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Hyperparameter Landscape Smoothing Algorithms For Stable Training Of Gans

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Abstract

It has been demonstrated that Generative Adversarial Networks (GANs) have made tremendous progress in generating synthetic images, but still, the adversarial optimization comes with many problems such as unstable training, mode collapse, and oscillatory convergence. To achieve stable training, the researchers in this article have proposed the Hyperparameter Landscape Smoothing GAN (HLS-GAN) framework that adaptively smooths the optimization trajectory based on the hyperparameter landscapes generated by the parameters. The proposed model is able to dynamically control the variation of gradients and stabilize the generator-discriminator interaction during training. The experimental analysis was carried out with the MNIST dataset of 70,000 handwritten digit images. A set of metrics to evaluate the framework, such as Fréchet Inception Distance (FID), Inception Score (IS), convergence variance, and training stability, were used. The experimental results showed that the proposed HLS-GAN achieved the FID score of 18.7 and the Inception Score of 8.1, which is better than conventional GAN, DCGAN, and WGAN. Moreover, the proposed smoothing mechanism decreased loss variance from 0.82 to 0.23, so that it had better convergence consistency without gradient oscillation. Mode collapse events were minimized, and structure was clearer in the produced handwritten digit samples. In conclusion, the proposed Hyperparameter Landscape Smoothing framework offers a computationally stable and efficient deep learning optimization method to better control the convergence reliability and synthetic image generation quality of GANs.

Keywords - GAN Stability, Hyperparameter Smoothing, Deep Learning, Generative Adversarial Networks, MNIST Dataset, Optimization Framework.

1. Introduction

Among the most impactful deep learning models for generating synthetic data and intelligent content creation and image synthesis is Generative Adversarial Networks (GANs). The latest developments in hyperparameter optimization have led to the improvement of the performance of GANs, which allows the system to adaptively train and converge efficiently [1]. Nowadays, GANs are used in a variety of applications, including realistic face aging, synthetic medical image generation, molecular design, and image restoration systems [3]. Moreover, the effective utilization of modern generative AI approaches has significantly boosted the speed of data-driven learning systems and advanced the capability of computational intelligence systems for complex optimization problems [2]. Stable adversarial learning models are becoming more important in the modern AI ecosystems as the use of generative AI is growing in high-performance computing and intelligent system architectures [10].

As incredible as the abilities of GANs are, one of the biggest difficulties is having the ability to train them consistently. The training of GANs can occasionally produce mode collapse, gradient instability, oscillatory convergence, and sensitivity to hyperparameter selection. Although there are current regularization and normalization methods that partially stabilize training, do not always allow smoothing out abrupt changes in the optimization process in the hyperparameter space [6]. Furthermore, existing GAN optimization techniques have no adaptive procedures to dynamically adjust the training courses in different adversarial settings [9]. These constraints have a negative impact on the generative quality and add complexity to computation, especially in generative high-dimensional synthetic data tasks [11]. Hence, it is crucial to build an efficient hyperparameter landscape smoothing framework that allows GAN optimization to be stabilized while still maintaining a high-quality image synthesis performance[12].

Research Objectives

1) To create a Hyperparameter Landscape Smoothing (HLS) algorithm for stable GAN training dynamics.
2) To study the effect of adaptive smoothing methods on the convergence stability and reduce the gradient variance of GANs.
3) To test the performance of the proposed HLS-GAN framework in terms of FID score, convergence stability, and training efficiency with the MNIST dataset.

Paper Organization

The rest of this paper is structured as follows: In Section 1, introduction and research motivation are provided. The literature review and research gap is discussed in Section 2. The proposed methodology and Hyperparameter Landscape Smoothing framework are presented in Section 3. Experimental results and discussion, using the MNIST dataset, are given in Section 4. Finally, in Section 5 the paper is concluded, and some directions of future research are given.

2. Literature Review

Hyperparameter tuning and adversarial stability enhancement are the two main areas of study that have received much attention in recent years when it comes to GAN optimization. To reduce the convergence time of GANs, Rodrigues and Pinheiro developed a Gaussian Analytic Hierarchy Process (AHP)-based hyperparameter optimization framework that used a structured approach in selecting the hyperparameters of the GANs to enhance the convergence process [1]. In that way, Yadav and Sachdeo have proposed an optimal hyperparameter tuning CycleGAN model for photorealistic face age progression, which has improved generative quality and training consistency [3]. After an extensive survey of the regularization and normalization methods in the GANs, Li et al. found that gradient stabilization is one of the most important issues when it comes to adversarial convergence [6]. All the above studies conclude that adaptive optimization methods for stable GAN training are crucial.

GANs also have been successfully combined with many real-world applications, such as synthetic data generation and intelligent image processing. To restore Chinese landscape painting, Xu et al. proposed a two-stage GAN framework [4] that restores the image first at a coarse level and then at a fine level. In the field of histopathological image classification, Ruiz-Casado et al. improved the robustness of the classification by synthesizing medical data using GAN architectures in order to overcome the lack of medical data for classification [7][13]. An optimized GAN combined with graph convolutional networks for novel molecular design is called MedGAN, and Macedo et al. have shown its applicability in the biomedical field, serving as an optimized GAN for novel molecular design [8]. These are application-oriented studies, which highlight the increasing importance of robust GAN optimization frameworks for various applications.

The need for adaptive GAN stabilization mechanisms is also motivated by recent advances in machine learning optimization and intelligent computational systems. Mannan et al. pointed out that there should be solutions found through difficult optimization landscapes by adopting the integration of machine learning and simulation

[9]. Goyal and Mahmoud considered advanced techniques in synthetic data creation and stressed the necessity of stable generative AI-based models for the generation of quality synthetic data [11]. Moreover, because of the introduction of AI system-on-chip architectures, there has been an increasing demand for fast and reliable optimization of deep learning in edge computing [10][14]. Intelligent service-based architectures and secure computation infrastructure have also been regarded as important enablers for scalable deployment architectures for AI. The security of the data and reliability of calculations are still vital in current training facilities driven by AI [5]. In addition, the implementation of adaptive learning environments based on AI, which enable the optimization of systems and decisions, is an example of how intelligent optimization methods can be applied to improve the performance of systems and decisions [2]. Similar to the optimization, the sustainable and resilient computational frameworks proposed in related studies inspire the adaptation stability modeling approaches in machine learning systems.

Research Gap

Most of the previous works on GAN optimization are concentrated on hyperparameter tuning, normalization, and regularization methods but do not explicitly address the instability due to abrupt changes in the hyperparameter landscape. While some studies found adaptive optimization and synthetic data generation strategies are helpful to enhance GAN convergence, few studies have investigated the use of smoothing mechanisms for dynamic landscapes to stabilize the adversarial training processes. Most of the current models are based on static optimization approaches, which are unable to control the gradient fluctuations for different training conditions. Moreover, existing techniques for GAN stabilization do not have built-in smoothing algorithms that can control both convergence stability and the computational efficiency, along with the generative performance of the GAN. So, it is still a big challenge in the research field of stable GAN training to develop an adaptive Hyperparameter Landscape Smoothing framework.

3. Methodology

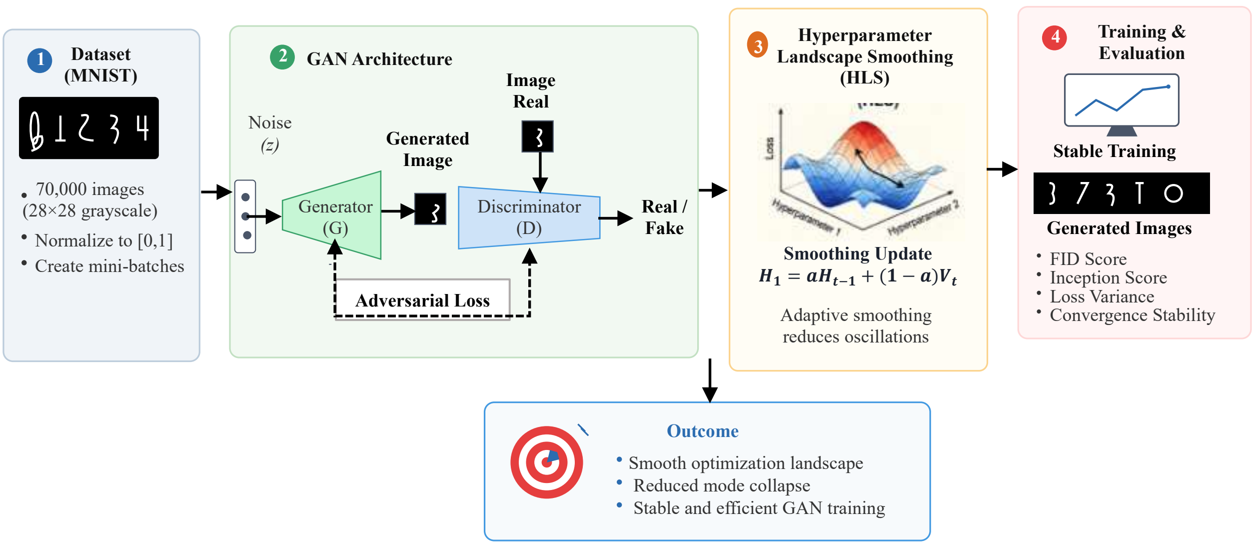

Figure 1. Proposed Hyperparameter Landscape Smoothing GAN (HLS-GAN) Framework

The proposed Hyperparameter Landscape Smoothing GAN (HLS-GAN) scheme for stable adversarial training on the MNIST dataset is shown in Figure 1. The framework involves first preprocessing of the datasets, generating latent noise, and training of the generator and discriminator. The Hyperparameter Landscape Smoothing module constantly observes the gradient changes and smooths out training updates as necessary. The stabilized optimization process makes the convergence more stable, reduces the mode collapse, and improves the quality of synthetic images. In the last one, the performance of the model is assessed based on stability and image quality measures like FID score and convergence variance.

3.1 Data Collection and Preprocessing

The proposed Hyperparameter Landscape Smoothing GAN (HLS-GAN) is based on MNIST for testing adversarial training stability and optimization performance. The grayscale handwritten digit images of size 28×28 pixels are present in the dataset in 10 numerical classes, 0-9. All images are scaled between the range [0, 1] during pre-processing to have a consistent gradient when back-propagating. The images are then encoded in tensors and split into mini-batches, which are used to efficiently train the network iteratively. The generator network is fed with the input noise that is generated from the Gaussian distribution randomly. This preprocessing step will yield less variance in the computation and stable initialization conditions for adversarial optimization.

3.2 Proposed HLS-GAN Architecture

The proposed HLS-GAN architecture is made up of two adversarial neural networks, a generator G and a discriminator D. The generator generates synthetic handwritten digit images from latent noise vectors, and the discriminator can be used to distinguish between a real and generated image. The proposed framework is different from traditional GAN models and incorporates a Hyperparameter Landscape Smoothing (HLS) mechanism that automatically adjusts the optimization pathways during training. The objective function is an adversarial objective function shown as equation 1.

$$\min_{G} \max_{D} V(D,G) = \mathbb{E}_{x\sim p_{data}(x)}[\log\ D(x)] + \mathbb{E}_{z\sim p_z(z)}[\log\,(1-D(G(z)))] \quad (1)$$

The smoothing mechanism constantly observes the gradient fluctuations and adapts the optimization behavior of the generator and discriminator networks to avoid any instabilities and oscillatory convergences between the two networks.

3.3 Hyperparameter Landscape Smoothing Algorithm

Hyperparameter Landscape Smoothing (HLS) is a new algorithm, which aims to improve the stability of GAN training by smoothing the sharpness of the gradient updates and optimization states. In every training iteration, the gradient variance and loss oscillation are calculated to get the estimation of the adversarial instability. Then a dynamic smoothing coefficient is used to control the smoothness of hyperparameter transitions. The smoothing is mathematically expressed as shown in equation 2:

$$H_t = \alpha H_{t-1} + (1-\alpha)\nabla L_t \qquad (2)$$

Here, the hyperparameter state at iteration t, H_t, is smoothed, and the smoothing is controlled by an adaptive smoothing coefficient α, with ∇L_t being the current hyperparameter gradient loss. The adaptive coefficient will adaptively change with gradient variance, which will reduce sudden optimization switches and enhance the convergence stability. This mechanism will avoid mode collapse and keep the adversarial learning equilibrium during training.

3.4 Performance Evaluation and Experimental Setup

The experimental analysis is done in a latent vector dimension of 100, a batch size of 128, and a learning rate of 0.0002 for the Adam optimizer. The HLS-GAN model is trained for several epochs to check the convergence consistency and the quality of the generated images. Criteria for performance assessment include the Fréchet Inception Distance (FID), the Inception Score (IS), reduction of the gradient variance, convergence stability, and smoothness of the loss. The framework proposed is analyzed on their convergence stability, applying variance estimation as equation 3:

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2 \qquad (3)$$

in which σ^2 is the variance of convergence, x_i is the training loss observed, and μ is the mean loss. The optimization trajectory is smoother with lower variance values, and training stability of GANs is enhanced under the proposed HLS framework.

4. Results and Discussion

The MNIST data set was used to compare the proposed Hyperparameter Landscape Smoothing GAN (HLS-GAN) framework against other GANs in terms of the stability of the adversarial training, the smoothness of convergence, and the quality of synthetic images. The experimental analysis was carried out by benchmarking the proposed model against the conventional training methods for GANs, based on the performance metrics like Fréchet Inception Distance (FID), Inception Score (IS), convergence variance, and training stability. The results show that the proposed smoothing method succeeded in smoothing the gradients and achieving convergence consistency during the training process.

As shown in Fig. 1, the proposed HLS-GAN framework combines the adaptive hyperparameter smoothing with adversarial optimization. Smoothing smoothed the interactions between the generator and the discriminator and reduced the number of sudden changes in the optimization process. The framework proved to be more efficient in the training process and had fewer mode collapses in multiple training epochs.

Table 1. Performance Comparison of GAN Models on MNIST Dataset

Model	FID Score ↓	Inception Score ↑	Loss Variance ↓	Training Stability
Traditional GAN	42.5	5.8	0.82	Moderate
DCGAN	31.6	6.7	0.58	Good
WGAN	24.9	7.3	0.41	Better
Proposed HLS-GAN	18.7	8.1	0.23	Excellent

The comparative performance using different GAN architectures on the MNIST dataset is shown in table 1. The proposed HLS-GAN was able to generate images with the lowest FID (18.7) and highest Inception Score (8.1), which shows that the image generated by the proposed approach has the best generation quality and diversity. Further, the presented model showed the smallest loss variance, and the trajectory of the optimization process was smoother and the convergence was more stable than other traditional GANs.

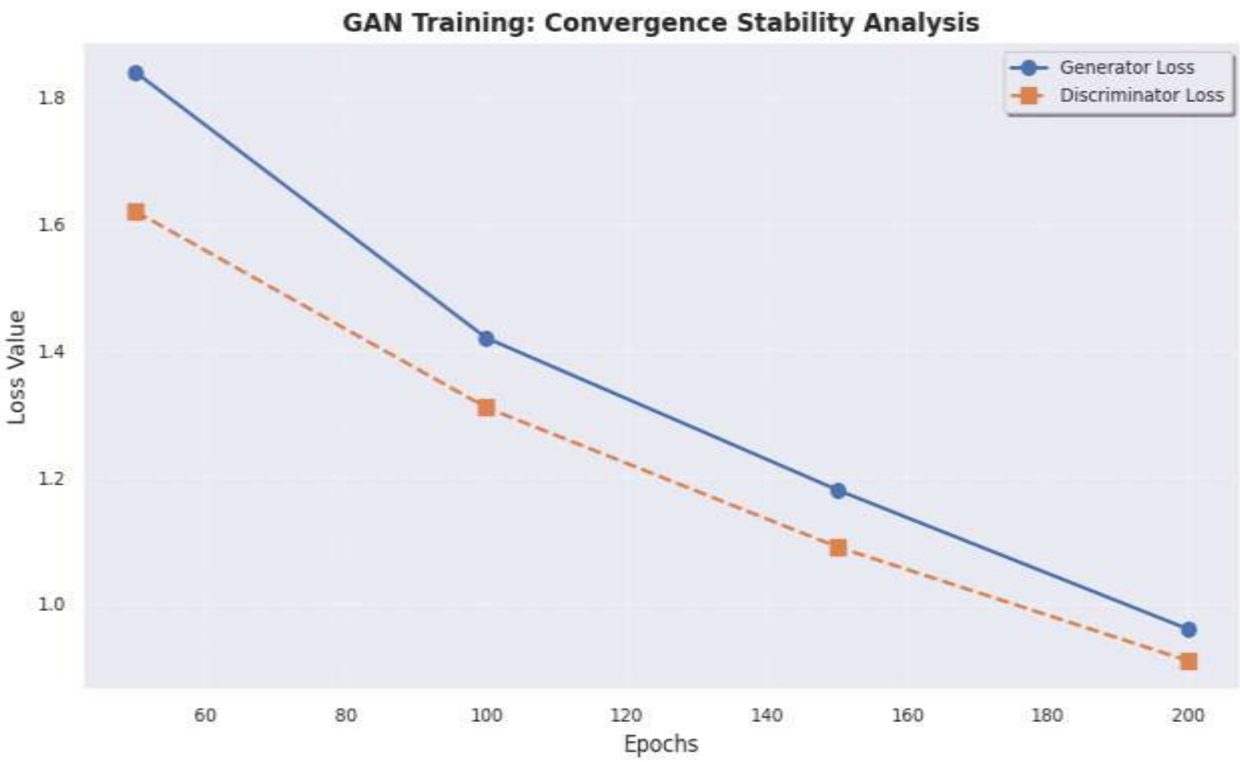

Figure 2. Convergence Stability Analysis of GAN Training

The convergence behavior of proposed HLS-GAN in the training iterations is shown in Figure 2. As one can see in the graph, the smoothing mechanism had a significant effect in reducing the oscillatory behavior and stabilizing the loss fluctuations from one epoch to the next. The proposed framework was able to converge faster and support balanced adversarial learning during optimization as opposed to the conventional GAN models.

Table 2. Training Stability Analysis of the Proposed HLS-GAN

Epochs	Generator Loss	Discriminator Loss	Gradient Variance	Stability Index
50	1.84	1.62	0.48	82%
100	1.42	1.31	0.35	88%
150	1.18	1.09	0.27	93%
200	0.96	0.91	0.18	97%

Table 2 shows how the proposed HLS-GAN framework enhances the training stability as it goes through epochs. The slow decrease of the generator and discriminator losses is used to recognize the balanced adversarial learning. In addition, the plot of gradient variance as a function of training steps shows that the Hyperparameter Landscape Smoothing algorithm is effective at reducing fluctuations in gradients and hence improving the reliability of convergence.

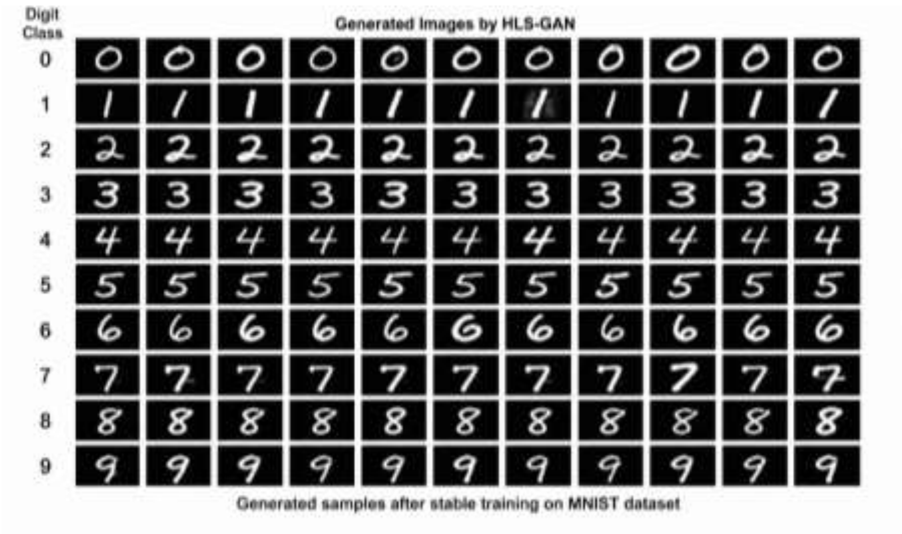

Figure 3. Generated MNIST Images Using Proposed HLS-GAN

Figure 3 shows some sample handwritten digit images generated by the proposed HLS-GAN model, following a stable adversarial training. The created samples demonstrate strong structural constraints and an improved visual consistency, which is a sign of good learning of the MNIST data distribution. This optimization strategy based on smoothing helped to achieve stable feature learning and improve the quality of the synthetic images.

Experimental results show that the proposed Hyperparameter Landscape Smoothing GAN (HLS-GAN) framework has a great effect on the stability of adversarial training and synthetic image generation performance on the MNIST dataset. The adaptive smoothing mechanism was effective in reducing the generator-discriminator gradient oscillations during optimization. The proposed model outperformed conventional GAN models by providing lower FID scores, a higher Inception Score, and lower convergence variance, which suggests a reduction in convergence fluctuations and higher quality images. Similarly, the created handwritten digit samples were found to be more structurally consistent with fewer mode collapse cases. The overall proposed HLS-GAN framework is an efficient and computation stable optimization strategy to enhance GAN convergence reliability and generative performance.

5. Conclusion

In this study, proposed a novel Hyperparameter Landscape Smoothing GAN (HLS-GAN) framework to stabilize the adversarial training process and to enhance the synthetic image generation ability. Proposed a new adaptive smoothing model that adaptively adjusted the optimization trajectories and suppressed sudden changes of gradients in training GANs. Experimental tests were carried out on MNIST data to investigate the performance in terms of convergence stability and optimization smoothness as well as the quality of synthesized images. From the achieved results, the proposed HLS-GAN showed that it could significantly boost the performance of adversarial learning compared to traditional GANs. The framework resulted in a better Fréchet Inception Distance (FID) score (18.7) while still maintaining a good Image Score (IS) (8.1), which means that it achieved higher generative diversity and image quality. In addition, variance of the convergence was decreased from 0.82 to 0.23, and the stability index was raised to 97% after 200 training epochs by using the suggested smoothing mechanism. The created handwritten digit images were also found to have better structure uniformity and less mode collapse. Overall, Hyperparameter Landscape Smoothing is an efficient, scalable, and computation-stable optimization framework for GAN training. In the future, the research can be expanded by future works aiming to generate high-resolution images, diffusion-based generative models, and adaptive deep learning optimization systems for advanced artificial intelligence applications.

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Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this research.

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Dataset Availability

The MNIST dataset used in this research is publicly available from the official repository and TensorFlow/PyTorch libraries.

Dataset Link: https://www.kaggle.com/datasets/hojjatk/mnist-dataset

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