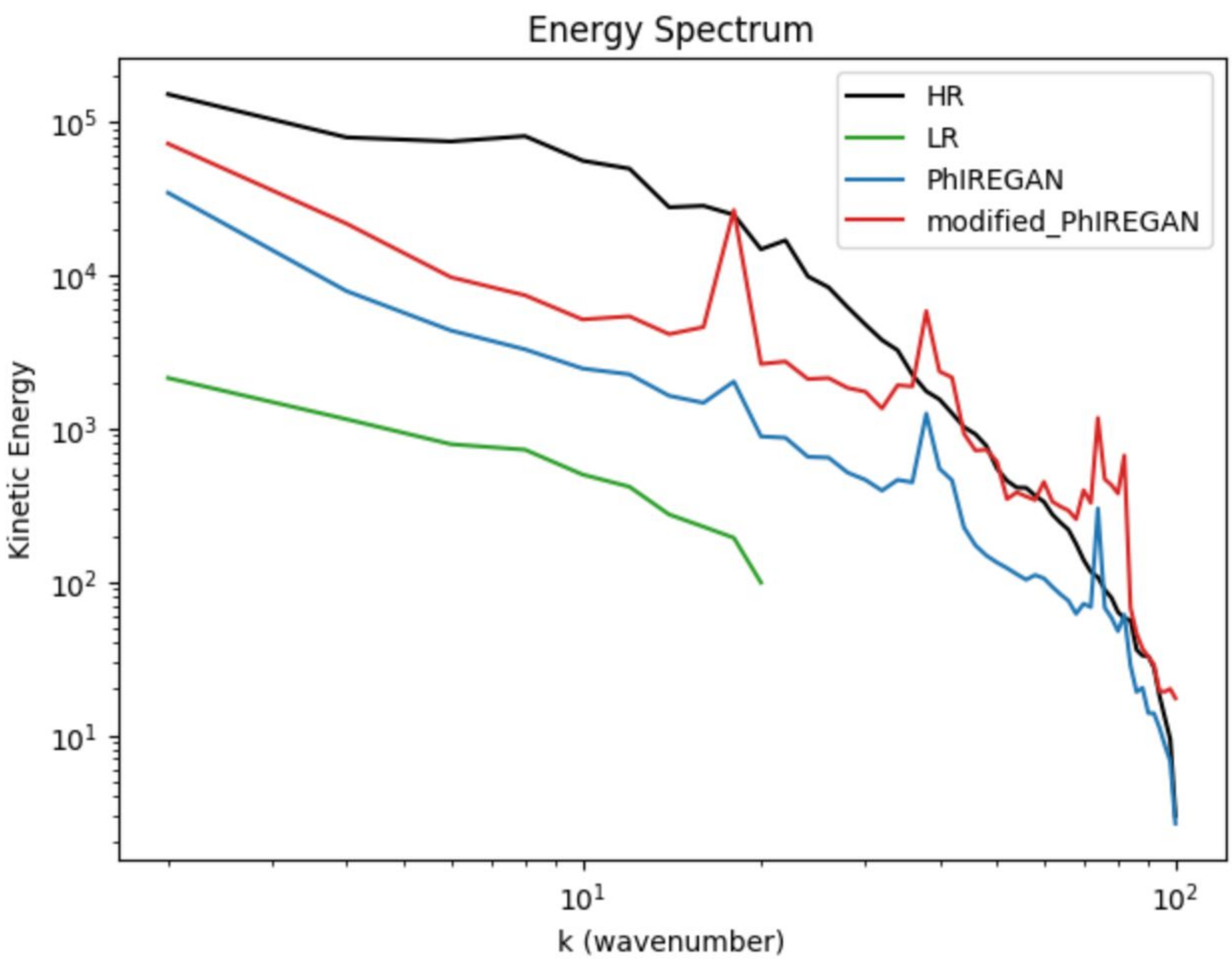

Fig. 5. Energy Spectrum

Model	Count	Mean	Std	Min	25%	50%	75%	Max
Phiregan	512.000	0.326971	0.095316	0.111003	0.260149	0.320631	0.393466	0.679266
Modified PhIREGAN	512.000	0.342373	0.101341	0.110963	0.267343	0.339107	0.416598	0.727428

TABLE II
SUMMARY STATISTICS FOR SSIM VALUES

Model	Count	Mean	Std	Min	25%	50%	75%	Max
Phiregan	512.000	28.664554	0.414457	27.792197	28.381619	28.626888	28.899795	29.942152
Modified PhIREGAN	512.000	29.199558	0.409768	28.295579	28.905975	29.153864	29.472500	30.693748

TABLE III
SUMMARY STATISTICS FOR PSNR VALUES

Parameters and Hyper Parameters	Values
Train data set	10240 Images
Test data set	512 images
LR dimensions	10 x 10
MR dimensions	20 x 20
HR dimensions	100 x 100
Learning Rate	0.001
Batch size	50
Epochs	50
Estimated processing time	10 hours
Optimiser	Adam

TABLE IV
PARAMETERS AND HYPER PARAMETERS