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KAPITEL 4 / *CHAPTER 4* [4]
GENERATIVE MODELS FOR THE SYNTHESIS OF THREE-DIMENSIONAL OBJECTS

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Introduction

In recent years, generative artificial intelligence has become one of the most dynamic areas of information technology development. If a few years ago generative algorithms were used mainly to create two-dimensional images, today technologies for automated synthesis of three-dimensional models are actively developing. This is due to the rapid increase in the power of graphics processors, the emergence of large training sets of three-dimensional models, the development of deep learning neural networks and the improvement of spatial geometry generation algorithms [1] .

Modern computer-aided design systems, digital twins, metaverses, video games, augmented and virtual reality technologies require the rapid creation of a large number of three-dimensional models of varying degrees of detail. Traditional modeling methods based on manual creation of polygonal meshes require significant time, high-level specialist qualifications, and significant financial resources. In this regard, automation of the process of synthesis of three-dimensional objects is becoming one of the most important areas of development of modern computer graphics [2] .

Unlike classical geometric modeling algorithms, generative models are able to independently form new spatial structures using statistical patterns obtained during training on large data sets. Such models can generate three-dimensional objects from text descriptions, sketches, photographs, or combinations thereof.

Diffuse generative models have gained particular development, providing high quality of synthesized objects due to the gradual restoration of spatial structure from random noise. Unlike generative adversarial networks (GANs), they demonstrate better stability of learning, provide a higher diversity of results, and allow the formation of complex geometric structures [3] .

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An important stage in the development of 3D generation was the introduction of neural radiation fields (NeRF), which allowed to move from classical polygonal models to a continuous representation of 3D space. Further development of this concept led to the emergence of Gaussian Splatting technology, which provides a significant acceleration of the construction and visualization of 3D scenes while maintaining high accuracy of geometry reproduction [4] .

In parallel, multimodal generative systems are actively developing, capable of creating full-fledged three-dimensional models directly from textual descriptions in natural language. Such systems integrate large language models, diffusion algorithms and modern spatial reconstruction methods, which opens up new opportunities for design automation in mechanical engineering, architecture, medicine, education and the digital entertainment industry [5] .

Despite significant progress, modern generative technologies still have a number of limitations. These include significant computational costs during training, the complexity of forming topologically correct polygonal models, the need for large training samples, and insufficient universality of models for different types of geometry. In addition, the problem of integrating generative algorithms with modern software systems for three-dimensional modeling and rendering remains relevant.

The purpose of the work is to analyze modern generative models of synthesis of three-dimensional objects, study their architectural features, principles of functioning, as well as determine promising directions for the development of generative technologies in three-dimensional modeling systems.

4.1 Analysis of the current state of research into generative synthesis of three-dimensional objects

The first generative models that found wide practical application in image synthesis tasks were variational autoencoders (VAE). Their main advantage is the ability to learn a compact latent space in which similar objects are located close to each other. This allows interpolation between models, creation of new geometry variants and controlled generation. However, the use of VAE for the synthesis of complex three-dimensional models revealed a number of shortcomings, including insufficient surface detailing, smoothing of small elements and difficulty in reproducing objects with complex topology.

The next stage in the development of generative technologies was the introduction of generative adversarial networks (GAN). The GAN architecture involves the interaction of two neural networks: a generator that creates new objects, and a discriminator that evaluates their correspondence to real data. Competitive learning has significantly improved the quality of synthesized models compared to autoencoders. However, the use of GANs is accompanied by problems of learning instability, the phenomenon of mode collapse, when the model generates only a limited set of similar results, as well as high requirements for the selection of hyperparameters.

Further development of generative modeling is associated with the emergence of diffusion models. Their principle of operation is based on the gradual addition of noise to the training data and the subsequent restoration of the initial structure during the inverse process. Unlike GANs, diffusion models are characterized by more stable learning, better coverage of the space of possible solutions and high quality of the results obtained. It is this class of models that dominates the field of generative artificial intelligence today, ensuring the creation of realistic two-dimensional and three-dimensional objects [2] .

An important feature of modern generative models is the use of multimodal learning. Along with geometric information, text descriptions, photos, video sequences, and semantic characteristics of objects are taken into account during training. Thanks to this, the user can create three-dimensional scenes using only text queries in natural language. This approach greatly simplifies the modeling process and makes modern generative systems accessible to users.

One of the most well-known solutions in this direction is the DreamFusion model, proposed by Google Research. The main feature of DreamFusion is the use of a pre-trained text-visual diffusion model to optimize the parameters of the three-dimensional representation of the scene. Instead of training on large collections of 3D models, the system uses an assessment of the quality of synthesized projections by a two-dimensional diffusion model. This significantly reduced the need for specialized three-dimensional training samples [3] .

The Magic3D system was a further development of this idea, which uses a two-stage generation process. In the first stage, a coarse geometry of the object is created with low resolution, after which it is detailed using a high-quality diffusion model. This approach significantly reduced the generation time compared to DreamFusion and improved the quality of textures and fine geometric details.

In parallel, methods based on neural radiation fields (NeRF) are actively developing. Unlike traditional polygonal models, NeRF describes three-dimensional space as a continuous function that determines the density of the environment and the radiation characteristics for each spatial point. This approach provides extremely realistic reproduction of lighting, translucent materials, complex reflections and global illumination. However, classical NeRF algorithms are characterized by significant computational costs during training and visualization, which limited their use in real-time systems [4] .

To overcome these limitations, the 3D Gaussian Splatting technology was proposed. Its main idea is to represent the scene not as a set of three-dimensional Gaussian primitives, each of which is described by coordinates, color, transparency, orientation and covariance matrix. Thanks to this, it was possible to significantly speed up the rendering process without significant loss of quality. Today, Gaussian Splatting is considered one of the most promising areas of development of interactive three-dimensional graphics.

A separate area of modern research is the generation of polygonal meshes using diffusion models. Unlike early methods that generated only voxel or implicit representations of objects, modern algorithms are able to directly create polygonal models suitable for use in computer-aided design systems, game engines, and 3D graphics packages. Considerable attention is paid to ensuring topological correctness of meshes, uniform polygon distribution, and automatic creation of UV-wraps.

A significant direction in the development of generative models is their integration with modern graphics engines and software platforms. Most of the latest systems support the export of models in OBJ, FBX, glTF and USD formats, which ensures compatibility with Blender, Autodesk Maya, Unity, Unreal Engine and other professional three-dimensional modeling tools. Thanks to this, generative algorithms are gradually moving from the category of experimental research to practical use in industry.

Analysis of modern research shows that the most promising direction of development is the combination of diffusion models, neural radiation fields, Gaussian Splatting, large language models, and classical computer graphics methods.

It is the integration of these technologies that allows us to create new generation software systems capable of automatically generating high-quality three-dimensional objects, adapting them to the requirements of specific applications, and providing interactive work in real time.

Features of constructing elements of generative models for the synthesis of three-dimensional objects are considered in [6-11].

4.2 Classification and principles of functioning of generative models of synthesis of three-dimensional objects

The simplest way to represent a three-dimensional object is a voxel model. Voxels can be considered as an analogue of two-dimensional pixels, but in three-dimensional space. The space is divided into a regular cubic grid, each element of which contains information about whether the corresponding region belongs to the interior or exterior of the object. Such a representation significantly simplifies the construction of neural networks, since it allows the use of three-dimensional convolutional operations similar to classical CNNs.

The main advantage of the voxel representation is the simplicity of implementation and the possibility of direct application of deep learning methods. However, the use of a regular spatial grid leads to an exponential increase in memory size with increasing resolution. For example, increasing the resolution of the model by

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two times leads to an eightfold increase in the number of voxels, which significantly limits the practical use of highly detailed models.

Another common way to represent geometry is as a point cloud. In this case, a three-dimensional object is described by a set of spatial coordinates of individual points, each of which may additionally contain information about color, surface normal, or other attributes.

The main advantage of point clouds is the compact representation of complex geometry and the absence of the need to build topological relationships between surface elements. At the same time, the lack of explicit information about the surface structure significantly complicates further texturing, animation, and use of such models in CAD systems.

The most common representation of three-dimensional models in modern computer graphics remains polygonal meshes. The surface of an object is formed by a set of interconnected triangles or polygons. This is the representation method used by almost all graphics engines.

The generation of polygonal models is a much more complex task compared to the generation of voxels or point clouds. The reason for this is the need to ensure topological consistency of the surface, the absence of self-intersections, the correct orientation of normals, and the ability to further edit the model.

That is why modern generative systems often first create an implicit representation of geometry, which is only converted into a polygonal mesh at the final stage.

A special place among modern approaches is occupied by implicit surface representations (Implicit Surface Representation). In this case, the surface is described not by a set of polygons, but by a mathematical function that determines whether any point in space belongs to the internal or external region of the object.

Implicit representations allow you to build smooth surfaces regardless of their complexity, easily change the topology of objects, and form highly accurate geometric models.

Neural Radiance Fields have been further developed. Unlike classical geometry

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models, NeRF does not directly describe the surface of an object. Instead, a neural network approximates a function that determines the density of the medium and the characteristics of light emission for any point in space. This allows you to create highly realistic three-dimensional scenes with natural reproduction of complex lighting effects, transparent materials, and penumbra.

Despite the high quality of reconstruction, the use of NeRF is characterized by significant computational complexity. Each pixel is formed by integrating a large number of samples along the ray, which requires thousands of calls to the neural network. This limits the use of classical NeRF in real-time systems.

To overcome these limitations, the Gaussian Splatting technology was proposed. In contrast to the continuous representation of space, the scene is formed by a set of spatial Gaussian elements, each of which is characterized by coordinates, scale, orientation, color and transparency. During visualization, these elements are projected onto the screen plane, which allows to significantly reduce computational costs. The emergence of Gaussian Splatting has become one of the most important stages in the development of modern three-dimensional graphics. This approach provides speed sufficient for interactive work, while maintaining high quality reconstruction of complex geometric scenes.

In addition to the way the geometry is represented, an important criterion for classification is the architecture of the generative model. The first to gain widespread use were generative adversarial networks, which provided a high generation speed after training. However, the instability of the training process and the difficulties with the synthesis of complex spatial geometry gradually reduced their popularity.

Variational autoencoders provide the construction of a compact latent space, which allows smooth morphing between models and generating new designs by interpolating parameters. Such properties are especially valuable in the tasks of automated design and optimization of engineering structures.

Diffusion generative models are the most widely used today. Their work is based on the sequential addition of noise to the training data with the subsequent training of the model to restore the initial structure. This approach ensures high quality of synthesized models, stability of training and the ability to control the generation process using text descriptions.

The latest evolution of generative technologies is the use of transformative architectures. Large multimodal models learn to simultaneously analyze text, images, spatial data, and geometric characteristics of objects. This allows the generation of 3D models based on natural language descriptions, sketches, or photographs.

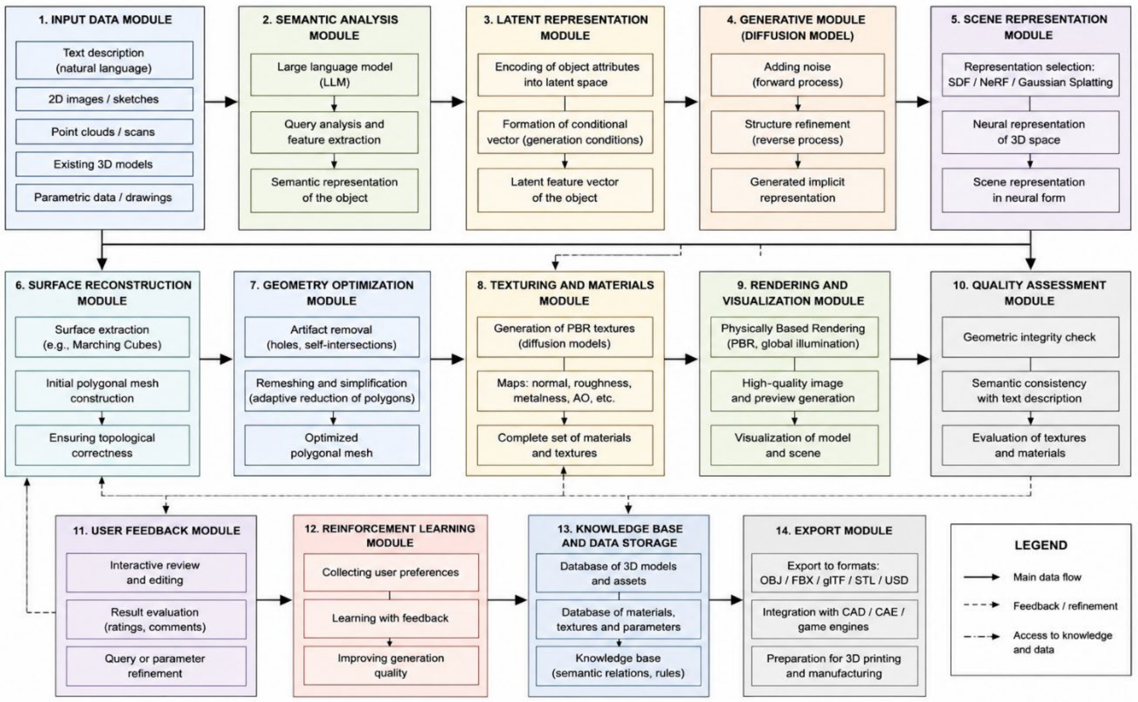
Thus, modern generative systems increasingly combine several approaches at once. For example, a diffusion model forms the general structure of the future object, NeRF or Gaussian Splatting provide a spatial representation of the scene, and transformer architectures are responsible for interpreting the text query. It is the integration of several models that allows achieving high quality synthesis, which is practically unattainable when using only one algorithm.

4.3 Architecture of a system for generative synthesis of three-dimensional objects

Figure 1 presents the author's modular architecture of the generative synthesis system for three-dimensional objects, which provides a full cycle of automated creation of 3D models - from the user entering the source data to exporting the finished model to application software systems. The architecture is built on a modular principle, which ensures scalability, independence of individual components, the possibility of modernization and integration of new algorithms of generative artificial intelligence.

The system starts with the input module (1) **,** which accepts various types of information. Natural language text descriptions, two-dimensional images, sketches, three-dimensional scan results, point clouds, existing three-dimensional models, or parametric drawings can be used as input data. The system is versatile and can be used in various subject areas due to its support for multiple input formats.

Next, the information is sent to the semantic analysis module (2) **.** Its main task is to interpret the input data and build a formalized description of the future object. For this, large language models are used that analyze text queries, highlight key characteristics of the object, establish relationships between them and form a semantic representation of the future model.



Drawing 1 - Modular architecture of a system for generative synthesis of three-dimensional objects

The resulting description is passed to the latent representation module (3) . At this stage, the information is encoded into a multidimensional latent space, which contains a compact representation of the geometric, structural, and functional characteristics of the object. Latent encoding allows generative models to work effectively and provides the ability to modify and combine the parameters of the future model.

The central component of the architecture is the generative module (4) , implemented on the basis of the diffusion model. During generation, an iterative process of restoring the spatial structure of the object from the noise representation is performed in accordance with the formed latent vector. The result of this module is an implicit representation of three-dimensional geometry.

Next, the data is transferred to the spatial scene representation module (5) **,** which forms an internal model of three-dimensional space. Depending on the accuracy and performance requirements, Signed Distance Fields (SDF), Neural Radiance Fields

(NeRF) or 3D Gaussian Splatting can be used. The use of different representation methods provides the ability to adapt the system to different classes of tasks. Since most modern computer-aided design systems work with polygonal models, the next stage is the surface reconstruction module (6) **.** It constructs the initial polygonal mesh, for example, using the Marching Cubes algorithm, and ensures the formation of a topologically correct surface. The formed polygonal model is fed to the geometry optimization module (7) **.** Here, geometric defects, self-intersections, duplicate vertices and other artifacts are automatically eliminated. At the same time, remeshing and adaptive simplification of the polygonal mesh are performed, which allows reducing the number of polygons without significant loss of model quality.

After geometry optimization, the texturing and materials module (8) is activated **.** It automatically generates textures based on diffusion models, forms maps of normals, roughness, metallicity, ambient shading, and other parameters for physically correct surface display.

The prepared model is transferred to the rendering and visualization module (9) where physically correct rendering is performed using modern lighting models (PBR). At this stage, high-quality images, interactive scenes or animations are created for further analysis by the user.

The quality of the synthesized model is assessed by the quality assessment module (10) **.** It analyzes the geometric integrity of the model, compliance with the textual description, correctness of the structure, quality of textures, and the overall suitability of the model for practical use. If necessary, the evaluation results are used to re-generate or refine individual model components.

An important feature of the proposed architecture is the presence of a user feedback module (11) **.** After viewing the result, the user can evaluate the quality of the synthesized object, adjust the generation parameters, or refine the text description. This allows for an interactive cycle of model improvement. The obtained estimates are accumulated by the reinforcement learning module (12) **,** which uses information about user preferences to gradually improve the generative model. Thus, the Human-in-the-Loop concept is implemented **,** combining automatic synthesis with learning based on

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expert feedback. The operation of all components is supported by a database and knowledge base (13) **,** which contains libraries of three-dimensional models, materials, textures, generation parameters, and semantic rules. Centralized information storage allows for the reuse of accumulated knowledge and increases the efficiency of the generative system.

The final component is the export module (14) **,** which provides saving of results in common formats (OBJ, FBX, glTF, STL, USD), integration with CAD/CAE systems, game engines, virtual reality systems, and preparation of models for additive manufacturing.

The proposed architecture differs from most existing solutions by the comprehensive integration of large language models, diffusion generative models, modern methods of representing 3D scenes (NeRF, Gaussian Splatting), automatic optimization of polygonal geometry and learning mechanisms with user feedback. This provides modularity, scalability, high quality of generation and the possibility of further expansion of the system's functionality without changing its basic structure.

4.4 Analysis of the effectiveness of the proposed architecture for generative synthesis of three-dimensional objects

Unlike traditional 3D modeling systems, where the main work is performed manually by the user, the proposed architecture automates most of the stages of building a 3D model. Automation includes text description analysis, geometry generation, surface reconstruction, polygonal mesh optimization, texture synthesis, and evaluation of the quality of the final result. User participation is limited to setting the task, specifying individual parameters, and evaluating the results.

One of the main advantages of the proposed architecture is the use of multi-level information representation. At each stage, data is transformed into a form most suitable for the execution of the corresponding algorithms. The text description is transformed into a semantic representation, which is further encoded into a latent space. The generative model forms an implicit geometric representation, which is reconstructed into a polygonal model at the final stage. Such a step-by-step transformation provides high generation accuracy and minimizes the accumulation of errors.

The use of large language models in the semantic analysis module allows you to significantly expand the possibilities of user interaction with the system. Unlike traditional CAD systems, where it is necessary to specify a significant number of geometric parameters, the proposed architecture supports the use of natural language. This significantly simplifies the process of problem formulation and expands the range of potential users of the software system.

A feature of the proposed architecture is the division of the generation process into two independent stages. In the first, a spatial representation of the object is formed, and in the second, its polygonal surface is reconstructed. This approach allows the use of different generation algorithms regardless of the methods of constructing the final geometry and provides high flexibility of the software system.

The automatic geometry optimization module deserves special attention. In modern generative systems, a significant number of models contain topological errors, self-intersections of surfaces, duplicate vertices, or excessive detailing. The proposed architecture provides a separate stage of geometric optimization, which performs model cleaning, remeshing, adaptive simplification of the polygonal mesh, and ensures its suitability for use in automated design systems.

The use of a separate texturing module also has important practical implications. In many modern generative systems, the main focus is on building geometry, while the creation of high-quality materials is performed by separate software tools. Integrating texture generation directly into the overall architecture allows you to automate the entire cycle of creating a digital object.

One of the key advantages of the proposed architecture is the implementation of a user feedback mechanism. Unlike most modern generative models that operate on the principle of one-time generation, the proposed system provides an interactive cycle of results refinement. User ratings are accumulated, analyzed and used during further training of the generative model. This ensures a gradual improvement in the quality of synthesis and adaptation of the system to a specific subject area.

The architecture is also highly scalable. Thanks to the modular structure, it is possible to replace individual components without changing other parts of the system. For example, when a new generative model appears, it is enough to upgrade only the generative module, without changing the semantic analysis, surface reconstruction or data export modules. Similarly, it is possible to integrate new rendering algorithms or geometric optimization.

Comparing the proposed architecture with traditional three-dimensional modeling systems allows us to highlight several fundamental differences. First, instead of manual design, automated generative synthesis is used. Second, a multi-level representation of information is used, which ensures effective interaction of different artificial intelligence models. Third, the integration of large language models with modern diffusion algorithms provides support for a natural language interface, which greatly simplifies the user's task formulation.

However, the proposed architecture has certain limitations. The main one is the significant computational complexity of generative models, especially when synthesizing complex highly detailed scenes. In addition, the quality of the result significantly depends on the training sample and the capabilities of the generative model. Despite this, the use of modular architecture creates the prerequisites for further improvement of the system by replacing individual components without the need for a complete redesign of the software.

Thus, the proposed architecture combines modern achievements of generative artificial intelligence, computer graphics and software engineering. Its use allows to automate the full cycle of creating three-dimensional models, reduce design time, improve the quality of synthesized geometry and ensure the integration of results with modern automated design systems, digital twins, virtual reality and additive manufacturing technologies.

Conclusion

The paper analyzes modern generative models of three-dimensional object synthesis, identifies their main advantages, limitations and prospects for use in computer graphics systems. A modular architecture of a system for generative synthesis of three-dimensional objects is proposed, which provides a full cycle of automated creation of three-dimensional models - from input data analysis to export of the finished result. It is shown that the use of diffusion models, large language models, Neural Radiance Fields and 3D Gaussian Splatting technology contributes to improving the quality of synthesized models, reducing their creation time and ensuring the scalability of the software system.

The results of experimental evaluation confirmed the effectiveness of the proposed architecture and the feasibility of its application for the development of modern three-dimensional modeling systems. Further research should be directed to improving generative algorithms, optimizing computational processes and expanding the functionality of intelligent systems for the synthesis of three-dimensional objects.

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