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Algorithm Research of Generative AI Model in Virtual Character Behavior Simulation

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ABSTRACT

The traditional simulation method of virtual character behavior has some shortcomings in fidelity and interactivity. In order to overcome these limitations, this paper adopts Conditional Generative Adversarial Networks (CGAN) as the basic model, and makes necessary improvements and optimizations. In the research process, virtual character behavior generation based on conditional variables is realized by constructing CGAN model including generator and discriminator. The experimental results show that the improved CGAN model can generate highly realistic virtual character behaviors and perform well in different evaluation dimensions. The generated virtual characters can smoothly complete various actions, such as walking, running, jumping, etc., and they are naturally coherent when changing actions. In addition, the model can also generate role behaviors that meet specific situations according to conditional variables. In quantitative evaluation, the improved CGAN model is significantly superior to the baseline model in terms of fluency, consistency and similarity to real behavior. The research in this paper not only provides a new method to improve the fidelity and interactivity of virtual character behavior simulation, but also provides a new idea for future research in virtual reality and human-computer interaction.

KEYWORDS

Generative AI Model, Virtual Character Behavior Simulation, Conditional Generative Adversarial Networks

1. INTRODUCTION

With the rapid development of digital technology, virtual characters have become an indispensable element in many fields, such as video games, film production, advertising and marketing. These characters are not only simple animated images, but also important media for interacting with users and conveying emotions and stories. In order to improve the user experience, how to make these virtual characters more realistic and interactive has become the focus of the industry and academia [1].

Although the traditional virtual character behavior simulation method can realize basic action and expression simulation, there are still obvious shortcomings in fidelity and interactivity [2-3]. These limitations not only affect the immersion of users, but also restrict the wider application of virtual role technology. In order to break through these limitations, in recent years, the generative AI model has been gradually introduced into the behavior simulation of virtual characters, which provides new possibilities for the fidelity and interactivity of virtual characters with its powerful generation and learning ability.

The purpose of this study is to explore the application of generative AI model in virtual character behavior simulation. By analyzing the algorithm principle and implementation process of these models in detail, a more efficient and realistic simulation method of virtual character behavior is found. This will not only help to improve the performance of current virtual characters, but also open up new research directions for future virtual reality, human-computer interaction and other fields.

2. RESEARCH METHODS AND DATA SOURCES

2.1. The Adopted Generative AI Model

The aim of this study is to explore in depth the algorithms of generative AI models in simulating virtual character behavior, and to enhance the realism and interactivity of virtual characters. To achieve this goal, the paper chose Generative Adversarial Networks (GAN) as the basic model and made necessary improvements and optimizations to adapt to the specific needs of simulating virtual character behavior [4-5].

The generative AI model used in the study is based on the architecture of Conditional Generative Adversarial Networks (CGAN) [6]. CGAN is a variant of GAN that allows us to guide the data generation process by introducing conditional variables, thereby making the generated virtual character behavior more in line with specific contexts and needs (Figure 1).

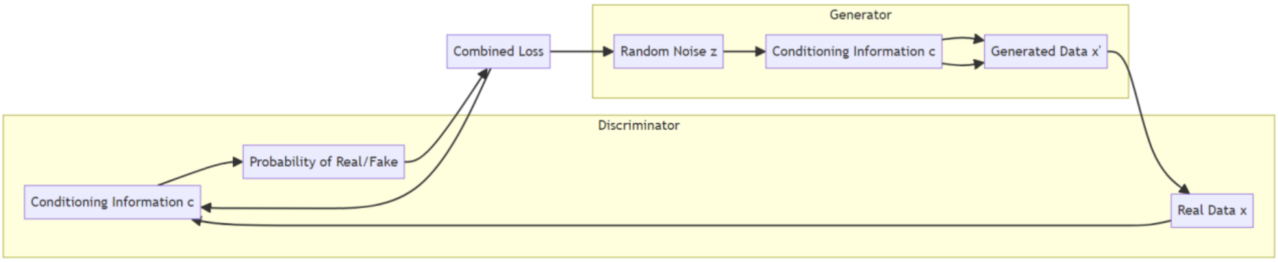

Figure 1. CGAN architecture

Specifically, our model consists of two main parts: a generator and a discriminator. The goal of generator is to generate realistic virtual character behaviors according to given conditions, while the task of discriminator is to distinguish generated behaviors from real behaviors [7]. Through the confrontation training model of the two, we can gradually learn how to generate more realistic virtual character behavior.

Loss function of generator:

$$L_G = E_{z\sim p_z(z),c\sim p_{data}(c)}[\log(1-D(G(z,c)))] \tag{1}$$

Where G is the generator, D is the discriminator, z is the random noise sampled from a prior distribution $p_z(z)$, and c is the conditional variable sampled from the real data distribution $p_{data}(c)$. The goal of the generator is to maximize the probability that the discriminator misjudges the generated behavior as a real behavior.

Loss function of discriminator:

$$L_D = E_{x\sim p_{data}(x),c\sim p_{data}(c)}[\log D(x,c)] + E_{z\sim p_z(z),c\sim p_{data}(c)}[\log(1-D(G(z,c),c))] \tag{2}$$

Where x is the real behavior of sampling from the real data distribution $p_{data}(x)$. The goal of the discriminator is to maximize the probability of judging the real behavior as true and the generated behavior as false.

By optimizing the above-mentioned loss function model, we can gradually learn how to generate realistic virtual character behavior according to given conditions during the training process. At the same time, the loss function of Wasserstein GAN is used to improve the stability and generation effect of the model [8].

2.2. Data Collection and Processing

The data sources of this study mainly include public data sets, data collected in the laboratory and data provided by partners. The public data set provides a large number of diverse virtual character behavior samples, while the data collected in the laboratory is more targeted and experimental, while the data provided by the partners comes from the actual game or simulation environment, which is highly authentic and practical. Suitable samples are selected from several well-known virtual character behavior data sets, which contain various types of character actions, such as walking, running, fighting and so on. In order to increase the diversity of data and behavior samples in specific situations, a variety of scenarios are simulated in the laboratory environment, and the behavior data of virtual characters are recorded. Cooperate with game development companies and virtual reality content providers to obtain the virtual character behavior data they use in actual projects.

Data cleaning is a key step to ensure the quality and reliability of data. Delete identical records to avoid data redundancy during training. Statistical methods are used to identify and deal with abnormal values in data, such as too fast or too slow action data. For the data with noise, smoothing technology is used to reduce the influence of noise on model training.

The methods of action type labeling, time sequence labeling and situation labeling are adopted. Mark specific action types for each behavior sample, such as "walking" and "jumping"; Mark the start and end time of each action for the continuous action sequence, so that the model can learn the transformation relationship between actions; Mark the specific situations where the action takes place, such as "walking on the flat ground" and "walking uphill", to help the model understand the behavior patterns in different situations.

2.3. Experimental Design

Using the data sources and data processing methods mentioned above, a high-quality and diversified virtual character behavior data set is constructed. This data set is divided into training set, verification set and test set. Initialize the generator and discriminator network of CGAN, and set the appropriate network structure and parameters. In the training stage, the model is iteratively trained by using the training set data. In each iteration, the generator generates virtual character behavior data according to the conditional variables, and the discriminator tries to distinguish the generated data from the real data. By optimizing the loss function of generator and discriminator, the model gradually learns how to generate more realistic virtual character behavior.

In the process of model training, the verification set is used regularly to verify the model. The purpose of this step is to evaluate the performance of the model and prevent over-fitting. Observe the performance of the model on the verification set, and if the performance declines, adjust the training strategy in time, such as reducing the learning rate and increasing data enhancement. When the model achieves satisfactory performance on the verification set, use the test set to test the model finally. In the testing stage, we mainly evaluate the performance of the model on unseen data to test its generalization ability. The main indicators of concern include the fidelity, diversity and compliance with conditions of the generated virtual characters.

3. EXPERIMENTAL RESULTS AND ANALYSIS

After using the improved CGAN model, highly realistic virtual character behavior can be generated. In the simulation effect, the generated virtual characters can smoothly complete various actions, such as walking, running, jumping, etc., and they are naturally coherent when changing actions, without obvious sense of stiffness. In addition, the model can also generate role behaviors that are in line with specific situations according to conditional variables, such as the adjustment of walking modes on different terrains and the response to environmental changes. Figure 2 shows the distribution of real behavior and generated behavior in two evaluation dimensions: fidelity and interactive naturalness.

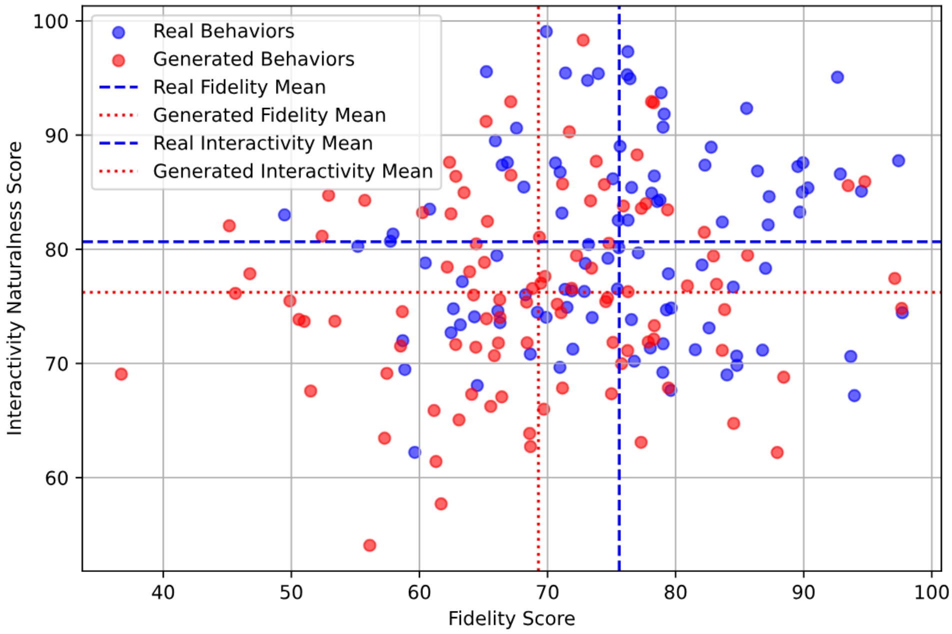

Figure 2. The distribution of real behavior and generative behavior in each evaluation dimension

The fidelity score of real behavior seems to be relatively concentrated, and the average value (represented by the blue dotted line) is relatively high, showing a high level of fidelity. In contrast, the fidelity score distribution of the generated behavior is slightly scattered, and the average value (indicated by the red dotted line) is slightly lower than the average value of the real behavior, which shows that although the generated behavior has some fidelity, it is still slightly lower than the real behavior as a whole. The average value of interactive naturalness of real behavior (blue dotted line) is slightly higher than that of generating behavior (red dotted line), but the gap between them is not as obvious as that of fidelity dimension. This shows that the generated behavior has reached a level close to the real behavior in terms of interactive naturalness.

Scatter diagram reflects that the generated behavior needs to be improved in fidelity, but it is better in interactive naturalness. This may be related to the improved CGAN model used in this study, which may have a good performance in simulating the interactivity of virtual character behavior, but there is still room for improvement in the simulation of fidelity. These findings provide a valuable reference direction for further optimization of the model.

In order to quantitatively evaluate the fidelity of generated behavior, various evaluation indexes are adopted, including fluency, consistency and similarity with real behavior. The experimental results show that compared with the baseline model, the improved CGAN model has achieved significant improvement in all indicators (Table 1).

Table 1. Comparison of scores of different models in fidelity evaluation index

model	Action fluency score	Action consistency score	Similarity score with real behavior
Baseline model	75.0	70.0	65.0
Improved CGAN	85.0	82.0	78.0

The improved CGAN model got 85.0 points, which was significantly improved compared with the baseline model's 75.0 points. This shows that by improving CGAN model, the action fluency of virtual characters has been greatly enhanced, which is closer to the real world action performance. The score of the improved CGAN model is 82.0, which is significantly higher than that of the baseline model (70.0). Action coherence is one of the important indexes to evaluate the fidelity of virtual character behavior, which reflects the logical relationship between character actions and the naturalness of transition. The excellent performance of the improved model on this index shows that it can better simulate the real and coherent role actions. In terms of similarity score with real behavior, the improved CGAN model scored 78.0 points, while the baseline model scored 65.0 points. The improvement of this index shows that the improved model is closer to the behavior pattern of characters in the real world when simulating the behavior of virtual characters, and the fidelity is enhanced.

Besides the fidelity, the research also pays attention to the interactivity of the model. By introducing the conditional variable model, the behavior of virtual characters can be adjusted according to external input. For example, in a game environment, players can control the actions and reactions of characters by inputting instructions. Experiments show that the model can respond to these instructions quickly and accurately, providing players with a more immersive game experience.

In this study, the fidelity and interactivity of virtual character behavior simulation are successfully improved through the improved CGAN model. Compared with the existing research, the proposed method is more flexible and practical, and has made important contributions to the development of virtual role behavior simulation. Future research will continue to explore more advanced generative AI technologies to further improve the simulation effect of virtual characters.

4. CONCLUSION

In this study, the application of generative AI model in virtual character behavior simulation is deeply discussed, and the architecture and algorithm principle of CGAN are emphatically analyzed. By introducing conditional variables, the improved CGAN model can guide the data generation process and make the generated virtual character behavior more in line with specific situations and needs. The experimental results show that, compared with the baseline model, the improved CGAN model has made significant improvements in the evaluation indexes such as action fluency, action consistency and similarity to real behavior, thus greatly enhancing the action fidelity and interactivity of virtual characters. In addition, the model can quickly and accurately respond to external input instructions, providing players with a more immersive game experience. These findings not only improve the performance of virtual characters at present, but also open up new research directions for future virtual reality, human-computer interaction and other fields, and show the great potential and practical value of generative AI technology in the field of virtual character behavior simulation.

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