Multimode Generative Adversarial Networks for Sequence Data Generation

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Abstract. As a new type of artificial intelligence technology, generative adversarial network (GAN) has good data understanding and generation capabilities, and has a wide range of application prospects in the fields of image and speech. However, due to the lack of prior knowledge, its training process is less robust and prone to occur the pattern ignore. Its development is restricted to a certain extent, and its application scope still needs to be expanded. To solve the above problems, this paper introduces a knowledge confidence multimode GAN (KC-MGAN) algorithm, calculates the confidence of the input data through the reasoning method, and then puts the confidence and the input data into the GAN system to generate new sample data. During the training process, the confidence of the input data is continuously calculated, while the generated data samples are continuously evaluated. The training process will end until the GAN system reaches a stable condition. Finally, this paper takes the generation of UAV flight trajectory data as an example to verify the effectiveness of the proposed method. Some explorations have been made for the application of data generation and GAN's training mode with the prior knowledge.

1. Introduction

In recent years, artificial intelligence technology has received extensive attention from all walks of life, and more and more appear in our daily lives. Artificial intelligence is a very broad concept. Any program or device that is manufactured by humans and can show the level of intelligence can be called artificial intelligence. The generative adversarial network is an important branch of artificial intelligence, which is one of the latest research results of deep learning. Traditional deep learning methods mainly realize effective pattern recognition functions, and have fruitful results in machine vision, semantic recognition and information processing. However, how to achieve an accurate understanding of information or even generate similar information has not been an important breakthrough in deep learning methods.

Until 2014, Goodfellow and others creatively proposed the generative adversarial network [1], which draws on the zero-sum game thinking. It combines two deep neural networks, one of which is a generative network and the other is a discriminant network. In a way of confronting each other, the performance of the two is improved respectively, and finally a dynamic balance is achieved. Once the technology was proposed, it has received extensive attention from the academic community. Many scholars have proposed a variety of derivative methods based on it, and soon made important breakthroughs and applications in the fields of image generation, video prediction, and style transfer.
However, each method has its limitations. On the one hand, GAN as an unsupervised learning model, due to its lack of prior knowledge, causes the freedom of the training process and shows a high degree of sensitivity to the initial parameters, which also has a certain impact on its practical application. Especially if there are certain key small samples in the training sample, it is easy to be ignored in the training process. On the other hand, GAN technology is still mostly used in traditional deep learning fields. How to apply it in aerospace and industrial applications is still a problem worth exploring. This paper will try to introduce knowledge inference methods to improve the training stability of the GAN method and avoid the lack of key small sample data.

2. GAN

The classic GAN mainly includes a generator and a discriminator. The main function of the generator is to imitate the distribution of real data as much as possible, while the discriminator is to discriminate the authenticity of the data as much as possible, that is, knowing input is the real data or fake data from the generator [2]. In other words, the generator is constantly trying to cheat the discriminator, and the discriminator is constantly seeing through the scam. Therefore, this embodies a kind of zero-sum game thinking, through training the forgery and discrimination capabilities of the two have been improved, and finally reached a dynamic balance. The typical structure of this method is shown in the figure below.

![Figure 1: Typical structure of GAN method](image)

It can be seen from the above analysis that the GAN model has two key parameters, one is the degree of difference between the fake data generated by the generator and the real data, and the other is the accurate discrimination rate of the discriminator on the real data. These two key parameters are defined as $L_G$ and $L_D$, as shown below.

$$L_G = -E_{z \sim P_z}[D(G(z))]$$  \hspace{1cm} (1)  

$$L_D = -E_{x \sim P_x}[D(x)] + E_{z \sim P_z}[D(G(z))]$$  \hspace{1cm} (2)

After training, the GAN is expected to achieve a dynamic balance. In this process, we hope that $L_G$ is as small as possible and $L_D$ is as large as possible, and the entire GAN system tends to a steady state. This process can be defined as,

$$\min_{G} \max_{D} V(G,D) = E_{x \sim P_x}[D(x)] - E_{z \sim P_z}[D(G(z))]$$  \hspace{1cm} (3)

The above is a mathematical perspective analysis of the classic GAN model. In recent years, many scholars have made many improvements to GAN, mainly the following typical representatives. (1) Conditional Generative Adversarial Network (CGAN) [3] model, which adds classification information labels to the input data of the generator and the discriminator to solve the divergence problem in the training process. (2) The LAPGAN model [4] mainly adopts up-sampling and down-sampling methods. Its prominent advantage is that in each update operation, only the residual between the real data and the production data needs to be considered, which significantly improves the convergence of the algorithm effectiveness. (3) The SeqGAN model [5] introduces a new way to generate the consequence discrete
data. It is believed that the essence of the generator is an energy function, and its value depends on whether it is the real data and the similarity with the real data, which improves the model’s interpretability. In addition, there are many methods that have made corresponding improvements to the GAN model. These methods have achieved remarkable results in different application scenarios.

3. Formatting the text
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Therefore, it is necessary to add corresponding prior knowledge to the GAN method to ensure that it still meets the sensitivity requirements of the system under certain conditions. In this paper, by designing a simple knowledge reasoning and case adding mechanism, the expert knowledge is digitized and used as prior knowledge into the GAN method to improve the training stability of the GAN method and avoid the occurrence of pattern ignore.

The realization process of knowledge reasoning and case adding mechanism is shown in Figure 2.

![Figure 2: The realization process of knowledge reasoning and case adding mechanism](image-url)

Among them, knowledge reasoning is given in the form of membership function in fuzzy reasoning, and case adding is given in the form of IF-Then rules. The specific implementation is as follows.
The realization of the membership function is to divide the value of each attribute into \( n \) intervals \([x_{i-1}, x_i), [x_i, x_{i+1}), \ldots, [x_{n-1}, x_n]\). Defined \( f(x^k) \) as its membership function, when the \( n \)th input value of the attribute falls within the \( i \)th interval, the membership function value is shown as below.

\[
BrX^k = \frac{x - x_{i-1}}{x_i - x_{i-1}} \ast [f(x_i) - f(x_{i-1})] + f(x_{i-1})
\]

(4)

Marking the set of IF-Then rules as \( R \), sub-rules \( R_k \in R \), described as follows:

\( R_0 \): If \( X_i \subseteq R_0 \), Then \( R(X_i) = 0 \);

\( R_1 \): If \( X_i \subseteq R_1 \), Then \( R(X_i) = 1 \);

……

\( R_k \): If \( X_i \subseteq R_k \), Then \( R(X_i) = R_k \);

……

Among them, \( R_0 \) and \( R_1 \) are respectively called constraint rules and perfect rules, and then through the fusion method, the membership function and rule reasoning results are combined, taking the confidence calculation of the \( i \)th M-dimensional input \( X \) as an example, the calculation method is as follows.

\[
Con(X_i) = R(X_i) \ast \frac{1}{M} \sum_{k=1}^{M} BrX^k
\]

(5)

Through the above method, a confidence level can be calculated for each input data. This confidence level represents the reliability of the data from the perspective of expert knowledge, and is added to the GAN training process as one of the inputs. In addition, a certain number of generators are used to generate sequence discrete data at the same time, which are named multimode GAN (MGAN). However, the above process is called the KC-MGAN model, and its implementation process is shown in Figure 3.

![Figure 3. KC-MGAN method implementation process](image)

4. Sections, subsections and subsubsections

With the development of science and technology, various industrial entities are becoming more and more complex, and high-precision equipment or sensitive equipment such as spacecraft or new unmanned aerial vehicle (UAV) is difficult to obtain effective and sufficient using data, due to the limited number of manufactures or the characteristics of one-time use. The lack of data has always restricted the progress and development of related technologies. However, the GAN method brings a new idea. As a generative model, the GAN is different from the massive training data requirements of traditional machine learning methods. The amount of data required is significantly reduced, and it is suitable for expanding small-scale data. In many technical fields, data is extremely sensitive, and small differences may cause major accidents and disasters. Therefore, better requirements are put forward for
the robustness of the generation algorithm, and it is even necessary to formulate corresponding rules to avoid the problem occurred.

From the above analysis, we can see that the KC-MGAN method proposed in this article is suitable for the expansion of sensitive and small data samples, combined with corresponding knowledge to generate appropriate rules, and can effectively guarantee the reliability of the generated data set.

This paper uses a UAV flight case to verify the effectiveness of the KC-MGAN method.

Suppose a certain type of UAV needs to travel through valleys at low altitude depending on the terrain, but due to the small size of the UAV, its flight trajectory is significantly unstable. After a small amount of actual flight, it is planned to use simulation technology to generate a larger-scale flight path for subsequent analysis and optimization.

To simplify related issues and improve the versatility of the method. This article adopts the information set in [6] (section 3.3), including the threat position, the initial UAV position and other information.

Combining related threat sources and the characteristics of UAV flight, the following key data nodes of the membership function are given.

| Threat type       | Kill zone | First alert | Second alert | Buffer | Safety Zone |
|-------------------|-----------|-------------|--------------|--------|-------------|
| Radar             | 4         | 60          | 90           | 120    | 140         |
| Missile           | 3.5       | 50          | 75           | 100    | 120         |
| High artillery    | 3         | 4.5         | 6            | 6      | 8           |
| Atmosphere        | 2         | 4.5         | 6            | 7      | 10          |
| Confidence        | 0         | 0.3         | 0.5          | 0.7    | 1           |

Meanwhile, based on the actual flight characteristics of UAVs, the following rules are proposed.

a. When the confidence of a certain item of data is less than or equal to 0, the data is determined to be invalid and regenerated.

b. When the actual displacement of the UAV within 10 seconds is less than 50% of the theoretical uniform linear motion displacement, it is judged as the UAV overload maneuvering state, the data is invalid, and need to regenerated.

Taking the threat source setting of the 270-360 degree search direction as an example, the search algorithm uses the standard ACO algorithm to bring the generated flight data into the SeqGAN and KC-MGAN methods at the same time. The GAN architecture reference in [7], using Adam optimization algorithm is used in the training process. The SeqGAN and KC-MGAN methods can produce distribution data similar to the original data through training, and Wasserstein distance is commonly used to measure this similarity [8]. Calculate the Wasserstein distance changes of SeqGAN and KC-MGAN in the above experiment with the increase of training cycles, and the results are shown in Figure 4.
Figure 4: Wasserstein distance changes of GAN and KC-MGAN with the increase of training cycles

As can be seen from the above figure, the KC-MGAN method introduces prior knowledge, which effectively improves the convergence speed of the algorithm and can generate data with similar distributions faster.

Next, check the reliability of the generated data, calculate the average trajectory cost of the original data, the generated data of the SeqGAN and the generated data of the KC-MGAN algorithm. The calculating standard reference [6], and the results are shown as below.

Table 2. Trajectory cost

|               | 0-90° | 90-180° | 180-270° | 270-360° |
|---------------|-------|---------|----------|----------|
| Initial data  | 0.203 | 0.237   | 0.312    | 0.197    |
| SeqGAN        | 0.312 | 0.285   | 0.442    | 0.374    |
| KC-MGAN       | 0.254 | 0.220   | 0.376    | 0.395    |

The above experimental results show that, compared with the traditional SeqGAN method, the KC-MGAN method proposed in this paper can generate more reliable sample data due to the introduction of expert knowledge as prior knowledge. The data is well represented without overfitting, and the availability of the generated data is close to the traditional method. In short, the KC-MGAN method has a good engineering practice value.

5. Conclusion

This paper first introduces the development of artificial intelligence, and aims at the lack of prior knowledge caused by the pattern ignore and the limited application scope of the GAN method. Then, A GAN method based on knowledge-confidence is proposed and applied to the generation of UAV flight data, which has achieved good experimental results. This method verifies the effectiveness of introducing prior knowledge into the GAN method and expands the application range of GAN. For the follow-up research and application, some exploration has been carried out. However, the introduced reasoning method is relatively simple and difficult to apply in complex situations, and the selected case has a small amount of data and cannot be verified on a larger-scale data set. Therefore, there still need some further researches.
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