**Signal Dependent Noise Robust General Adversarial Networks**

Signal Dependent NRGANs are used to train neural networks where the training data has a noise that changes with the pixel by pixel values of the image. This makes it a much more complex distribution and hence more difficult to train, unlike its signal independent counterpart where all the noises are random irrespective on the input vector. Ambient GANs and NR-GANs both are able to use signal dependent noised images. Ambient GAN requires prior knowledge about the noise distribution type, signal-noise relationship, and noise amount. This makes it less flexible. NRGANs do not require all three of the fore mentioned parameters to function well. This makes them much more flexible on images with less information.

**“Assumption 1 (i) The noise n is conditionally pixel-wise independent given the signal x. (ii) The noise distribution type (e.g., Gaussian) is priorly known. Note that the noise amount need not to be known. (iii) The signal x does not follow the defined noise distribution.”[1]**

**“Assumption 2 (i) The noise n is rotation, channel-shuffle, or color-inverse-invariant. (ii) The signal x is rotation, channel-shuffle, or color-inverse-variant.”[1]**

**“Assumption 3 The signal-noise relationship is priorly known. Note that the noise amount needs not be known.”[1]**

**SD-NR-GAN-I**

The first and third assumption hold for SI-NR-GAN-II. The third assumption says we have the signal-noise relationship of the images. This unlike Ambient GANs lesser number of information about the data and hence is more flexible.

A signal noise relational procedure is incorporated into SI-NR-GAN-I explicitly to produce SD-NR-GAN-I. Two special configurations are handled-Multiplicative Gaussian Noise and Poisson Noise.

Multiplicative-Gaussian Noise

y = x + n, where n ∼ N (0, diag(σ · x) 2 )

σ is generated using the noise generator. Then a signal-noise relational function R is used and reparameterization is done as in SI-NR-GAN1. The noise amount σ is trainable which helps it handle signal dependent noise.

**SD-NR-GAN-II**

Assumption 1 holds while Assumption 3 doesn’t have to hold. We plan to learn the signal-noise relational function implicitly. This is an extension of SI-NR-GAN-I with the image latent vector input to both the image generator and the noise generator. We then use the reparameterization trick .

SD-NR-GAN-II can internally learn R(x, σ) hence can also be used for signal-independent noise and combination of multiple noises.

R(x,σd,σi) = σd · x + σi

**SD-NR-GAN-III**

In this case both the noise distribution and signal noise relationship are not known. This makes it the most flexible NRGAN which requires no information about the error in the training data. An assumption similar to 2nd assumption is made. Rotation and channel shuffle cannot be used for signal dependent noise. Hence 2nd assumption holds only for colour inversion.

SD-NR-GAN-III learns the signal-noise relationship implicitly by making the noise generator take the image latent vector. Similar to SI-NR-GAN-I, a transformation constraint on Gn. The transformation constraint T is defined as colour inversion. The noise origin is learnt through training. Hence SD-NR-GAN-III can be used for all types of noises without modification in the model. This makes it the most noise robust and flexible GAN.

nˆ = Gn(zn, zx)

n = T(nˆ)

