

1 We thank the reviewers for their careful review and insightful comments. We address the comments in the following.

2 **Limited nature of the contribution:**

3 Through this work, our primary goal is to demonstrate that statistics of natural scenes, and the ability of IQA algorithms
4 to quantify the naturalness of a scene have an important role to play in the generative modeling of natural images. The
5 WGAN-GP framework provides us a good setting to convey our idea effectively. Nevertheless, we believe that the core
6 idea of imposing a “naturalness” constraint in generating natural scenes would be effective wherever the discriminator
7 function is smooth. This includes the 1-Lipschitz functions in WGAN-GP and PGGAN, hinge-loss objective function
8 based Self-attention GAN and Spectrally normalized GAN, CT-GAN and WGAN-LP etc. Also, since we impose no
9 constraints on the generator, we expect it to work well in the conditional GAN setting too.

10 To further justify our claim and implement reviewer suggestions, we have applied the proposed regularizers to the
11 PGGAN architecture (both original and growing) at resolutions of 128×128 and 256×256 on the CelebA dataset, and
12 show the results in Fig. 1. Interestingly and importantly, we observed that the proposed regularizers resulted in faster
13 convergence and improved visual quality of the generated images. We hope that these results also address concerns
14 about the effectiveness of QAGANs at higher resolutions. While memory and time constraints limited our testing to a
resolution of 256×256 and 6K iterations, we are optimistic that our method would work at higher resolutions as well.



Figure 1: Top: 128×128 . Bottom: 256×256 . Left: PGGAN, $FID_{128 \times 128} = 64.50$, $FID_{256 \times 256} = 62.86$. Center: PGGAN with SSIM, $FID_{128 \times 128} = 47.46$, $FID_{256 \times 256} = 38.324$. Right: PGGAN with NIQE, $FID_{128 \times 128} = 49.80$, $FID_{256 \times 256} = 44.84$. These are results after 6K iterations on the CelebA dataset.

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16 **Comparison with the work by Kancharla and Channappayya, ICIIP 2018 [Kancharla2018]:**

17 While their work is similar in spirit, we present several fundamental differences in the following. First, our work clearly
18 discusses the issues with the direct application of IQA algorithms as cost functions and proposes novel perceptual quality
19 regularizers that are fine-tuned to the GAN framework - either that nicely fit the GAN math framework (SSIM-based)
20 or that capture/model the local statistics of discriminator gradients (NIQE-based). Kancharla2018 on the other hand
21 does a straightforward application of the MS-SSIM index and uses NIQE only for performance evaluation and not
22 as a cost function. Next, our work presents a systematic stability analysis in the WGAN-GP setting and guarantees
23 stability (please see supplementary material) while Kancharla2018 only presents empirical analysis. Also, they mention
24 instabilities when the MS-SSIM term is given higher weightage. Further, we have conducted detailed experimental
25 analysis and validation in our work. Finally, a qualitative comparison is shown in Fig. 2 from which it is clear that our
26 method not only generates images with better structural information but also has greater diversity. This can be attributed
to two main factors: our quality based regularizers and the improvements due to WGAN-GP relative to BEGAN.



Figure 2: Left image: Montage from Kancharla2018 (permission obtained from IEEE), with $FID = 205$. Right image: Montage from QAGAN with NIQE with $FID = 86$ (50K iterations). Note improved structural information and diversity.

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28 **Clarifications:**

29 - We do not intend to portray that the SSIM index has not been used as a cost function in the literature. Rather, what we
30 want to convey is that while IQA algorithms are indeed very effective, their usage as cost functions has not been as
31 widespread as one would like due to their typically unwieldy mathematical formulation.

32 - Since the SSIM index can be negative, it no longer satisfies the requirement of a metric in the mathematical sense (i.e.,
33 $x, y \in \mathcal{X}$ for some set \mathcal{X} , $d(x, y) \geq 0$). We do not imply that the boundedness renders it an invalid metric.

34 - WGAN-GP uses the average of the error norm between the real and fake samples (without correspondence) as one of
35 the elements of the cost function (Proposition 1, primal form in [Gul+17]). We reason that d^Q would be a better choice
36 than error norm (in the average sense) for measuring the *perceptual distance* between the real and fake image sets. We
37 also observed that average $d^Q(X, Y)$ values reduce with iterations.

38 - We have presented a convergence/stability analysis (for any $\lambda > 0$) of the proposed regularizers in the supplementary
39 material provided with the initial submission. We point the reviewer to Sections 1 and 3 in that document.

40 - The λ s were not tuned individually for FID and IS results. There were no stability issues with variation in λ s.
41 Nevertheless, our choice of λ s is based on performance.

42 - We will incorporate presentation improvements in the final version if the submission is accepted.

43 Again, we thank the reviewers for their insightful comments that has led to important discussions and clarifications.