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3D Generative Techniques and Visualization: A Brief Survey

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Abstract

The quality and quantity of data in the datasets is the key factor in producing accurate results for artificial intelligence applications. Real data is costly both from the time of gathering and from the labeling point of view. Moreover, the data property problem, the anonymization, and the representativeness are important factors that limit the dimension of the real datasets, making Synthetic Data Generation (SDG) the only alternative to produce large, high-quality datasets. The process of creating 3D synthetic data involves several steps, such as choosing the 3D model tool, creating the 3D model, applying texture and materials, setting up lighting, defining camera parameters, rendering the scene, augmenting data, adding depth and annotations, compiling the dataset, and performing validation and testing. Our paper explores the current landscape of 3D SDG, including generative methods, metrics, areas of application, existing packages to generate 3D data, and visualization of the generated data. The main objective is to focus on the specifics of 3D data, with an emphasis on the very recent state-of-the-art generative adversarial network techniques and assessment methods. We also discuss limitations of current 3D data generation techniques, challenges, and promising research directions.

Keywords: synthetic data generation, 3D generative methods, 3D visualization, evaluation metrics for synthetic data

1 Introduction

Many modern Artificial Intelligence (AI) problems are limited by insufficient data. This occurs when datasets are either too small or, even if the dataset is large enough, labeling it requires an unreasonable amount of resources. AI generative data methods aim to produce large training datasets, which are the fundamental foundation for AI learning and generalization. Generative AI (GAI) learns patterns from initial data (such as text, images, audio, or video) and produces new content that matches the structure, complexity, and style of the input data. The quality and diversity of the initial input data set are essential features in the production of valuable generative data. The well-known methods used to acquire the input data set include crowd-sourcing, web crawling and scraping, public datasets, user-generated content, data augmentation, customer data, and SDG. The result of a successful AI generative process is a new dataset comprising realistic, meaningful, and coherent data. The main properties of the synthetic data that prove their usefulness include fidelity to the training data, diversity, coherence, novelty, robustness to noise, interpretability and control, scalability, and more.

SGD is an active area of research in the broader machine learning community. For example, synthetic image generation is a domain with remarkable results (see, for instance, [1]), unfortunately including deepfake image generation [2]. More recently, 3D data generation became a very hot research area. This is caused by the new 3D AI application areas. For example, 3D synthetic data can be used to develop and test autonomous vehicle solutions in a simulation environment, reducing testing and training times.

Synthetic 3D data are particularly useful in fields like computer vision, robotics, the medical area, urban planning, and graphics, where large amounts of diverse data are needed for both training and testing AI algorithms. The process of creating 3D synthetic data involves several steps, such as choosing the 3D model tool, creating the 3D model, applying texture and materials, setting up lighting, defining camera parameters, rendering the scene, augmenting data, adding depth and annotations, compiling the dataset, and performing validation and testing.

Measurement of visual quality, as perceived by human observers, is important in many applications. Many natural image databases have been annotated with subjective ratings of the images by human observers [3]. Labeling of synthetic 3D data is available for some datasets. For example, synthetic data for the simulation of autonomous vehicles[1]. However, ratings of the visual quality of such synthetic 3D scenes is much harder to provide. Even for producing 3D digits, urban planning, or brain images that can be visually interpreted, the combination of metrics used to evaluate data realism is still not well understood.

Another difficulty comes from the labeling of synthetic data. This can be accomplished with the help of a classifier trained on a real dataset. Such a labeling process is affected twice by accuracy issues: once when the classifier is trained and once when the synthetic data are classified.

These challenges, which added to the interestingness of the potential applications, created the motivation for our brief survey. We summarize and discuss the most prominent recent 3D generative methods. We present evaluation metrics and visualization tools used for 3D synthetic data. We also depict some of the current most significant applications of 3D generated data.

The need for large datasets in AI applications has made the SDG topic a hot research topic. Although SDG is quite widely approached by AI community researchers, by the time we started to write this survey, we could find only two relevant surveys that specifically cover 3D synthetic content generation: Bauer *et al.* [4] and Liu *et al.* [5].

When this brief survey work started, in January 2024, searching for *"synthetic data generation"* on DBLP reports 574 articles, the relevant ones starting from 2014 when Goodfellow *et al.* [6] introduced the Generative Adversarial Networks (GANs). Searching for *"3D synthetic data generation"* narrowed the results to 15 articles. Using DBPL for *3D visualization* the number of related articles is 1890. *"3D data visualization"* returns 366 results, few of them related to the AI area. The above results lead to the conclusion that the number of relevant papers covering the research area of our survey is around 100 for the DBLP search engine. As of the end of October 2024, the number of articles has not increased significantly, as shown in Figure 1. Papers on *Synthetic Data Generation* rose modestly from 574 to 670, while papers specifically focused on *3D Synthetic Data Generation* saw only a slight increase, from 15 to 20 articles. Similarly, the number of articles on *3D Visualization* and *3D Data Visualization* showed minimal variation, increasing from 1,890 to 1,928 and from 366 to 375, respectively.

However, the results present only the articles including the search words in the title, articles from the computer science field.

[1]https://analyticsindiamag.com/top-10-popular-datasets-for-autonomous-driving-projects/

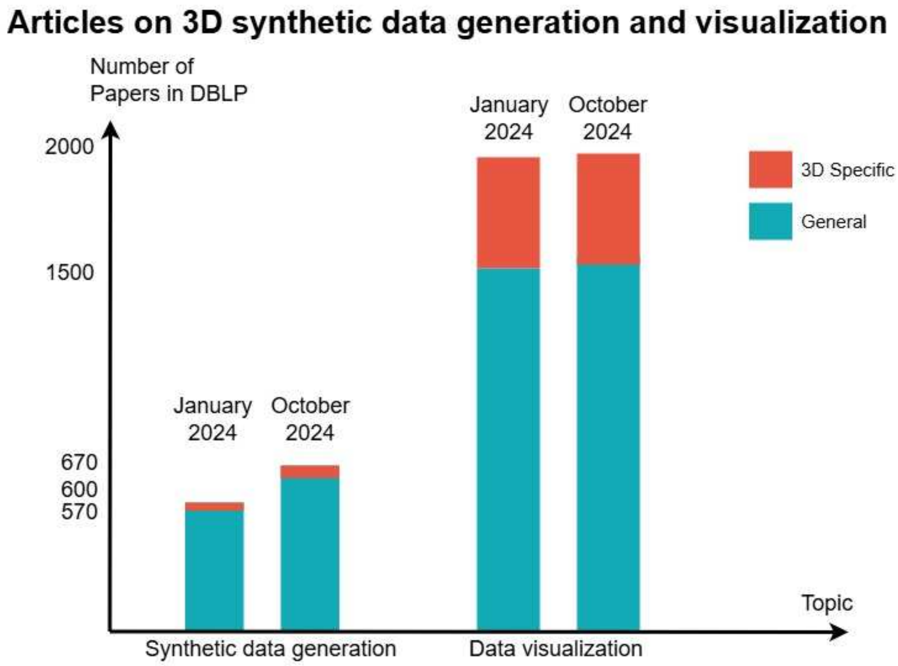

Figure 1: Evolution of Research Publications during 2024.

The strategy for gathering valuable information for this paper can be summarized as follows. We started collecting data from the e-nformation[2] portal (which provides access to the IEEE database), then we used the well-known academic search engines (DBPL, Google Scholar, Base) and eventually moved to the Cornell University open access archive (*arXiv*) to find the latest articles, some of them even not published yet.

The pool of related papers published in scientific conferences and journals is continuously increasing, but an abundant number of studies were released after 2023. We decided to include in this study both classical papers on prominent 3D generative methods and papers describing specific applications of 3D generative content and 3D visualization. As many of the selected articles were published in late 2023 and early 2024, they were available exclusively on *arXiv* at the time of writing this survey.

The remainder of the paper is structured as follows. Section 2 summarizes the most recent and significant 3D data generation methods. In Section 4 we focus on some main current applications of synthetic 3D data. Section 5 lists the existing 3D SGD and visualization software packages. Section 6 discusses SDG in the context of Green AI technologies. Section 7 contains our final remarks.

2 Current 3D Data Generative Techniques

The number of published papers on 3D data generation has increased significantly during the last two years. Researchers focused their creative energy towards both adapting existing techniques and creating new ones in order to open new directions in the 3D generative field. This section summarizes some significant approaches, with an emphasis on the most recent results associated with GANs. We focus especially on the applications of 3D synthetic data generation and visualization.

The importance of SDG has increased with the rapid development of AI, driven by the learning process that requires huge datasets to produce accurate models. Privacy issues have further accelerated the need for synthetic data. Research on this subject has become a growing trend in the AI field, as the accuracy of AI results depends not only on the selected method and architecture but also on the quantity and quality of data used for training and testing.

In practice, it can be noticed that the collected data (real data) are sparse and do not adequately cover the input space. Moreover, real datasets are often unbalanced, as some cases occur in very rare situations. Based on the structure of real datasets, synthetic data is needed to increase the coverage of

[2]https://www.e-nformation.ro/

the input space and to reduce the imbalance of real datasets. Today, the classic taxonomy for datasets used in training and testing processes (real data, synthetic data, and hybrid data) has shifted towards a two-category classification: hybrid data and fully synthetic data. Real datasets are used to generate synthetic data, sometimes in conjunction with predetermined constraints, to produce hybrid datasets. Privacy issues can occur and, in such cases, anonymization techniques must be applied either to the real data before using them to produce synthetic data or to the final hybrid dataset.

The need for 3D synthetic data has a forty-year history, driven by both the games and film industries. Aside from AI generative techniques, collections of 3D assets have been created either by CAD or by scanning real objects. A growing form of these assets is procedural assets, which use sets of conditional rules algorithms to produce unlimited variations of 3D objects. Procedural assets are described by a set of parameters that allow a diversity of new objects to be created by either choosing specific parameters or simply randomizing them. Procedural techniques can be applied to generate new environments/scenes to place the 3D procedural assets, creating realistic synthetic 3D data. The procedural content has proven to be a solid method for achieving 3D synthetic data. Applications such as Unity Shader Graph, Adobe Substance 3D, and Houdini are successfully used in the market[3].

Several 3D synthetic data generators have been introduced in recent years, as the need for 3D data in medical and nonmedical field applications has reached a new level. 3D visualization brings a better understanding of the data, as it provides depth compared to 2D visualization and allows slicing, rotation, translation, and compression operations that can improve the perception of the features contained in the datasets. The most prominent methods used in 3D GAI are GANs, VAE, Contrastive Learning, Neural Radiance Field, Diffusion Models, Flow-based Generative Models, and Autoregressive Models.

Bauer *et al.* presented a detailed survey on general SDG, analyzing methods, functionality, and improvements, providing a new classification and trend analysis [4].

2.1 Generative Adversarial Networks

The comprehensive study on data generation with GANs by Ferreira *et al.* [7] is focused on 3D volumetric data generation. According to this study, given the good results achieved by the Vanilla GAN generative model, several variations of this model were proposed:

Deep Convolutional GAN (Radford *et al.* [8]) adjusted convolutional network for both the generator and the discriminator for the generation of synthetic images.

Least Squares GAN (Mao *et al.* [9]) improved the quality of the images produced and prevents the problem of gradient vanishing by using the least squares loss function for the discriminator.

Conditional GAN (Mirza *et al.* [10]) introduced an extra input information "y" in both the generator and the discriminator, which plays the role of conditioning the generative process.

WGAN (Arjovsky *et al.* [11]) used the Earth Mover(EM) distance (Wasserstein-1) for learning distributions. Considering that EM is both continuous and differentiable; the training process can be performed until the gradient approaches 0, avoiding the vanishing/exploding gradient issue. WGAN has proven to be more reliable than DCGAN, showing no collapse mode.

Progressive GAN (Karras *et al.* [12]) introduced the idea of progressively increasing the spatial resolution of both the generator and the discriminator, allowing high-resolution synthesis and a faster training phase. A new metric based on the Laplacian pyramid combined with the Wasserstein distance has been used to assess the authenticity of the generated content.

BigGAN, or Large Scale GAN aims to optimize the gradient through the benefits of larger models and larger batches. Brock *et al.* [13] conjectured that BigGAN improves the gradients of both networks, the generator and the discriminator, by scaling up both the model and the batch - allowing to cover more modes. Although in fewer iterations BigGAN achieves better performances, it was noticed that it may become unstable and training can collapse. However, this new GAN model can improve the Inception Score and the Frechet Inception Distance compared to previous GAN versions, generating high-fidelity synthetic images and increasing the variety of samples.

[3]https://blog.unity.com/industry/getting-started-with-3d-content-for-synthetic-data

Based on the progressive GAN architecture, *Style GAN* (Karras *et al.* [14]) has an intermediate latent space that controls the generator, without following the probability density of the training data. Style mixing is possible by using two random latent codes for generation, instead of just one.

Ideally, a successful GAN training process leads to 50% discriminator accuracy. In such a case, the discriminator is performing random guessing, as it cannot distinguish between real data and synthetically generated data.

2.2 Variational Autoencoders

Variational Autoencoder (VAE), introduced in [15, 16], consists of two neural networks, an encoder and a decoder, and a loss function. The goal of the encoder is to produce a compressed hidden representation z of the VAE input x. This latent representation is then fed into the decoder network, generating an output z, to reconstruct the input x. Using the loss function, the network is trained without supervision to produce output z similar to the input of the encoder x, minimizing the lost information. In the generative process, the decoder network is used to produce synthetic output by sampling from the continuous latent space. For the data generation process, the main difference between VAE and Vanilla autoencoders is the VAE's continuous latent space allowing for easy interpolation, in constrast with the sparse latent space associated to the Vanilla autoencoders.

2.3 Autoregressive Models

Autoregressive Models (AR) forecast future behavior based on data on past behavior. AR variations used for image generation are PixelRNN and PixelCNN [17]. AR captures the entire data distribution, generating typically low-resolution images as a result of the high computational power required. In order to achieve higher resolution and fidelity, Subscale Pixel Networks and Multidimensional Upscaling were introduced[4].

2.4 Contrastive Learning

Contrastive Learning (CL) is a learning method that focuses on extracting meaningful representations by contrasting positive and negative pairs of instances, so similar instances are close together in the representation space, while dissimilar instances are far apart. It can use the triplet loss function, where an anchor instance, a positive sample, and a negative sample are given, and the objective is to minimize the distance between the anchor and positive sample and maximize the distance between the anchor and the negative sample. Additionally, an N-pair loss function can be employed, which extends this idea by selecting multiple positive and/or negative samples to refine the representation further. A comprehensive study of visual representation with CL is presented in [18].

2.5 Neural Radiance Field (NeRF)

A NeRF [19] uses a sparse set of input views to optimize a continuous volumetric scene function. Novel views of a complex scene are generated, providing a static set of images as input to the NeRF. It represents the revolutionary AI technology in scene rendering. Some drawbacks of this method are: a NeRF trained for a specific scene cannot be used for a different one, it is slow in training and rendering, and it is used for static scenes. Several derived methods were proposed to overcome the Vanilla NeRF: pixelNeRF, Mega-NeRF, Mip-NeRF, Plenoxels, and RegNeRF.

2.6 Diffusion Models

Inspired by non-equilibrium thermodynamics, Diffusion Models (DM) [20] consist of a forward process called "the diffusion process" and a reverse process, also known as "the reverse diffusion process". During the forward process, noise is successively added to the input, which generally is an image, while in the reverse process, the noise is processed to obtain a sample from the target distribution. This is a non-aggression method, avoiding the disadvantages like slow and unstable training, the need of

[4]https://towardsdatascience.com/generating-high-resolution-images-using-autoregressive-models-3683f9af0db4

large amount of data, and vulnerability to collapse mode. DM bring better image quality, high resolutions, an interpretable latent space and exhibit robustness to overfitting. DM gained popularity with DALL-E 2 and is a core method for the Image generation applications like GLIDE, Sora, Midjourney, Imagen, etc. Ling *et al.* [21] summarize the methods, applications, and directions for DM.

2.7 Flow-Based Generative Methods

Flow-based generative methods (FBGM) use the true data distribution to generate the data. To learn the probability distribution, FBGM uses invertible transformation functions to map data x to latent representations z. These functions should have an easy-to-calculate Jacobian determinant to keep the computation power at a decent level. The generative process samples the latent space z and applies the inverse transformation to produce synthetic data. Improved variants of FBGM were developed: NICE [22], Planar Flow [23], Real Non-Volume Preserving [24], Generative Flow (Glow) [25], Masked Autoregressive Flow (MAF) [26], and Continuous Normalizing Flow (CNF) [27].

3 Evaluation Metrics for Synthetic 3D Data

The generated data sets are useful if we can assess their quality. This looks like an easy job for images, where a human subject can visually assess the quality of a fake image, but for complex 3D data, we need specific metrics to assess quality, size, complexity, and other attributes. Such metrics refer to quantitative measures or characteristics employed to evaluate data aspects. This mechanism allows AI practitioners to objectively select consistent datasets for their applications. This section reviews such evaluation metrics.

Synthetic data must be assessed with respect to three aspects: fidelity, utility, and privacy[5]. Each of these aspects is measured with specific metrics. Studies have demonstrated that to achieve the best synthetic dataset, a trade-off is needed while optimizing the aforementioned three categories. The scores for these three aspects cannot be optimized simultaneously, so the suitable combination is chosen based on the intended purpose of the dataset.

For fidelity, the most common metrics are Statistical Similarity, Kolmogorov-Smirnov and Total Variation Distance Test, Category and Range Completeness, Boundary Preservation, Incomplete Data Similarity, Correlation, and Contingency Coefficient. Utility metrics considered to assess synthetic data include Prediction Score, Feature Importance Score, and QScore. Popular metrics for privacy are Exact Match Score, Row Novelty, Correct Attribution Probability Coefficient, Inference, Singling-out, and Linkability.

The evaluation of SDG depends not only on the targeted application but also on the generating model. The SDG must follow the same statistical model as the real data used for the dataset generation phase. For example, a Gaussian distribution that models the real dataset must also be found in the SDG in terms of mean and variance.

Obviously, the statistics depicted by the metrics presented above include the statistics generated by the trained model. Hence, the model is implicitly considered within the synthetic data evaluation process, as it follows the statistics described by the training dataset.

The quality of the 3D SGD is demonstrated by the performance of the trained model based on the dataset produced. This implies that metrics such as accuracy, precision, recall, and the F1 score should be evaluated on relevant tasks of the application, which gives the utility of the generated data on downstream tasks. Some of the most relevant metrics for the 3D SDG evaluation are visual quality, geometric accuracy, semantic accuracy, diversity, generalization, robustness to noise and perturbation, and computational efficiency. Similarly to general synthetic data, 3D SDG must obey the trade-off between fidelity, utility, and privacy.

Some of the most popular 3D datasets among the scientific community are: 3DMnist[6], Data Science

[5]https://syntheticus.ai/blog/how-to-evaluate-synthetic-data-quality
[6]https://www.kaggle.com/datasets/daavoo/3d-mnist

Bowl[7], Joint 2D-3D-Semantic (2D-3D-S) Dataset[8], Street View Image, Pose, and 3D Cities Dataset[9], ObjectNet3D Dataset[10], Stanford Drone Dataset[11] and others[12]. These large datasets contributed to the constantly growing popularity of 3D-oriented AI applications.

4 Applications of 3D Synthetic Data

In the following, we will look at some of the most promising and recent applications of 3D generated data.

3D synthetic data AI applications are increasingly important in various industries for training, testing, and improving machine learning models. Some of the most prominent domains of application are medicine and healthcare, autonomous driving, augmented reality and virtual reality, robotics and automation, architecture and construction, manufacturing, entertainment and media, environmental and geospatial analysis, education and training, security and surveillance. Building such an application involves key technologies such as 3D modeling and rendering software, deep learning frameworks, simulation platforms, and data augmentation. Although most of the 3D synthetic data generation applications refer to scenes, object, and human, the content can be more diverse. *Infrared imaging* for thermography, surgical assistance, security, industry maintenance and quality control, *LiDAR* for autonomous vehicle mapping the environment and robot navigation, *RADAR* for aerospace, defense and marine applications, and *Hyperspectral imaging* for agriculture and environment monitoring are sensing technologies beyond the human vision involved in 3D SDG applications.

Table 1 collects relevant work on 3D SDG using GAN-derived methods to produce high-quality data for mainstream applications.

Liu *et al.* [5] presented a detailed survey on 3D SDG, analyzing both implicit and explicit 3D representations, oriented on native, 2D prior-based, and hybrid 3D generative methods applied on objects, scene, and human avatar. The authors provided a chronological overview of the three categories of methods. Table 2 depicts results from [5], updated with very recent applications found by us.

Xu *et al.* [37] conducted a study on GAI for smart city. This survey presented the ability of GAI to facilitate data augmentation, synthetic data and scenario generation, automated city modeling, and generative urban design and optimization. The usage of urban digital twin applications (replicas of real cities) has the goal to process real data closer to the source, with less bandwidth and latency, to enable real-time responses on nowadays digital world urban environment problems.

Another pioneering paper (Zhao *et al.* [38]), presented the main challenges in the generation of 3D content. Although there have been advances in text and image generation, 3D content generation is still in its early stages due to data scarcity and the need of huge computing resources involved in the 3D generative content. The authors proposed the usage of pre-trained diffusion models as an opportunity in 3D content generation.

A current hot research area is AI applications in robotics. Perception, localization, and navigation are essential tasks for such applications. In order to create stable consistent robot AI solution, multiple 3D possible environment configurations must be used in the learning phase, hence the SDG plays here an important role. The Ming *et al.* [92] survey focuses on autonomous operation, including 3D reconstruction, segmentation, pose estimation, simultaneous localization and mapping (SLAM), navigation and planning, and interaction. The potential of AI generative methods in the design of complex robotic systems is explored by Chang *et al.* [93], using the latent diffusion model to learn the distribution of data. Nasiriany *et al.* [94] explored 3D synthetic generative methods to create kitchen environments enhanced with 3D assets, to provide large datasets required by robots in everyday tasks at home, such as preparing coffee, soaking pans, restocking kitchen supplies, etc. Surgical robotics automation has great potential to improve efficiency and safety using the estimation of 6D pose of surgical instruments, as presented by Barragan *et al.* [95]. They proposed a set of techniques both

[7]https://www.kaggle.com/c/data-science-bowl-2017/data
[8]http://buildingparser.stanford.edu/dataset.html
[9]https://github.com/amir32002/3D_Street_View
[10]https://cvgl.stanford.edu/projects/objectnet3d/
[11]https://cvgl.stanford.edu/projects/uav_data/
[12]https://cvgl.stanford.edu/resources.html

Table 1: Relevant articles focused on GAN-based 3D synthetic data generation.

Article	Topic	Generative Method	Application	Dataset
Peng [28]	generating 3D from a 2D image	cGAN	nonmedical synthetic aperture radar	custom based on MSTAR
Karnewar [29]	remixes of a single 3D scene	3inGAN	nonmedical static 3D scene reshuffling	custom
Mangalagiri [30]	generate 3D images for COVID	cGAN	medical - COVID detection create largest COVID dataset generate consistent CT from white noise	IRB Proprietary
Mok [31]	3D Lidar intensity rendering	CycleGAN with modified Loss function	nonmedical generate environment for military vehicles	unannotated real data
Chong [32]	generate realistic 3D MRI brain images	WGAN-GP pix2pix GAN	medical - healthy brain 3D model create Dataset to detect brain tumor	HCP ADNI
Chu [33]	generate 3D point cloud from RGB image	custom pix2pixHD GAN	nonmedical autonomous robots remote-controlled systems	NYU-Depth V2
Dundar [34]	generate 3D realistic model from single view image	GAN multistage training pipeline results comparable with StyleGAN	both nonmedical and nonmedical limitation on holes and categories of objects	LSUN Car LSUN horse NABirds
Dundar [35]	3D model reconstruction from multi-view images 3D model reconstruction from single-view images	GAN multistage training pipeline attention mechanisms pre-trained DNN for noisy silhouettes and camera parameters	both nonmedical and nonmedical limitation on holes and categories of objects	Tripod Pascal 3D+ CUBS
Zheng [36]	High quality 3D shape generation reduce dissimilarities between generated shape and a shape collection	SDF-StyleGAN proposed FID for 3D StyleGAN2 for pre-training	both nonmedical and nonmedical Shape reconstruction from point clouds Shape completion Shape generation from single images Shape style editing	ShapeNet Core V

Table 2: 3D synthetic data applications.

Application	Year	Generative Method	Category
DreamFussion [39]	2022	2D prior-based 3D	Object
Magic3D [40]	2022	2D prior-based 3D	Object
AvatarCLIP [41]	2022	2D prior-based 3D	Human
SceneDreamer [42]	2023	2D prior-based 3D	Scene
TEXTure [43]	2023	2D prior-based 3D	Object
Fantasia3d [44]	2023	2D prior-based 3D	Object
Text2Room [45]	2023	2D prior-based 3D	Scene
ProlificDreamer [46]	2023	2D prior-based 3D	Object
HeadSculpt [47]	2023	2D prior-based 3D	Human
DreamHuman [48]	2023	2D prior-based 3D	Human
DreamGaussian [49]	2023	2D prior-based 3D	Object
TEXFusion [50]	2023	2D prior-based 3D	Object
LucidDreamer [51]	2023	2D prior-based 3D	Scene
SceneTex [52]	2023	2D prior-based 3D	Scene
DreamControl [53]	2023	2D prior-based 3D	Object
InfiniCity [54]	2023	2D prior-based 3D	Scene
CityCraft [55]	2024	2D prior-based 3D	Scene
SMPL [56]	2015	native 3D	Human
Text2Shape [57]	2018	native 3D	Object
GRAF [58]	2020	native 3D	Scene
SMPLicit [59]	2021	native 3D	Human
HeadNeRF [60]	2021	native 3D	Human
gDNA [61]	2021	native 3D	Human
ShapeCrafter [62]	2022	native 3D	Object
GAUDI [63]	2022	native 3D	Human
Point-E [64]	2022	native 3D	Object
NeuralField-LDM [65]	2023	native 3D	Scene
Shap-E [66]	2023	native 3D	Object
TextField3d [67]	2023	native 3D	Object
LRM [68]	2023	native 3D	Object
DMV3D [69]	2023	native 3D	Object
XCube [70]	2023	native 3D	Scene
SofGAN [71]	2022	hybrid 3D	Human
MAV3D [72]	2023	hybrid 3D	Scene
Cascade-Zero123 [73]	2023	hybrid 3D	Object
One-2-3-45 [74]	2023	hybrid 3D	Object
MVDiffusion [75]	2023	hybrid 3D	Scene
HumanNorm [76]	2023	hybrid 3D	Human
Wonder3D [77]	2023	hybrid 3D	Object
DreamCraft3D [78]	2023	hybrid 3D	Object
Consistent4D [79]	2023	hybrid 3D	Dynamic
Instant3D [80]	2023	hybrid 3D	Object
ControlRoom3D [81]	2023	hybrid 3D	Scene
SceneWiz3D [82]	2023	hybrid 3D	Scene
4DGen [83]	2024	hybrid 3D	Dynamic
One-2-3-45++ [84]	2024	hybrid 3D	Object
DreamGaussian4D [85]	2024	hybrid 3D	Scene
Animate124 [86]	2024	hybrid 3D	Dynamic
GSGEN [87]	2024	hybrid 3D	Object
SyncDreamer [88]	2024	hybrid 3D	Object
MVDream [89]	2024	hybrid 3D	Object
SGAM [90]	2024	hybrid 3D	Scene
CityDreamer [91]	2024	hybrid 3D	Scene

to enable automatic generation of large datasets for 6D pose estimation of surgical instruments and to produce an improved surgical scene. Alonso *et al.* [96] estimated the depth map, a representation that encodes the distance of objects or surfaces in a scene from a specific viewpoint, using three cameras to avoid the use of expensive equipment to locate, plan and navigate the robot within the environment. Although this is not a 3D generative study it is worth to be mentioned as a possible part of an environment AI generative application.

The entertainment industry is one of the key areas that drove the evolution of the 3D SDG. Synthetically generated short films have been a topic covered in the last decade. Song *et al.* [97] introduce a new methodology to create synthetic, high-quality data for long movies. They propose MovieLLM, a framework to generate such movies, including a pipeline with three stages: movie plot generation, style immobilization process and video instruction data generation. Related works on this topic are presented in [98, 99, 100].

Character clothing in synthetic data for the entertainment industry as well as the digital fashion industry rely on clothing datasets containing 3D clothing segmentation. Antic *et al.* [101] introduced CloSe-D, the first dataset based on 3D color clothing segmentation, to acquire a higher level of realism and personalization. To improve the pose generalization they incorporated human body information in the publicly available dataset.

In [102], Sklyarova *et al.* proposed a realistic 3D human hair modeling, based on a two-stage pipeline: first stage applies implicit volumetric representations to reconstruct coarse hair, bust shapes and hair orientation, while the second stage involves an optimization process oriented on hair constraints learned from synthetic generated 3D data.

Urban planning and city development applications benefit from 3D synthetic data sets by providing realistic, scalable, and customizable models that can simulate various scenarios, enhance decision making, improve resource allocation, and facilitate stakeholder engagement through immersive visualizations. Xu *et al.* [37] summarized the advantages of using generative techniques in smart city digital twins. Deng *et al.* [55] introduced an innovative framework that enhances both the diversity and the quality of urban scene generation, with the aim of facilitating application-oriented autonomous driving, smart city development, and traffic simulation. They used a 2D to 3D approach, starting from a diffusion transformer, generating a 2D city layout, applying an LLM to produce the land layout, and finally applying assets for precise scene reconstruction. CityDreamer is a generative model introduced by Xie *et al.* [91]. They synthesized new city scenes by using a composition of different types of neural fields, such as building instances and background stuff.

Most of the papers presented above are very recent, from 2024, currently available only on *arXiv*.

5 3D Synthetic Data Generation and Visualization Packages

When assessing the accuracy of an AI application, the two main factors are interconnected: the algorithm and the dataset. These factors are crucial for successfully developing and deploying machine learning models that can deliver real-world value. The diversity and size of the dataset are key aspects that lead to a successful learning phase, which forms the foundation for an effective inference phase. This is why a lot of effort has been concentrated on creating synthetic data generation platforms and developing libraries and tools to support the generative process. Several 3D data generation and visualization platforms are available on the market, and we will refer to them in the following.

Multiple commercial platforms for 3D data generation have recently been developed. Anyverse[13] generates static and dynamic scenes. Bifrost[14] produces complex 3D labeled environment scenes, with the aim of achieving simulation applications. Hexa[15] converts 2D images into 3D data for advertising and market purposes.

Several open-source platforms are also available. Open3D [103], released under the MIT license, is a comprehensive open source library coded in C++ and Python that produces 3D SDG. It has 3D ML support with PyTorch and TensorFlow. Libraries like Matplotlib or Plotly are used in Python to

[13] https://anyverse.ai/synthetic-data-solutions/
[14] https://www.bifrost.ai/
[15] https://www.prodwaregroup.com/our-solutions/hexa/

create 3D visualizations by choosing three significant features of the data in the dataset to be mapped into the 3D space.

In Python, there are several packages available for 3D SDG, including testing algorithms, training models, and data visualization. The most prominent packages are Scikit-learn[16], NumPy[17], Mayavi[18], PyTorch3D[19], MNE-Python[20], OpenAI Gym[21].

In R, there are also some popular packages for synthetic 3D data generation. Among the most noticeable are plotly[22] and rgl[23] which have visualization as their primary purpose but can be extended for 3D generative tasks. Scatterplot3d[24] is designed for 3D scatter plot and is adaptable for 3D visualization. Other packages like scattermore[25] and rayshader[26] are oriented toward specific 3D data visualization, with no generative functionality.

Visualizing data sets is crucial for both understanding the data and communicating the results [104, 105]. 3D visualization tools are designed to present multivariate data representation, allowing depth perception, cluster identification, and pattern recognition. The interactive exploration of data makes the 3D visualization appealing for presentations and reports, allowing better data interpretation.

Some of the common general methods used for visualization include scatter plots, histograms, kernel density plots, cumulative distribution functions, box plots, violin plots, Q-Q plots, heatmaps, dimensionality reduction, statistical tests, domain-specific plots, and interactive visualizations.

The current trend in 3D visualization is to use PyTorch3D. It benefits from efficient 3D operators, advanced rendering API, and extended batching capabilities to solve the 3D challenges related to representation, batch processing, and speed. The main reason behind this choice is the versatility of this product, which can support both research and development needs. PyTorch3D is described as having simple model definitions and easy hyperparameter settings, which, along with the comprehensive documentation provided, makes this package an attractive option both for beginners and experienced AI practitioners. However, PyTorch3D is still growing as the 3D visualization AI community needs to become more specific.

A comprehensive overview of recent progress in the 3D generative field is provided in [106]. The impact of NeRF and 3D Gaussian Splatting has increased the realism of the synthetically generated content.

3D General Line Coordinates, a technique that combines three types of GLC (Shifted Paired Coordinates, Shifted Tripled Coordinates, and General Line Coordinates-Linear, used so far in 2D) can be used for interactive visual pattern discovery [104, 105, 107]. This method allows a lossless representation of the information in n dimensions in 3D [108] and allows a better visualization while migrating from 2D to 3D plots.

Recently, *eWeek*[27] analyzed the best 3D generators on the market, which are mainly geared to 3D scene reconstruction, body motion, gaming, architecture, e-Commerce, using text-to-3D, image-to-3D, or even video-to-3D methods.

6 The Pivotal Role of Synthetic Data in the Era of Green AI

SDG plays a significant role in AI development by providing the large datasets that modern AI applications require to achieve desired performance levels. However, this generative process also leads to energy consumption (EC). Therefore, the energy consumption associated with the SDGs should

[16] https://scikit-learn.org/stable/
[17] https://numpy.org/
[18] https://docs.enthought.com/mayavi/mayavi/
[19] https://pytorch3d.org/
[20] https://mne.tools/stable/index.html
[21] https://openai.com/research/openai-gym-beta
[22] https://plotly.com/r/
[23] https://cran.r-project.org/web/packages/rgl/vignettes/rgl.html
[24] http://www.sthda.com/english/wiki/scatterplot3d-3d-graphics-r-software-and-data-visualization
[25] https://cran.rstudio.com/web/packages/scattermore/index.html
[26] https://www.rayshader.com/
[27] https://www.eweek.com/artificial-intelligence/best-ai-3d-generators

be added, and sometimes weighted, to the overall consumption of AI applications that utilize these synthetic or hybrid datasets to accurately report complete resource usage.

The resources needed to develop AI applications keep growing, which presents challenges due to the high cost of equipment and the significant energy involved. An AI research project can take months of training and fine-tuning. Local hardware is no longer a reliable resource for consistent and fast training; therefore, several cloud-based platforms now offer access to more powerful computational assets.

These platforms can be categorized as free platforms (which provide limited resources) and paid platforms (which offer remote processing environments with more advanced capabilities). Some free platforms also provide enhanced options through paid subscriptions.

Prominent free platforms include Google Colaboratory, Kaggle Kernels, Microsoft Azure Notebooks/Azure Machine Learning, Amazon SageMaker, IBM Watson Studio, and Paperspace Gradient. Notable paid platforms include Google Cloud AI Platform Notebooks, Run.ai, FloydHub, CoCalc, Deepnote, and Hugging Face Spaces.

Whether using local or cloud-based hardware, the need to train large datasets across numerous epochs results in significant energy consumption. As the development process involves iterative refinements, such as the adjustment of the model architecture, retraining, and fine-tuning parameters, energy consumption tends to increase.

The term 'Green AI' was introduced in 2019 by Schwartz *et al.* [109]. It refers to an energy-efficient and environmentally sustainable approach to AI development that is gaining widespread attention among AI practitioners. This approach contrasts with 'Red AI', which prioritizes maximizing the performance of AI applications without considering costs or environmental impact.

Green AI aims to strike a balance between performance and resource consumption by optimizing algorithms, developing energy-efficient hardware, and adopting more efficient data processing techniques. The concept of green AI promotes transparency by encouraging researchers to report not only the performance metrics achieved in their studies but also the resource costs involved, such as the carbon footprint.

The AI community has responded to the need to comply with Green AI principles. In 2023, Zhou *et al* [110] published a comprehensive survey on this topic, introducing four key components that define Green AI: Measures of Greenness, Energy-Efficient AI, Energy-Efficient Computing Systems, and AI Use Cases for Sustainability. Clemm *et al.* [111] explored the current status of approaches to environmental assessment and ecodesign of AI systems, proposing a life-cycle framework based on four key elements of these software-hardware systems: model, data, server, and cloud. They provided a detailed study of the carbon footprint associated with the relevant computing hardware.

The study of Asperti *et al.* [112] marked a pioneering effort to address the environmental sustainability of the SDG. This study analyzes several versions of variational autoencoders from an energy consumption perspective, focusing on encoder and decoder optimizations to reduce the time required for the generative process.

When discussing the SDG within the context of Green AI, it is essential to emphasize that energy consumption affects the AI application development process in two key ways:

- Energy is consumed to create new datasets during the generative process.
- The quality of the data set influences the training process, thereby affecting energy consumption during the development and deployment of AI applications.

During the generative phase, selecting the most effective method and the appropriate architecture with optimal hyperparameters is crucial to optimize resource usage. In the AI application development process, the energy consumption overhead generated by synthetic dataset production can be offset during subsequent steps, such as training, fine-tuning, and evaluation and testing. High-quality synthetic datasets can help reduce computational time and energy requirements, considering faster training, reduced iterations, and the ability to avoid costly data collection. Clearly, the deployment and refinements steps are also influenced by the quality of the data set. It can be concluded that the energy saved in the later stages of AI development process offsets the energy spent on data generation.

7 Conclusion

We explored current advances in 3D SDG, which included generative methods, evaluation metrics, application areas, and available software packages. Our focus was on 3D data and we addressed the challenges faced in this domain, highlighting promising research directions.

Current deep learning models need very large but also relevant training datasets. Synthetic data can be used successfully to augment training data. This makes SDG and GAI highly important research areas with significant potential application.

Traditionally collected datasets, especially the unstructured ones like the images used for the 3D case referred to in the current paper, need to be preprocessed and analyzed before being used. This requirement generates a bottleneck in the way of producing really large datasets, mainly due to the extremely high costs and long time consumed to achieve such datasets, so generative methods proved to be the bypass to this bottleneck[28].

Applications of 3D SGT gain popularity, in both the medical and nonmedical fields, involving specific techniques and evaluation metrics. Packages for 3D SDG and 3D visualization have been recently developed and are widely used in both research and industry area applications.

The use of GAI must be carried out in accordance with the AI code of ethics. Similarly to any AI application, GAI techniques must address the responsibility gap, ensuring that the generated data are high-quality, anonymous, and bias-free data.

In March 2024[29] The European Union unanimously endorsed the AI Act, affirming the political agreement reached in December 2023. European Artificial Intelligence Board has the role to advise and assist in deploying the set of laws for all member states in order to implement ethical AI, to inhibit the possible harmful AI usage. EU decided to adopt the classification of AI system as high risk. GAI must comply with these set of rules for all applications developed and operated in the EU. This can be seen both as a fracture in the fast-growing pace of general AI application development and as a challenge in the evolution of scientific progress in this research area.

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