A REVIEW OF DEEP LEARNING-DRIVEN ADVERSARIAL GENERATIVE ALGORITHMS IN SEISMIC EXPLORATION

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ABSTRACT

Today, due to the increasing recognition of the capabilities of machine learning and deep learning algorithms, the use of these algorithms is undergoing significant development. This ongoing evolution has led to the creation and enhancement of numerous algorithms and their variants. These advancements not only enhance the accuracy of algorithms but also pose challenges for researchers in terms of their understanding and utilization. The increasing capabilities of these algorithms have resulted in a dramatic rise in their utilization within seismic exploration. Among these, generative adversarial algorithms stand out due to their unique abilities and rapid progress, making them a crucial part of deep learning algorithms applied to various seismic exploration challenges. One notable characteristic of this algorithm is its high complexity and the existence of multiple variants. In this article, we aim to provide a comprehensive yet concise overview of generative adversarial algorithms, focusing on their theoretical foundations and mathematical underpinnings as they apply to seismic exploration. By doing so, we facilitate researchers' initial understanding of this algorithm, allowing them to grasp its fundamentals before delving into its intricacies and more time-consuming aspects. This approach enables researchers to intelligently and purposefully explore the algorithm according to their specific goals.

KEY WORDS: Deep Learning Algorithm, Seismic Exploration, GAN method, Review research

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INTRODUCTION

The concept of deep learning initially surfaced in the scientific community in 1967, introduced by Ivakhnenko and Lapa. Subsequently, in 1972, Ivakhnenko developed a deep learning network grounded in the group method of data handling [1] [2].

Different capabilities in deep learning and machine learning algorithms have led to the development of various algorithms addressing challenges in geosciences and petroleum sciences. In 1993, Charlebois and his colleagues pioneered an integrated system grounded in artificial intelligence for remote sensing, introducing the concept of System of Experts for Intelligent Data Management [3].The following year, Dibble designed a versatile system capable of learning via genetic algorithms alongside Geographic Information Systems. This novel approach, known for its proportionality and efficiency, facilitated the assessment of absolute and relative spatio-temporal relationships within geographic databases [4].In 1996, Dysart develop machine learning-based system derived from a two-dimensional stochastic model. Utilizing gridded bathymetric blocks, Seafloor represented a concise set of model parameters describing the ocean floor's physical properties. This study delves into the inversion component, aimed at swiftly estimating model parameters sans iteration or initial values. Leveraging machine learning techniques, it achieves rapid inversions, circumventing many practical limitations associated with conventional least-squares methods [5]. The exploration of liquefaction potential stands as a pivotal element in geophysical and earth sciences, bearing significant relevance in the assessment of environmental hazards. In 2003, Barai undertook a systematic classification of regions susceptible to liquefaction by employing artificial neural networks (ANN) [6].In 2009, Su successfully assessed the stability of tunnel walls using the Gaussian machine learning algorithm, demonstrating its efficacy [7].

One of the most significant advantages of employing deep learning and machine learning algorithms lies in their simultaneous and integrated use. In 2012, Alimoradi et al. utilized seismic inversion data to forecast the porosity of oil reservoirs [8]. Furthermore, Bagheri and Riahi (2015) integrated multilayer perceptrons (MLPs), support vector classifiers (SVC), and K-nearest neighbor (KNN) algorithms to conduct Seismic Facies Analysis (SFA) [9].

In 2017, Lei.et al demonstrated the efficacy of deep learning algorithms in handling vast seismic data. By constructing a scalable model based on the CNN algorithm, they successfully extracted geological features from seismic data, showcasing the potential of these algorithms to manage large datasets effectively [10]. Building on this progress, Guoyin.et al 2018 utilized the same algorithm, along with continuous wavelet transforms (CWTs), to estimate lithology from seismic data. This marked another advancement in the integration of machine learning and deep learning methods within the realms of petroleum engineering and Geoexploration sciences [11].

As the field continues to evolve, the utilization of these algorithms remains promising. The complexities inherent in seismic inversion, coupled with the diversity of algorithms available, highlight the potential for machine learning and deep learning techniques to revolutionize this domain. In 2020, Rui et al. exemplified this potential by employing the deep residual convolutional neural networks (DRCNNs) algorithm to invert two-dimensional joint speed of sound waves using magneto telluric data, updating the sound resistance level and subsurface electromagnetic data using the Gauss-Newton method [12]. As previously mentioned regarding the role of seismic inversion, it serves as an exceptionally efficient tool in oil exploration. In 2022, Wang et al., and in 2024, Azizzadeh Mehmandost Olya et al., conducted seismic inversion using various iterations of the GAN algorithm, these endeavors resulted in a notable increase in both accuracy and speed of inversion [13] [14]

Another important potential of these algorithms is their versatility, as they have not only been applied to tabular and complex well report data but have also found widespread use in image data processing. In 2023, Azizzadeh Mehmandost Olya and Mohebian employed the CUDA Deep Neural Network Library Long Short-Term (CUDNNLSTM) algorithm, a deep learning algorithm designed to run on a graphics card, to predict the map of permeability potential for oil wells using core data [15]. Also, in 2023, Azizzadeh Mehmandost Olya and Mohebia successfully estimated the damping factor and quality factor of seismic waves using the CUDNNLSTM algorithm. [16] Additionally, in 2024, utilizing the YOLOV5 algorithm, which is a computer vision algorithm, Azizzadeh Mehmandost Olya and colleagues successfully transitioned from manual and conventional well wall fracture detection to automatic and real-time detection [17].

Having briefly reviewed the scope of deep learning algorithms and machine learning, we must acknowledge that generative algorithms stand out as one of the most crucial categories in deep learning today. Among these, generative adversarial algorithms (GANs) have gained significant traction in recent years due to their unique nature, particularly in the fields of petroleum sciences and earth sciences. In the following sections, alongside a bibliographic review, we will delve into the concepts and mathematics of this algorithm in an accessible manner. We will also explore its potential applications in geo-exploration and seismic explorations. This endeavor aims to equip researchers in this domain with not only a thorough understanding but also the tools to leverage these advancements for the future development of their research.

GAN bibliography

Bibliographic review is a critical aspect of scientific research, involving the systematic identification, evaluation, and synthesis of existing literature on a particular topic. This process is invaluable as it allows researchers to build upon previous work, avoid duplication, identify gaps in knowledge, and establish the context for their own investigations. By reviewing a wide range of articles, researchers can gain insights into the evolution of ideas, methodologies, and findings in their field, helping them to situate their research within the broader scholarly conversation.

Co-occurrence analysis within bibliographic reviews refers to the identification and analysis of patterns of occurrence of keywords, concepts, or terms across a body of literature. This technique helps researchers to uncover relationships between different ideas or topics, identify key themes or trends, and map the intellectual structure of a research area. By identifying frequently co-occurring terms or concepts, researchers can gain a deeper understanding of the interconnectedness of ideas within their field, which can inform the development of research questions, the design of experiments, and the interpretation of results. Overall, bibliographic reviews and co-occurrence analysis are essential tools for researchers to navigate the vast landscape of scientific literature, enhance the rigor and relevance of their work, and contribute meaningfully to the advancement of knowledge in their respective fields.

By selecting and examining the Scopus scientific database as a valid scientific resource and reviewing 1598 articles till 2024 related to the GAN algorithm in the fields of earth sciences, energy, and engineering, we created highly significant maps highlighting the importance of the GAN algorithm. As we can see in Figure 1, there have been numerous citations and links to the keyword "generative adversarial algorithm" in recent years, indicating the significance and prominence of this algorithm. In Figure 2, the density of research conducted on the three keywords "generative adversarial algorithm," "seismic waves," and "seismic data" is notably significant.

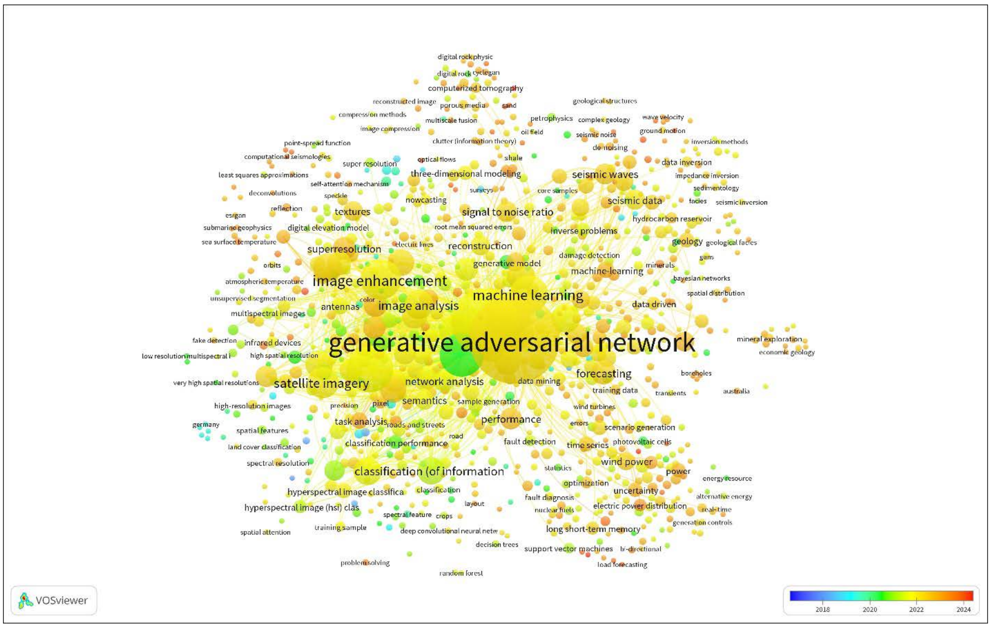

Figure 1:Analyzing the scattering and clustering bibliometrics of the Scopus database over time using VOS Viewer software, emphasize the pivotal role of GAN algorithms in realm of energy, earth science and engineering.

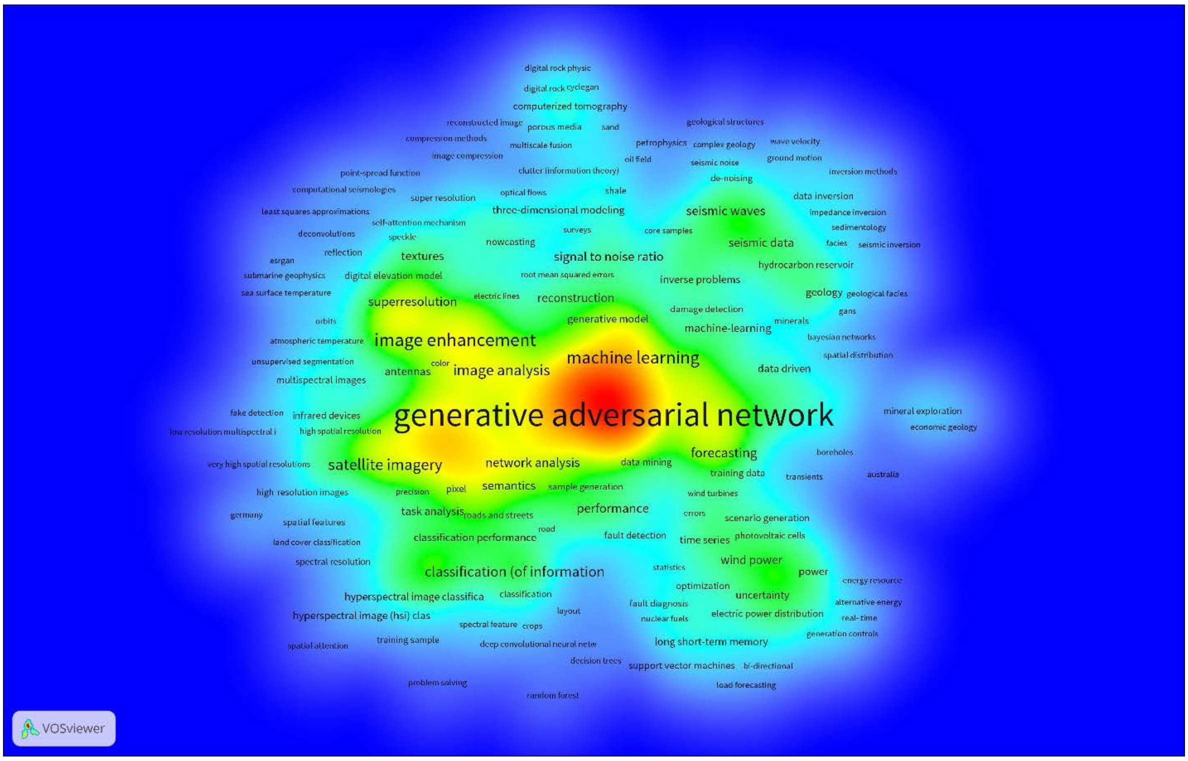

Figure 2:Topic density related to GAN algorithms in realm of energy, earth science and engineering, VOS Viewer software.

GANs

The concept of Generative Adversarial Networks (GANs) is a relatively recent innovation in artificial intelligence. The idea was first introduced in a research paper by Ian Goodfellow and his colleagues in 2014. This groundbreaking work laid the foundation for a powerful generative modeling technique that has since revolutionized fields like computer vision and natural language processing [18].Generative Adversarial Networks (GANs) represent a cutting-edge deep learning paradigm that has garnered substantial attention for its ability to perform generative modeling tasks. GANs excel at learning the intricate patterns inherent in a dataset and leveraging that knowledge to generate novel data that closely mirrors the original data distribution. The architecture of GANs comprises two neural networks engaged in an adversarial relationship. On one hand, the generator network functions as an adept fabricator, aiming to craft synthetic data that is virtually indistinguishable from genuine data. Conversely, the discriminator network (Adversarial Network) operates as a vigilant verifier, discerning whether the input data is real or synthetic [19]. During the training phase, the generator network refines its generative capabilities by incorporating feedback from the discriminator network. Simultaneously, the discriminator network enhances its discriminatory prowess to effectively distinguish between genuine and synthetic data instances. This iterative process fosters a competitive dynamic between the two networks, propelling them to continually enhance their performance. The iterative training process of GANs leads to a convergence where the generator network becomes adept at generating highly realistic data samples that align closely with the original dataset. This convergence is facilitated by the adversarial interplay between the generator and discriminator networks, which drives them towards optimizing their respective functions.

GANs represent a groundbreaking approach to generative modeling within the realm of deep learning. By leveraging adversarial competition between neural networks, GANs can achieve remarkable results in generating data that exhibits a high degree of fidelity to the underlying data distribution [20].

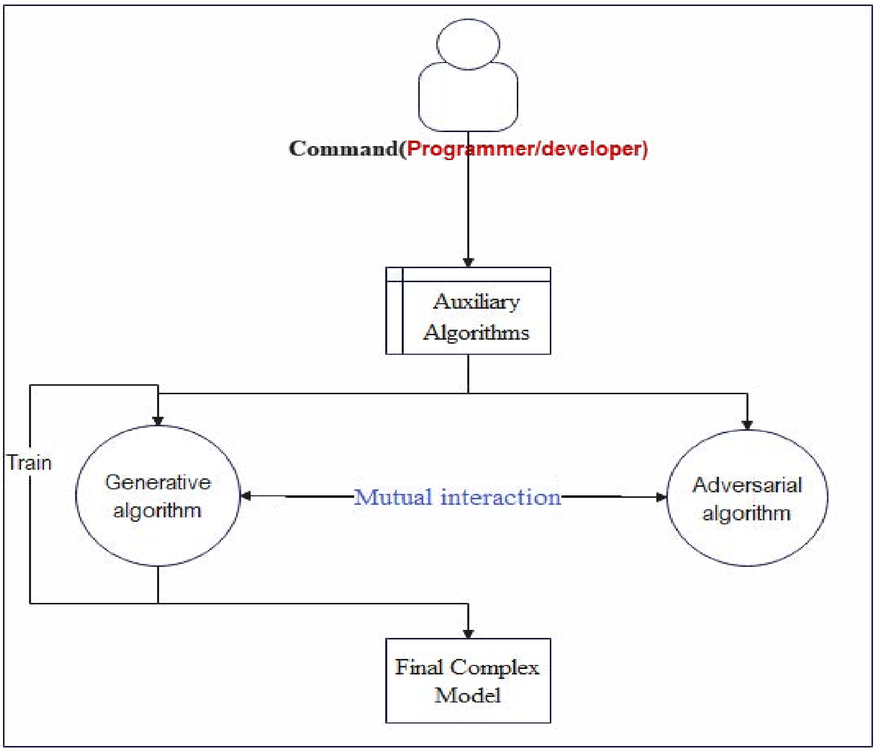

Figure 3:An Overview of the GAN Algorithm. In This figure auxiliary algorithms can be any algorithm used for pre-processing tasks.

How do GANs work?

Most explanations of GAN algorithms use the analogy of a forger and a detective, which is effective. However, this article offers a simpler explanation using a different game.

In 1970, a two-player board game called "Mastermind" was invented by Mordecai Meirowitz [21]. In this game, one player secretly arranges a code of 4 or 5 colored pegs from a set of available colors. The other player attempts to guess the hidden code within a limited number of tries (e.g., 15). After each guess, the first player provides feedback, indicating the number of correct colors and their positions (if any). This process continues until one player-side player prevails over the other side.

The generative adversarial network (GAN) is similar to Mastermind. The adversarial network acts like the player who arranges the hidden code, while the generative network is like the player trying to guess the code. The goal is to choose the number of training steps and optimization algorithms such that the generative network "wins" by creating an accurate model (Figure 4). However, if these parameters are not carefully chosen, the generative network may fail to learn the correct model.

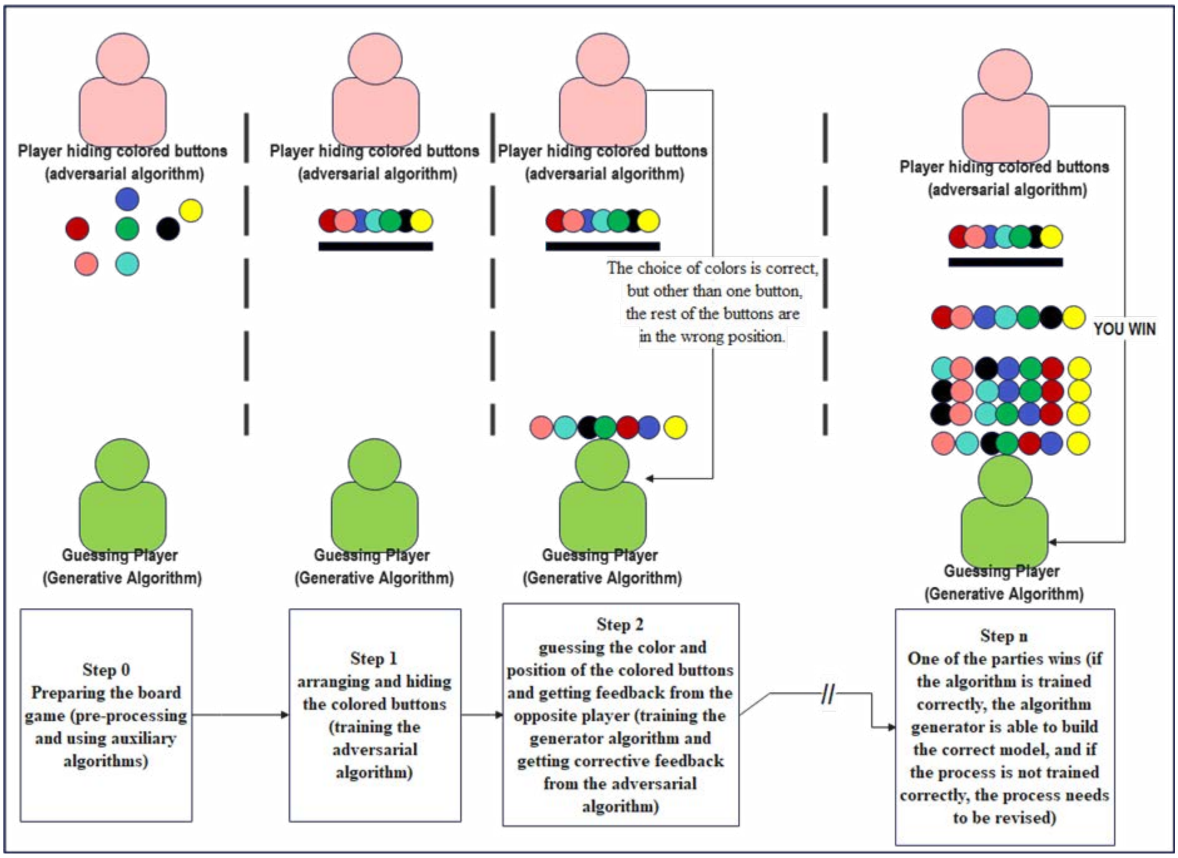

Figure 4:A general explanation of the training of the adversarial generative algorithm using the Mastermind game

Math behind the GAN

The Generative Adversarial Network (GAN) is a deep learning framework that involves two neural networks: the generator and the discriminator. The mathematics behind GANs is primarily based on game theory and optimization techniques. Let's break down the mathematics step by step and then provide an example.

Generator Network (G):

The generator takes random noise as input and generates data samples. It is represented by a function $(G(z))$, where (z) is the input noise vector sampled from a predefined distribution (often Gaussian).

Discriminator Network (D):

The discriminator evaluates the generated samples and tries to distinguish between real and fake data. It is represented by a function $(D(x))$, where (x) is the input data (real or generated).

Training Process:

During training, the generator and discriminator play a minimax game. The objective is for the generator to produce data that is indistinguishable from real data, while the discriminator aims to correctly classify real and fake data. Mathematically, the training objective is expressed as:

$$\min_G \max_D E_{x \sim p_{\mathrm{dt}}(x)} [\log D(x)] + E_{z \sim p_z(z)} \left[\log\left(1 - D\big(G(z)\big)\right)\right]$$

The first term maximizes the probability of the discriminator correctly classifying real data. The second term maximizes the probability of the discriminator incorrectly classifying generated data as real (hence the $(1 - D(G(z)))$).

Let's consider a simplified scenario where the generator (G) and discriminator (D) are feedforward neural networks.

Generator Network:

- Input: Noise vector (z) of size (n)
- Output: Generated data sample $(G(z))$ of size (m)

Discriminator Network:

- Input: Data sample (x) (real or generated) of size (m)
- Output: Probability $(D(x))$that (x) is a real sample

Training:

- Randomly sample noise (z) from a Gaussian distribution.
- Generate a fake sample $(G(z))$ using the generator.
- Feed real and fake samples (along with their labels) to the discriminator for training.
- Update the generator and discriminator using gradient descent to minimize/maximize the respective objectives.

Loss Function:

The discriminator's loss is typically binary cross-entropy loss, aiming to correctly classify real and fake samples. The generator's loss is the negation of the discriminator's loss (i.e., minimizing $(\log(1 - D(G(z))))$.

This process iteratively improves both the generator and discriminator until the generator produces high-quality samples that are difficult for the discriminator to differentiate from real data. Keep in mind that this is a simplified explanation, and actual implementations may involve additional complexities and optimizations.

GAN variants

Generative Adversarial Networks (GANs) have revolutionized the field of generative modeling, allowing us to create realistic and novel data. However, the original GAN formulation comes with certain challenges. To overcome these limitations, researchers have proposed numerous variants, each addressing specific shortcomings and excelling in particular tasks. Here's a deeper dive into some prominent GAN variations, along with their mathematical and statistical considerations.

Vanilla GANs introduced by Ian Goodfellow in 2014, vanilla GANs consist of a generator and a discriminator network. The generator tries to create data samples that mimic the real data distribution, while the discriminator tries to distinguish between real and fake samples. They are trained adversarially, with the generator trying to fool the discriminator and the discriminator trying to become better at distinguishing real from fake data [18].

In Conditional GANs (CGANs), both the generator and discriminator are conditioned on additional information, such as class labels. This allows for the generation of data samples conditioned on specific attributes, making them useful for tasks like image-to-image translation and generating samples with specific characteristics [22] [23]. Deep Convolutional GANs (DCGANs), proposed by Radford et al. in 2015, utilize deep convolutional networks in both the generator and discriminator. They stabilize training and generate higher-quality samples compared to vanilla GANs, making them popular for image generation tasks [24]. The Wasserstein GANs (WGANs) introduced by Arjovsky et al. in 2017, WGANs use the Wasserstein distance (Earth Mover's distance) instead of the traditional Jensen-Shannon divergence for training. This change leads to more stable training dynamics and improved convergence properties [25].

Least Squares GANs (LSGANs), proposed by Mao et al. in 2017, replace the binary cross-entropy loss used in traditional GANs with least squares loss functions. This modification helps address the problem of mode collapse and produces sharper images in image generation tasks [26]CycleGANs, introduced by Zhu et al. in 2017, are designed for unpaired image-to-image translation. They learn mappings between two domains without requiring paired data examples, making them useful for tasks like style transfer and domain adaptation [27].

StyleGANs, developed by Karras et al. in 2019, focus on generating high-resolution and realistic images by incorporating style-based architecture. They allow for controlling both the global structure and local details of generated images, leading to impressive visual quality [28]. BigGANs, introduced by Brock et al. in 2019, are designed to generate high-quality images at high resolutions. They achieve this by scaling up both the model architecture and the training process, using techniques like large minibatches and hierarchical latent spaces [29].

S Self-Attention GANs (AGANs), proposed by Zhang et al. in 2018, incorporate self-attention mechanisms into the GAN architecture. This helps capture long-range dependencies in images, leading to improved generation of coherent and detailed samples [30]. Adversarial Autoencoders (AAEs), introduced by Makhzani et al. in 2016, combine the concepts of autoencoders and GANs. They use an encoder-decoder architecture where the encoder maps input data into a latent space, and the decoder reconstructs the data. The adversarial training encourages the latent space to follow a specified distribution [31].

By reviewing the above source, in the table1, we'll explore various variants of the GAN algorithm. Here, we aim to discuss the capabilities, weaknesses, and strengths of these algorithms. It's important to note that in the realm of seismic or exploratory investigations, we need a precise understanding of the strengths of each variant in their respective fields.

Table 1:Comparison of GAN variants

Variant	**Key Features**	**Strengths**	**Weaknesses**
Vanilla GANs	Generator, discriminator	Versatility, simplicity	Mode collapse, training instability
CGANs	Conditional generation	Controlled generation, attribute manipulation	Requires labeled data
DCGANs	Deep convolutional networks	Stable training, high-quality image generation	Computational complexity
WGANs	Wasserstein distance	Stable training, convergence	Requires careful hyperparameter tuning
LSGANs	Least squares loss	Address mode collapse, sharper images	Mode collapse can still occur
CycleGANs	Unpaired image-to-image translation	Style transfer, domain adaptation	Limited to specific image translation tasks
StyleGANs	Style-based architecture	High-resolution, realistic images	Computational resources, training time
BigGANs	Large-scale architecture	High-quality images at high resolutions	Resource-intensive, complex training process
SAGANs	Self-attention mechanisms	Captures long-range dependencies	Computational complexity
AAEs	Autoencoder, adversarial training	Latent space control, reconstruction accuracy	May suffer from mode collapse

Nowadays, the development of models and complex algorithms has become more accessible and feasible due to the widespread knowledge of programming [32]. However, it should be noted that as algorithms become more intricate, three key characteristics undergo changes [33] [34]:

1. Convergence speed (measured in training iterations)

2. Computational complexity (measured in FLOPs - Floating Point Operations)

3. Sample quality (measured using the Inception Score metric for image generation tasks)

Convergence Speed (Iterations)

This indicator refers to how quickly the GAN algorithm converges during training. Faster convergence generally means that the model learns to generate realistic samples in fewer training iterations [35] [36] [37].

Vanilla GANs, CGANs, and CycleGANs show a moderate convergence speed, taking a moderate number of iterations to reach a stable training state. On the other hand, DCGANs, WGANs, and LSGANs exhibit faster convergence, reaching a stable state relatively quickly. StyleGANs, BigGANs, SAGANs, and AAEs have a slower convergence speed, requiring more iterations to achieve optimal results due to their complex architectures or training procedures [38] [39] [40] [41].

Computational Complexity (FLOPs)

Computational complexity refers to the amount of computational resources (measured in FLOPs) required to train the GAN model. Higher complexity typically demands more computational power and time [42].

Vanilla GANs and cGANs have relatively low to medium computational complexity, making them easier to train compared to more complex variants. DCGANs, WGANs, and LSGANs require a medium level of computational resources due to their use of deep convolutional networks and alternative loss functions. StyleGANs, BigGANs, and SAGANs exhibit high to very high computational complexity, requiring significant computational resources and longer training times. AAEs fall into the medium complexity range, as they combine elements of autoencoders and GANs without the extreme complexity of some other variants [40] [41] [43].

Sample Quality (Inception Score)

Sample quality refers to how realistic and diverse the generated samples are. The Inception Score metric, commonly used in image generation tasks, measures the quality and diversity of generated images [44] [45].

Vanilla GANs, cGANs, and CycleGANs produce samples with moderate quality, achieving a balance between realism and diversity. DCGANs, WGANs, and LSGANs generate high-quality samples with good diversity, often surpassing the performance of simpler variants. StyleGANs, BigGANs, and SAGANs excel in sample quality, producing very high-quality and diverse samples due to their advanced architectures and training techniques. AAEs demonstrate moderate sample quality, as they prioritize reconstruction accuracy and latent space control over pure sample generation performance [40].

In the following, Figure 5 shows the status of the three indicators stated for different variants of the GAN algorithm. Of course, it cannot be admitted that there is a variant that has perfect performance in all cases. It is not possible to say which variants are absolutely good or bad. It should be noted that, depending on the amount of data, the level of pre-processing, and the desired accuracy, each of them can have a favorable result. In the next part, we will try to delve deeper by examining the variants with an approach focused on seismic data analysis.

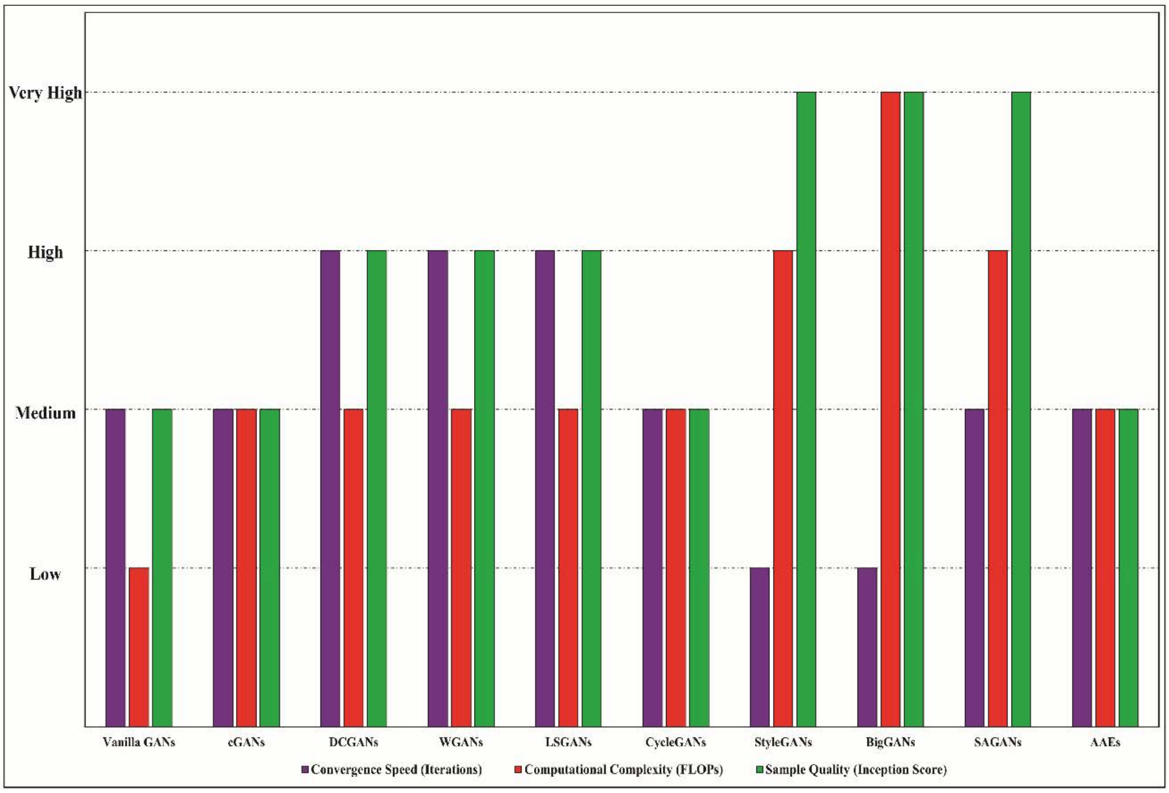

Figure 5:Comparison of different variants of the GAN algorithm based on three indicators: Sample Quality, Computational Complexity, and Convergence Speed.

GANs in Seismic exploration

Seismic data plays a crucial role in mineral and oil discoveries. Therefore, their processing, interpretation, inversion, and correction are vital [46] [47].

The GAN algorithm, as a deep learning algorithm, can play a highly effective role in seismic correction and inversion.

The traces of the use of GAN algorithms in the field of seismic exploration and the issues surrounding it can be seen in a concentrated and gradual manner since 2018. In 2018, Siahkoohi and his colleagues reconstructed seismic data using the vanilla GAN algorithm and integrated it with the convolutional neural network algorithm. This data reconstruction was done in several stages and with different levels of data loss (Figure 6). The results show that frequency data reconstruction using GANs is in the signal-to-noise range (SNR) of 23.25 dB to 35.66 dB [48].

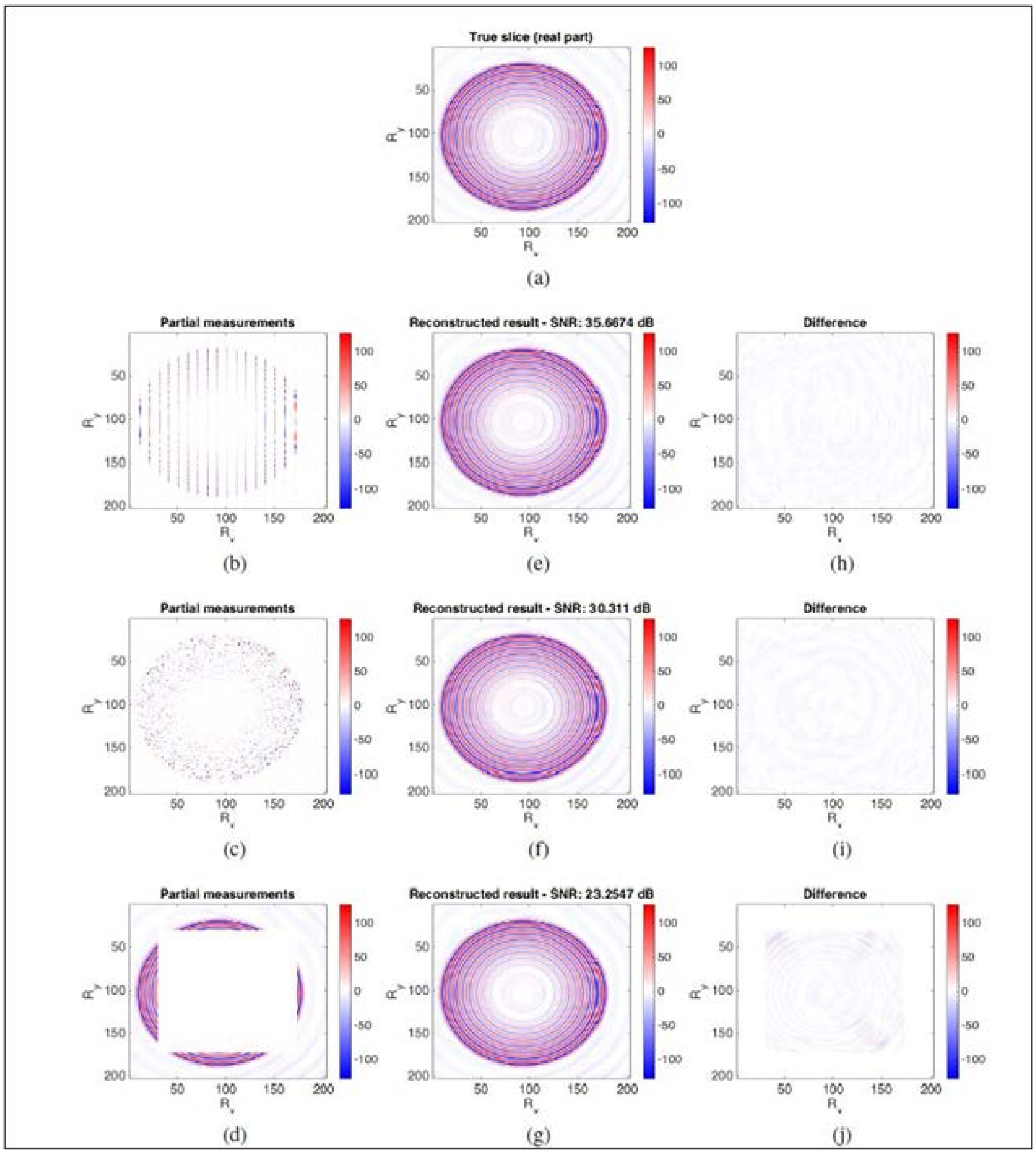

Figure 6:Reconstruction of missing seismic data by GAN algorithm by Siahkoohi, et al in 2018 [48].

The challenges of missing or flawed data in seismic acquisition and processing arise from various factors like physical limitations and operational issues. However, in 2018 Oliveira .et al study introduces a novel approach by evaluating the performance of a CGAN for interpolating post-stack seismic datasets, marking the first attempt at utilizing deep learning in this particular context [49]. Xie .et al in 2018 introduced and develop a deep-learning method for noise reduction in onshore seismic data, utilizing two 24-layer Deep Neural Networks based on the Generative Adversarial Network architecture with a total of 0.3 billion parameters. Correctly trained, these networks can meaningfully reduce processing time from weeks to seconds. The approach shows promise and can be extended to other processes like first arrival picking. Initial tests on real data, following 4 weeks of training, demonstrate hopeful outcomes. Within a framework of common shot processing, this technology promises reasonable real-time processing capabilities [50].

Analyzing seismic and lithologic facies through 3D reflection seismic data is crucial for understanding depositional environments and characterizing reservoirs in hydrocarbon exploration. Despite various machine-learning methods aiming to enhance interpretation and prediction accuracy, real-world challenges persist in 3D multiclass seismic facies classification. These challenges stem from intricate data representation, scarce labeled training data, imbalanced facies class distribution, and a lack of robust evaluation metrics. To address these hurdles, Liu. et al in 2020 novel approaches have been developed: they utilized a supervised convolutional neural network (CNN) and a semi supervised GAN for 3D seismic facies classification with differing levels of well data availability (Figure 7). These models leverage actual well log data, core analysis, or geological knowledge to predict 3D facies distribution, offering more consistent and meaningful insights compared to unsupervised methods [51].

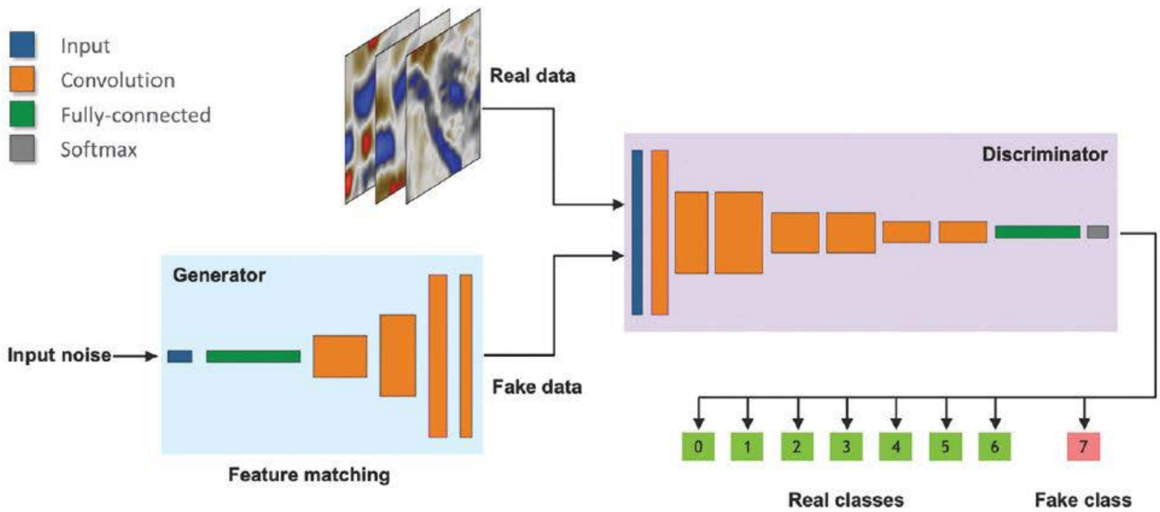

Figure 7:The algorithm architecture was designed by Liu et al. in 2020. The discriminative algorithm is based on CNN [51].

Meng, et al in 2020 introduce a semi-supervised deep learning approach using Generative Adversarial Networks for seismic impedance inversion. This workflow incorporates three networks: a generator, a discriminator, and a forward model. Training involves utilizing well logs for guidance and leveraging unlabeled data through the forward model. Testing on the Marmousi2 model demonstrates that the Meng,et al method, which combines labeled and unlabeled data, yields more consistent impedance predictions compared to traditional deep learning inversion techniques [52].

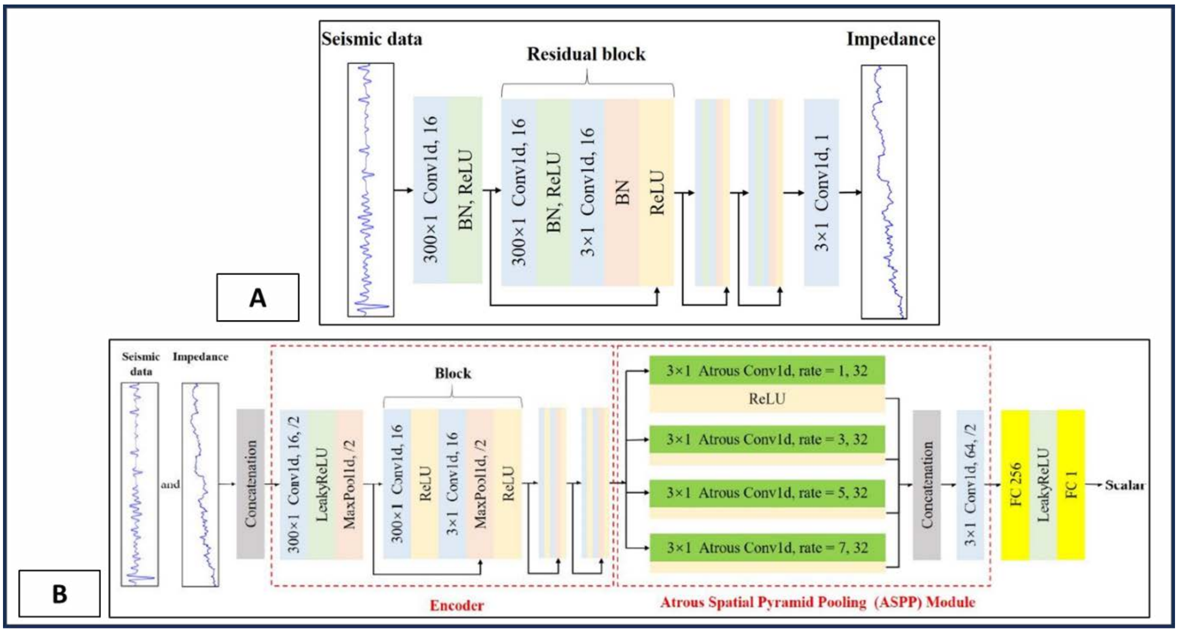

Figure 8:The algorithm architecture was designed by Meng et al. in 2020. This includes both the generative algorithm architecture (A) and the discriminative algorithm architecture (B) [52].

To enhance accuracy in processing seismic data, interpolation is often needed for irregularly missing data during acquisition. A solution lies in using a CGAN, comprising a generator and a discriminator, as a deep learning model for this task. However, CGANs are typically limited to the dataset they are trained on, hindering their applicability to different areas. Wei, et al in 2021 were involved in designing a CGAN based on Pix2Pix GAN specifically for interpolating irregularly missing seismic data. Unlike traditional methods requiring varied parameter selections, our CGAN-based interpolation method streamlines the process and proves cost-effective, with minimal processing time post-training [53].

Song, et al in 2022 utilized a CGAN to establish a connection between conventional Ocean Bottom Cable (OBC) seismic imagery and broader high-resolution imagery. Despite the training data being confined to the overlapping zone of these distinct acquisitions, Song, et al findings indicate that this mapping enables image translations, thereby enhancing the resolution and signal-to-noise ratio (SNR) of the entire initial OBC image volume. Additionally, the network's probabilistic layers facilitate model uncertainty analysis [54].

Sun, et al in 2023 were developed a novel approach involving Model-data-driven (MDD) GANs for estimating elastic parameters using prestack seismic data. Initially, a comprehensive elastic parameter dataset is generated through traverse sampling of the elastic parameter model space and Gaussian sampling. Subsequently, synthetic prestack amplitude-versus-angle (AVA) gathers are created using the Zoeppritz equations based on constructed reflection coefficient sequences. CGANs were then trained using these synthetic datasets to establish a link between synthetic prestack AVA gathers and elastic parameters. Evaluation Sun, et al of the MDD-CGANs on a 2D elastic parameter model indicates closer inversion results to the true values compared to limited-data-driven CGANs and fully convolutional networks [55].

Duan, et al in 2024 used seismic data from the California Strong Motion Instrumentation Program (CSMIP), and a CGAN model was trained and evaluated by them. This model establishes a joint conditional probability distribution among intensity measures at different depths, aiding in the stochastic prediction of shallow intensity measures. Its performance was assessed against empirical formulas across various site conditions and depth intervals using relative error coefficients. The findings of Duan, et al suggest that the CGAN model accurately predicts shallow seismic intensity measures, adhering to specific conditional distributions while retaining the stochastic nature of seismic motion. Compared to empirical formula models, the CGAN model demonstrates superior predictive capabilities [56].

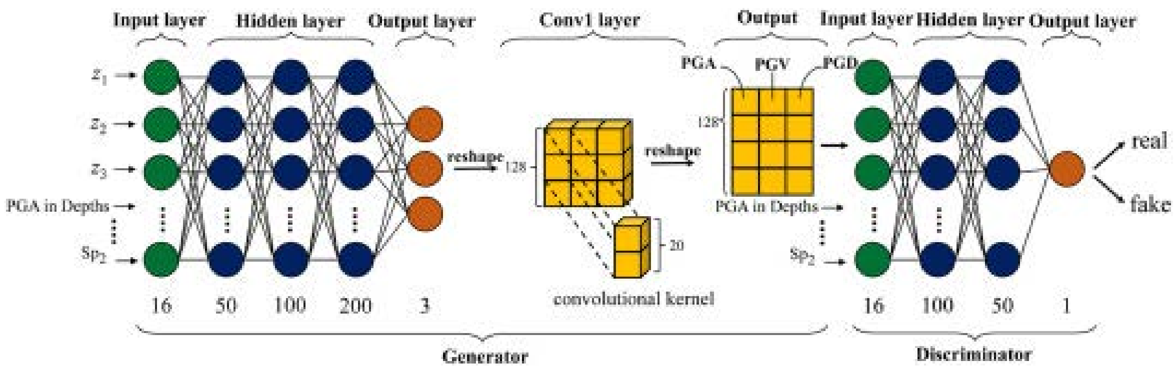

Figure 9:The CGAN architecture was developed by Duan et al. in 2024 [56].

DISCUSSION

In the previous sction, we reviewed the important effects of the GAN algorithm in seismic exploration. In this section, we will discuss the characteristics of each GAN variant and its ability to solve problems in the field of seismic exploration. We will attempt to determine which variant is suitable for different parts of seismic exploration based on the advantages of each variant.

Generally, seismic data is divided into two types: pre-stack and post-stack data [47]. Pre-stack data contain valuable information, including angular data, but their large volume poses a significant challenge in achieving convergence in results. In the previous section, we examined various variants of the GAN algorithm and evaluated them based on three key metrics. Based on this analysis, SAGANs and CycleGANs variants are well-suited for pre-stack data analysis. The reason for their suitability in handling pre-stack data lies in their processing speed and network complexity. It's worth noting that the SAGANs network is more complex than the CycleGANs network, requiring better hardware resources. However, both variants are expected to perform well in pre-stack data processing.

Seismic inversion is a process in which acoustic impedance is extracted from seismic traces. This process is one of the most challenging processes in seismic data analysis due to various factors such as limited data bands. Naturally, seismic inversion on post-stack data is much easier than on pre-stack data due to the lower volume of data [57].

Based on investigations conducted in previous sections, if high computing resources such as central processes unit (CPU), random access memory (RAM), and graphic processes unit (GPU) are available, using the BIGGANs variant can yield highly suitable results. However, we recommend using CycleGANs and WGANs variants for inversion (both post-stack and pre-stack) and avoiding the use of Vanilla GANs. This is due to issues such as mode collapse and training instability associated with Vanilla GANs, which can be problematic given the inherent uncertainties in the inversion process. A crucial point to note is that the WGANs variant heavily relies on the configuration of hyperparameters. Therefore, it is recommended to use this variant when there is reliable geological and seismic information available to validate and optimize the hyperparameters.

Seismic tomography is a crucial method in deep earth science studies, relying on the production of image data from the propagation of seismic waves [58]. Based on the review of GAN variants, DCGANs and StyleGANs are notable options. The DCGAN variant, noted for its high convergence speed in seismic comparisons, can be a highly desirable choice, offering excellent accuracy.

We do not recommend using the BigGANs variant in this context due to the substantial volume of seismic data involved. In seismic tomography, the high complexity of this variant's network can pose a significant challenge for optimization. However, it's worth noting that the BigGANs variant could be employed as an auxiliary option. For instance, the general tomography could be conducted using the mentioned variants, and if models with higher accuracy are needed locally, then the BigGANs variant could be utilized.

The problem of missing or removing parts of seismic data has always been one of the major challenges in utilizing this data. Given that the GAN algorithm primarily focuses on constructing realistic models, employing it to repair and modify seismic data can be highly beneficial. Thanks to the Self-attention mechanisms, the SAGANs variant emerges as a very suitable option for addressing this issue. However, its network complexity may pose a drawback, although this can be mitigated by parallelizing the processing.

CONCLUSION

The GAN algorithm is a very complex yet powerful algorithm that can solve many cases related to seismic exploration and geosciences with great accuracy and quality. It should be noted that although the use of machine learning algorithms has become much easier today due to the development of programming language libraries, we must be able to manage data and hardware resources while using them. The GAN algorithm is very dependent on data management and hyperparameters because their complexity requires attention to this issue. One of the most common problems of using deep learning algorithms is their high processing level, which is largely solved by using a GPU instead of a CPU, but we must note that the problem is not limited to this point. The limited amount of RAM space and the many processes of these algorithms cause many problems, including RAM overflow. In seismic processing and inversion using GAN algorithms, this problem can occur due to the large volume of data and RAM overflow calculations. To summarize, we can say that GAN algorithms are very significant algorithms, but according to the type of work, the volume of data, and the level of processing, appropriate variants should be used in cases related to seismic exploration.

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