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CREATING GENERATIVE DESIGNS FOR 3D CHARACTERS BASED ON STRUCTURAL IMAGE ANALYSIS

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Abstract. In recent years, generative models for creating 3D objects have shown significant progress, but existing approaches are often limited to creating models represented by a single polygonal mesh. This limits the functionality and adaptability of the created objects. This article discusses the need to develop 3D character generators based on deep generative models that are able to understand and analyze the structure of an object, and identify its components elements and create multigrid views. Unlike existing solutions that create a single polygonal mesh, the proposed approach is aimed at creating models with a clear division into functional components, which significantly increases their practical applicability.

The purpose. *Create a method that analyzes the structural composition of objects to generate 3D models composed of multiple functionally necessary parts, rather than a single mesh.*

Methodology. *The following methods were used in the study:*

1) analytical method by which the literature was analyzed;

2) theoretical and conceptual method, which allowed to determine the conditions necessary for the introduction of IT technology in cultural and artistic practice;

The study used methods of computer modeling and analysis, which increased the accuracy of the results.

Results. *Development of a New Method and successfully proposed an approach using pre-trained models to analyze object images.*

Scientific novelty*. Introduction of a new method for analyzing object structure that goes beyond traditional single-mesh generation and development of an innovative approach that combines pre-trained models for image analysis with segmented 3D model generation*

Practical relevance. *This practical significance demonstrates the research's value across multiple industries and applications, making it particularly relevant for real-world implementation.*

1. Simplifies the process of creating game characters

2. Enables dynamic real-time changes to character appearance and structure

3. Improves character animation capabilities through segmented models.

Keywords: generative model, polygonal mesh, 3D character, component element, computer modeling, single polygon mesh, visible segments, image analysis.

INTRODUCTION

Modern 3D modeling technologies are actively developing, offering more and more realistic and complex models. However, existing 3D character generators that use generative adversarial networks (GANs) and autoencoders create models that represent a single mesh (a monolithic 3D model) [5]. Transformers have a different problem. Since they use a single mesh that transforms its parts if necessary, this type of system is very limited by character typology. As a rule, these are anthropomorphic models. This places restrictions on the variety, editing, physical modeling, and functional use of objects. For example, in game or animation applications, it is required that the character be divided into segments: limbs, torso, accessories, etc. We offer an approach that is based on the analysis of the structure of the object and the generation of a 3D model from several functionally necessary parts. This method will enable the creation of adaptive models optimized for animation, simulation of physical interactions, and integration into complex virtual environments.

ANALYSIS OF PREVIOUS RESEARCH

1. Generation of a single polygon mesh:

Modern generative networks for creating 3D models usually work according to several basic principles:

Implicit Surface Representation:

In this approach, the network learns to represent a 3D object as a continuous function that, for each point in space, determines whether it is inside or outside the object. The most well-known examples are Neural Radiance Fields (NeRF) networks and their modifications.

Creating intermediate views:

a. The network first generates an intermediate representation of the object (for example, a voxel grid or point cloud)

b. This representation is then converted into a polygon model using algorithms such as Marching Cubes

Direct generation of polygon meshes: Some architectures are capable of directly generating the vertices and faces of 3D models. They often use graph neural networks to work with the topology of an object [11].

Modern systems often combine several approaches and may include:

Multi-view consistency to provide a realistic view from different angles. Physically Based Constraints for Creating Implementable Models.

Mechanisms of attention for a better understanding of the structure of an object.

Conditional generation based on text descriptions or reference images.

Most existing generators use a single mesh to represent a 3D object.

Limitations: complexity of animation, inability to flexibly edit individual parts of the model.

Generation using Point Clouds:

These methods provide a basic representation of the shape of an object, but require additional processing to convert to a polygon mesh.

Approaches using Voxels networks:

Although such models can be divided into segments, their high computational complexity makes them impractical for most applications.

PURPOSE

Image structure analysis: It is proposed to use pre-trained models to analyze the image of an object, isolate its key elements and functional segments, and then generate polygonal meshes based on a voxel model for each selected part of the object. Next, ensure segment compatibility through anchor points and topological consistency.

Possibility of further editing in professional 3D editors (Blender, Maya e.t.c.).

Neural Network Training:

Training a neural network to segment parts of a character involves several key steps. To successfully train a character segmentation model, you need to consider the following aspects:

1. Data preparation:

– Creating a dataset with marked parts of the character

– Each piece must have a unique label (e.g.: head=1, torso=2, arms=3, etc.)

– Data augmentation to improve generalization

2. Model Architecture:

– U-Net-like architecture with encoder and decoder is used

– Encoder extracts features from the image

– Decoder restores segmentation mask

– Skip-connections help to save detailed information

3. Features of training:

– Use of special loss functions (Cross Entropy for multiclass segmentation)

– Class balancing if the parts are of very different sizes

– Validation on a single data set

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4. Post-processing of results:

– Smoothing the boundaries between segments

– Elimination of artifacts and noise

– Ensuring connectivity of areas

To improve the quality of segmentation, you can:

– Add an attention mechanism to better highlight important features

– Use pre-trained models (e.g., ResNet) as an encoder [4].

– Apply regularization techniques to prevent overfitting

RESULTS AND DISCUSSION

Potential Applications of a Multigrid 3D Model

1. **Gaming Industry**: Simplify the process of creating game characters, including the ability to dynamically change their appearance and structure in real time.

2. **Virtual Reality and** Animation: Create adaptive and realistic models for films, VR applications, and animation projects.

3. **Engineering and prototyping**: Generation of technically functional models for simulations and prototypes [17].

Benefits of the Multigrid Presentation Approach

1. **Functional segmentation**: Dividing the model into segments (e.g., arm, head, legs) improves adaptability and makes it easier to customize the animation.

2. **Optimized for simulations**: Ability to use simplified grids for hidden parts of the character and detailed grids for visible segments.

3. **Improve the accuracy of interaction analysis**: Functional segments allow for better integration with physical models, such as clothing or collision simulations.

It is planned to obtain the following results:

1 **Image segmentation**: Using the U-Net architecture with attention mechanisms will achieve greater segmentation accuracy on the test dataset. For example, for characters with complex anatomy (e.g., fantasy creatures).

2 **Mesh Generation**: Converting segmented regions to voxel models followed by optimization using the Marching Cubes algorithm will provide a reduction in generation time on compared to point cloud-based methods.

3 **Segment Compatibility**: A system of "anchor points" between segments will reduce the number of artifacts when animating.

Key advantages of the proposed approach:

Editing flexibility: Segments can be modified individually, which is critical for customizing characters in games (e.g. changing armor or hairstyles).

Resource optimization: Using simplified grids for hidden areas (such as the torso under clothing) will reduce memory requirements.

Improved animations: Segmented models will have more natural movements due to separate joint treatments.

Limitations and further research:

The current version of the algorithm requires manual adjustment of anchor points for complex shapes.

Future work may include integration with text descriptions (e.g. through transformers) to automate segmentation.

CONCLUSIONS

The creation of 3D character generators based on an in-depth analysis of the structure of objects represents an important step forward in the field of 3D modeling. This approach will not only improve the quality and functionality of the created models, but also significantly expand their use in various fields. The development of algorithms capable of isolating and analyzing the components of objects will become the basis for a new generation of 3D generators that will meet the growing requirements of modern digital technologies [3, 17]. The proposed method of generating multi-grid 3D characters based on structural analysis of images significantly expands the capabilities of modern generative models. Key achievements include:

Innovative architecture: The combination of U-Net with attention and voxel optimization engines will ensure accurate segmentation and efficient mesh generation.

Practical Value: The method simplifies the creation of animated characters for games and movies, reducing the time spent compared to manual modeling.

Adaptability: Models can be integrated into game engines (e.g. Unity, Unreal Engine) for dynamic changes in real time.

This work opens up new areas for research, including:

Automation of segmentation through multimodal input data (text, thumbnails).

Using graph neural networks to improve topological consistency.

Optimize for mobile devices with limited computing resources.

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АНОТАЦІЯ

Петрушевський А. Створення генеративного дизайну 3D-персонажів на основі аналізу структурного зображення

Останніми роками генеративні моделі для створення 3D-об’єктів продемонстрували значний прогрес, однак наявні підходи часто обмежуються створенням моделей, представлених єдиною полігональною сіткою. Це обмежує функціональність й адаптивність створених об’єктів. У цій статті розглядається потреба в розробці генераторів 3D-персонажів на основі глибоких генеративних моделей, які здатні розуміти та аналізувати структуру об’єкта, визначати його складові елементи та створювати багатосіткові представлення. На відміну від наявних рішень, які створюють єдину полігональну сітку, запропонований підхід спрямований на створення моделей із чітким поділом на функціональні компоненти, що значно підвищує їх практичну застосовність.

Мета. *Створити метод, який аналізує структурний склад об’єктів для генерації 3D-моделей, що містять кілька функціонально необхідних частин, а не єдину сітку.*

Методологія*. У дослідженні використано такі методи:*

– аналітичний, за допомогою якого проаналізовано літературу;

– теоретичний і концептуальний, який дав змогу визначити умови, необхідні для впровадження ІТ в культурну та мистецьку практику. У дослідженні застосовувалися методи комп'ютерного моделювання та аналізу, що підвищило точність результатів.

***Результати**. Розроблено новий метод й успішно запропоновано підхід із використанням попередньо навчених моделей для аналізу зображень об'єктів.*

***Наукова новизна**. Упровадження нового методу аналізу структури об'єктів, який виходить за межі традиційної генерації єдиної сітки, та розробка інноваційного підходу, що поєднує попередньо навчені моделі для аналізу зображень із генерацією сегментованих 3D-моделей.*

***Практична значущість**. Ця практична значущість демонструє цінність дослідження для різних галузей і застосувань, роблячи його особливо актуальним для впровадження в реальному світі:*

1. Спрощує процес створення ігрових персонажів.

2. Дає змогу динамічно змінювати зовнішній вигляд і структуру персонажів у реальному часі.

3. Покращує анімацію персонажів.

Ключові слова: генеративна модель, полігональна сітка, 3D-персонаж, складовий елемент, комп'ютерне моделювання, єдина полігональна сітка, видимі сегменти, аналіз зображень.

АВТОРСЬКА ДОВІДКА:

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