

IMAGE GENERATION METHOD AND APPARATUS, NEURAL NETWORK TRAINING METHOD AND APPARATUS, DEVICE AND MEDIUM

TECHNICAL FIELD

[0001] The disclosure relates to the field of computer vision processing, and in particular, to an image generation method and apparatus, a neural network training method and apparatus, an electronic device, a computer storage medium and a computer program.

BACKGROUND

[0002] In the related art, Generative Adversarial Networks (GAN) achieve excellent performance in capturing high-dimensional representations of visual data and creating realistic images. A generative adversarial network usually requires a large amount of training data to achieve better performance. In the case of limited training data, it is a technical problem that needs to be solved urgently how to improve the image generation quality of the generative adversarial network.

SUMMARY

[0003] Embodiments of the disclosure provide technical solutions of image generation and neural network training.

[0004] Embodiments of the disclosure provide an image generation method, including:

obtaining an original image; and

inputting the original image into a trained generative adversarial network, and processing the original image using the trained generative adversarial network to obtain a

first generated image, where training data of the generative adversarial network includes a sample image set and a second generated image, the second generated image includes at least part of images in a generated image set, and the generated image set represents generated images obtained by processing the sample image set using the generative adversarial network.

[0005] In some embodiments, the method may further include:

obtaining an overfitting parameter, the overfitting parameter representing a degree of overfitting of a discriminator of the generative adversarial network; and

obtaining the second generated image matching the overfitting parameter in number from the generated image set.

[0006] In some embodiments, the obtaining an overfitting parameter includes:

obtaining at least one of a first discrimination result or a second discrimination result, the first discrimination result representing a discrimination result corresponding to the sample image set, and the second discrimination result representing a discrimination result corresponding to the generated image set; and

obtaining the overfitting parameter according to the obtained at least one of the first discrimination result or the second discrimination result.

[0007] In some embodiments, the obtaining the overfitting parameter according to the obtained at least one of the first discrimination result or the second discrimination result includes one of the following items:

taking a first average value as the overfitting parameter, the first average value representing an average value of a sign function of a logarithmic output of the first discrimination result;

taking an opposite number of a second average value as the overfitting parameter, the second average value representing an average value of a sign function of a logarithmic output of the second discrimination result; or

taking half of a difference between the first average value and the second average value as the overfitting parameter.

[0008] In some embodiments, the obtaining the second generated image matching the overfitting parameter in number from the generated image set includes:

determining a selection probability, the selection probability representing a probability of selecting an image from the generated image set;

updating a value of the selection probability according to a value of the overfitting parameter, to obtain an updated selection probability, the value of the overfitting parameter being positively correlated with the updated selection probability; and

selecting the second generated image matching the overfitting parameter in number from the generated image set according to the updated selection probability.

[0009] In some embodiments, the updating a value of the selection probability according to a value of the overfitting parameter, to obtain an updated selection probability includes one of the following items:

in a case where the value of the overfitting parameter is greater than a set threshold, increasing the value of the selection probability to obtain the updated selection probability; and in a case where the value of the overfitting parameter is less than or equal to a set threshold, decreasing the value of the selection probability to obtain the updated selection probability.

[0010] In some embodiments, the method further includes:

obtaining a preset selection probability; and selecting the second generated image from the generated image set according to the preset selection probability.

[0011] Embodiments of the disclosure provide a neural network training method, including:

inputting a sample image set into a generative adversarial network, and processing the sample image set using the generative adversarial network, to obtain a generated image set;

obtaining a second generated image, the second generated image including at least part of images in the generated image set; and

taking the image sample set and the second generated image as training data of the generative adversarial network, and training the generative adversarial network according to the training data.

[0012] In some embodiments, the obtaining a second generated image includes:

obtaining an overfitting parameter, the overfitting parameter representing a degree of overfitting of a discriminator of the generative adversarial network; and

obtaining the second generated image matching the overfitting parameter in number from the generated image set.

[0013] In some embodiments, the obtaining an overfitting parameter includes:

obtaining at least one of a first discrimination result or a second discrimination result, the first discrimination result representing a discrimination result corresponding to the sample image set, and the second discrimination result representing a discrimination result corresponding to the generated image set; and

obtaining the overfitting parameter according to the obtained at least one of the first discrimination result or the second discrimination result.

[0014] In some embodiments, the obtaining the overfitting parameter according to the obtained at least one of the first discrimination result or the second discrimination result includes one of the following items:

taking a first average value as the overfitting parameter, the first average value representing an average value of a sign function of a logarithmic output of the first discrimination result;

taking an opposite number of a second average value as the overfitting parameter, the second average value representing an average value of a sign function of a logarithmic output of the second discrimination result; or

taking half of a difference between the first average value and the second average value as the overfitting parameter.

[0015] In some embodiments, the obtaining the second generated image matching the overfitting parameter in number from the generated image set includes:

determining a selection probability, the selection probability representing a probability of selecting an image from the generated image set;

updating a value of the selection probability according to a value of the overfitting parameter, to obtain an updated selection probability, the value of the overfitting parameter being positively correlated with the updated selection probability; and

selecting the second generated image matching the overfitting parameter in number from the generated image set according to the updated selection probability.

[0016] In some embodiments, the updating a value of the selection probability according to a value of the overfitting parameter, to obtain an updated selection probability includes one of the following items:

in a case where the value of the overfitting parameter is greater than a set threshold, increasing the value of the selection probability to obtain the updated selection probability; and in a case where the value of the overfitting parameter is less than or equal to a set threshold, decreasing the value of the selection probability to obtain the updated selection probability.

[0017] In some embodiments, the method may further include:

obtaining a preset selection probability; and selecting the second generated image from the generated image set according to the preset selection probability.

[0018] Embodiments of the disclosure provide an image generation apparatus, including:

 a first obtaining module, configured to obtain an original image; and

 a first processing module, configured to input the original image into a trained generative adversarial network, and process the original image using the trained generative adversarial network to obtain a first generated image, where training data of the generative adversarial network includes a sample image set and a second generated image, the second generated image includes at least part of images in a generated image set, and the generated image set represents generated images obtained by processing the sample image set using the generative adversarial network.

[0019] In some embodiments, the first obtaining module is further configured to:

 obtain an overfitting parameter, the overfitting parameter representing a degree of overfitting of a discriminator of the generative adversarial network; and

 obtain the second generated image matching the overfitting parameter in number from the generated image set.

[0020] Embodiments of the disclosure provide a neural network training apparatus, including:

 a second processing module, configured to input a sample image set into a generative adversarial network, and process the sample image set using the generative adversarial network, to obtain a generated image set;

 a second obtaining module, configured to obtain a second generated image, the second generated image including at least part of images in the generated image set; and

 a training module, configured to take the image sample set and the second generated image as training data of the generative adversarial network, and train the generative adversarial network according to the training data.

- [0021] Embodiments of the disclosure also provide an electronic device, including a processor and a memory configured to store a computer program capable of running in the processor.
- [0022] The processor is configured to run the computer program to execute any image generation method described above or any neural network training method described above.
- [0023] Embodiments of the disclosure further provide a computer storage medium, having a computer program stored thereon. The computer program, when executed by a processor, implementing any image generation method described above or any neural network training method described above.
- [0024] Embodiments of the disclosure further provide a computer program, including a computer-readable code, where in a case where the computer-readable code runs in an electronic device, a processor of the electronic device executes any image generation method described above or any neural network training method described above.
- [0025] In the embodiments of the disclosure, at least part of the generated images may be inputted into a generator as a real image for training the generative adversarial network. The training process of the generative adversarial network is obtained based on the discrimination result of the discriminator on the image inputted into the generator and the generated image outputted by the generator. Since the generated image is a fake image, and the goal of the generator in the training process of the generative adversarial network is to generate a fake image that approximates the real image to deceive the discriminator, the accuracy of the discriminator to discriminate between real images and fake images can be reduced to a certain extent, thereby facilitating alleviating the overfitting problem of the discriminator, so that the trained generative adversarial network has a better image generation performance.
- [0026] It should be understood that the above general description and the following detailed description are only exemplary and explanatory, rather than limiting the disclosure.

BRIEF DESCRIPTION OF THE DRAWINGS

- [0027] The accompanying drawings, which are incorporated herein and constitute a part of the specification, illustrate embodiments consistent with the disclosure and, together with the specification, serve to explain the principles of the embodiments of the disclosure.
- [0028] FIG. 1A is a schematic diagram of a logarithmic output result of a discriminator in the case of training a generative adversarial network with a complete data set and partial data in the complete data set in the related art;
- [0029] FIG. 1B is a schematic diagram of an average value of a sign function of a logarithmic output result of a discriminator in the case of training a generative adversarial network with a complete data set and partial data in the complete data set in the related art;
- [0030] FIG. 1C is a schematic diagram of a change curve of FID (Fréchet Inception Distance) in the case of training a generative adversarial network with a complete data set and partial data in the complete data set in the related art;
- [0031] FIG. 2 is a flowchart of an image generation method according to an embodiment of the disclosure;
- [0032] FIG. 3 is a flowchart of a neural network training method according to an embodiment of the disclosure;
- [0033] FIG. 4 is a flowchart of training a generative adversarial network according to an embodiment of the disclosure;
- [0034] FIG. 5 is a schematic structural diagram of an image generation apparatus according to an embodiment of the disclosure;
- [0035] FIG. 6 is a schematic structural diagram of a neural network training apparatus according to an embodiment of the disclosure; and
- [0036] FIG. 7 is a schematic structural diagram of an electronic device according to an

embodiment of the disclosure.

DETAILED DESCRIPTION

[0037] The disclosure is further described in detail below with reference to the accompanying drawings and the embodiments. It should be understood that the embodiments provided herein are merely used for explaining the disclosure but are not intended to limit the disclosure. In addition, the embodiments provided below are part of the embodiments for implementing the disclosure, rather than providing all the embodiments for implementing the disclosure. In the case of no conflict, the technical solutions described in the embodiments of the disclosure can be implemented in any combination manner.

[0038] It should be noted that in the embodiments of the disclosure, the terms "including", "comprising" or any other variants thereof are intended to cover non-exclusive inclusion, so that a method or apparatus including a series of elements not only includes the explicitly described elements, but also includes other elements that are not explicitly listed, or elements inherent to the implementation of the method or apparatus. Without more restrictions, the element defined by the sentence "including a..." does not exclude the existence of other related elements in the method or apparatus including the element (for example, the steps in the method or the units in the apparatus, for example, the units may be part of the circuit, part of the processor, part of the program or software, etc.).

[0039] For example, the image generation method and the neural network training method provided by the embodiments of the disclosure include a series of steps. However, the image generation method and the neural network training method provided by the embodiments of the disclosure are not limited to the described steps. Similarly, the image generation apparatus and the neural network training apparatus provided in the embodiments of the disclosure include a series of modules. However, the apparatuses provided in the embodiments of the disclosure are not limited to include the explicitly described modules, and may also include modules that are provided for obtaining

relevant information or processing based on information.

[0040] The term "and/or" herein merely describes an association relationship for describing associated objects and represents that three relationships may exist. For example, A and/or B may represent the following three cases: only A exists, both A and B exist, and only B exists. In addition, the term "at least one" herein indicates any one or any combination of at least two of the multiple, for example, including at least one of A, B, or C, and may indicate including any one or more elements selected from the set formed by A, B, and C.

[0041] The embodiments of the disclosure can be applied to a computer system composed of a terminal and/or a server, and can operate with many other general-purpose or special-purpose computing system environments or configurations. Here, the terminal can be a thin client, a thick client, a handheld or laptop device, a microprocessor-based system, a set-top box, a programmable consumer electronic product, a network personal computer, a small computer system, etc. The server can be a small computer system, a large-scale computer system, and a distributed cloud computing technology environment including any of the above systems, etc.

[0042] An electronic device such as a terminal and a server may implement corresponding functions through the execution of program modules. Generally, the program modules may include routines, programs, object programs, components, logic, and data structures, etc. The computer system/server may be implemented in a distributed cloud computing environment. In the distributed cloud computing environment, tasks are executed by a remote processing device linked through a communication network. In the distributed cloud computing environment, the program modules may be located in a storage medium of a local or remote computing system including a storage device.

[0043] In the related art, after a generative adversarial network is trained with a large amount of training data, the trained generative adversarial network has higher image generation quality. However, in some practical scenarios, it is not feasible to collect enough training data, especially in some data sparse and privacy-sensitive application scenarios.

[0044] Generally, the generative adversarial network includes a generator and a discriminator. The process of training a generative adversarial network is a process of simultaneously training the generator and the discriminator. In the case of limited training data, an overfitting problem of the discriminator may occur in the process of training the generative adversarial network. The overfitting problem of the discriminator indicates that the discriminator determines the authenticity of the generated image with an excessive accuracy. The requirement of the generative adversarial network for the discriminator is that the probability of determining the authenticity of the generated image is around 0.5. Therefore, the overfitting problem of the discriminator may cause the trained generative adversarial network to be unable to stably obtain high-quality generated images.

[0045] The overfitting problem of the discriminator is exemplarily explained below through the accompanying drawings.

[0046] FIG. 1A is a schematic diagram of a logarithmic output result of a discriminator in the case of training a generative adversarial network with a complete data set and partial data in the complete data set in the related art. FIG. 1B is a schematic diagram of an average value of a sign function of a logarithmic output result of a discriminator in the case of training a generative adversarial network with a complete data set and partial data in the complete data set in the related art. In FIG. 1A and FIG. 1B, the data volume of the complete data set is 70K, and partial data in the complete data set is 10% of the complete data set, that is, the data volume of the partial data in the complete data set is 7K. It should be noted that, the data volume of the complete data set refers to the total number of images contained in the complete data set. For example, the data volume of 70K of the complete data set means that the complete data set contains seventy thousand images. Similarly, the data volume of the partial data in the complete data set refers to the number of images contained in the partial data. For example, the data volume of 7K of the partial data means that the partial data contains seven thousand images.

[0047] In FIG. 1A, the abscissa axis represents the training progress, and the ordinate axis represents the logarithmic output result of the discriminator. $D_{\text{real.70K}}$ represents the

logarithmic output of the discrimination result of the discriminator for the real image in a case where the generative adversarial network is trained with the complete data set. $D_{\text{fake}}.70K$ represents the logarithmic output of the discrimination result of the discriminator for the generated image in a case where the generative adversarial network is trained with the complete data set. $D_{\text{real}}.7K$ represents the logarithmic output of the discrimination result of the discriminator for the real image in a case where the generative adversarial network is trained with partial data in the complete data set. $D_{\text{fake}}.7K$ represents the logarithmic output of the discrimination result of the discriminator for the generated image in a case where the generative adversarial network is trained with partial data in the complete data set.

[0048] As can be seen from FIG. 1A, in the initial stage of the training, the logarithmic outputs of the discrimination results of the discriminator for the real image and the generated image are relatively close. Moreover, as the training progresses, compared with the solution of training a generative adversarial network with a complete data set, in the generative adversarial network that only uses limited training data (i.e., partial data in the complete data set), the logarithmic outputs of the discrimination results of the discriminator for the real image and the generated image may diverge faster.

[0049] In FIG. 1B, the abscissa axis represents the training progress, and the ordinate axis represents an average value of the sign function of the logarithmic output result of the discriminator. The $\text{sign}(D_{\text{real}}).70K$ represents an average value of the sign function of the logarithmic output of the discrimination result of the discriminator for the real image in a case where the generative adversarial network is trained with the complete data set. The $\text{sign}(D_{\text{fake}}).70K$ represents an average value of the sign function of the logarithmic output of the discrimination result of the discriminator for the generated image in a case where the generative adversarial network is trained with the complete data set. The $\text{sign}(D_{\text{real}}).7K$ represents an average value of the sign function of the logarithmic output of the discrimination result of the discriminator for the real image in a case where the generative adversarial network is trained with partial data in the complete data set. The $\text{sign}(D_{\text{fake}}).7K$ represents an average value of the sign function of the logarithmic output of the discrimination result of the discriminator for the generated image in a case where the generative adversarial network is trained with partial data in the complete data set.

[0050] As can be seen from FIG. 1B, compared with the solution of training a generative adversarial network with a complete data set, in the generative adversarial network that only uses limited training data (i.e., partial data in the complete data set), the average values of the sign function of the logarithmic outputs of the discrimination results of the discriminator for the real image and the generated image may diverge faster.

[0051] The overfitting problem of the discriminator may also make it difficult for the generative adversarial network to converge. In practical applications, FID (Fréchet Inception Distance) can represent the convergence trend of the generative adversarial network. FID represents the distance between the real image and the generated image in a feature layer. The smaller the value of the FID is, the more easily the generative adversarial network converges.

[0052] FIG. 1C is a schematic diagram of a change curve of the FID in the case of training a generative adversarial network with a complete data set and partial data in the complete data set in the related art. In FIG. 1C, the abscissa axis represents the training progress, and the ordinate axis represents the FID. FID.70K represents a change curve of the FID in the case of training the generative adversarial network with the complete data set. FID.7K represents a change curve of the FID in the case of training the generative adversarial network with partial data in the complete data set. As can be seen from FIG. 1C, as the training progresses, compared with the solution of training the generative adversarial network with the complete data set, the FID of the generative adversarial network that only uses limited training data (i.e., partial data in the complete data set) has a larger value, that is, it is more difficult for the generative adversarial network to converge.

[0053] In the related art, for the overfitting problem of the discriminator, the following two solutions can be adopted. In solution 1, in the process of training the generative adversarial network, the real image inputted to the generator and the generated image of the generator are enhanced using standard data, to increase the diversity of training data and reduce a degree of overfitting of the discriminator. In solution 2, the generative adversarial network is processed using an additional model regularization term. For example, the discriminator may be appropriately weakened by a method of introducing

noise or using gradient penalty, so as to improve the stability of the training process.

[0054] However, in the solution 1, the enhancement using standard data may additionally introduce a large amount of computational cost ;the solution 2 does not significantly improve the performance of the generative adversarial network and is more sensitive to the setting of weight parameters, which requires fine manual adjustment. For different image generation scenarios and different training states (the convergence state or the divergence state of the output of the discriminator), different model regularization terms need to be set, that is, only model regularization term can only be applied to one image generation scenario or one training state, and the applicability of the solution 2 is relatively narrow.

[0055] For the above technical problems in the related art, the embodiments of the disclosure provide an image generation method. The image generation method of the embodiments of the disclosure can be applied to image generation, image editing, image processing, image-to-image conversion, and video generation, video editing, short video applications, movie processing and other scenarios.

[0056] FIG. 2 is a flowchart of an image generation method according to an embodiment of the disclosure. As shown in FIG. 2, the process may include the following steps.

[0057] In step 201, an original image is obtained.

[0058] In the embodiments of the disclosure, the original image may be obtained in a variety of ways, for example, the original image acquired by an image acquisition device may be received, or the original image sent by other devices may be received by a communication apparatus, and the original image may also be locally saved in advance. In a case where the original image needs to be used, the original image is read locally.

[0059] The format of the original image may be Joint Photographic Experts GROUP (JPEG), Bitmap (BMP), Portable Network Graphics (PNG) or other formats. It should be noted that, only the format and source of the original image are exemplified here, and the embodiments of the disclosure does not limit the format and source of the original image.

[0060] In step 202, the original image is inputted into a trained generative adversarial network, and the original image is processed using the trained generative adversarial network to obtain a first generated image. Training data of the generative adversarial network includes a sample image set and a second generated image. The second generated image includes at least part of images in a generated image set. The generated image set represents generated images obtained by processing the sample image set using the generative adversarial network.

[0061] Here, the sample image set refers to an image collection for training the generative adversarial network. In practical applications, the sample image set may be obtained from a public data set, or the sample image set may be obtained from a local storage area. For example, the public data set may be an FFHQ data set, an AFHQ data set, an Anime data set, a CUB data set, a CUFED5 data set, a SUN data set, a Manga 109 data set, etc. In the embodiments of the disclosure, after the sample image set is inputted into the generator of the generative adversarial network, at least part of the generated images outputted by the generator of the generative adversarial network may be added to the sample image set, thereby updating the sample image set.

[0062] In the process of training a generative adversarial network, a sample image set may be obtained first. After the sample image set is obtained, the sample image set may be inputted into the generator of the generative adversarial network, and the sample image set is processed with the generator, to obtain a generated image set. Then, at least part of the images in the generated image set may be selected as the second generated images, the second generated images are inputted into the generator, and the second generated images are processed with the generator.

[0063] In the process of training the generative adversarial network, the authenticity of the image inputted to the generator and the generated image of the generator are determined using the discriminator of the generative adversarial network, to obtain a corresponding discrimination result. The discrimination result indicates the probability that the corresponding image belongs to the real image.

[0064] In the embodiments of the disclosure, a network parameter value of the generative adversarial network may be continuously adjusted according to the

discrimination result obtained by the discriminator. In a case where the generative adversarial network with the network parameter value adjusted does not satisfy a training end condition, at least part of the image in the generated image of the generator may be inputted into the generator to obtain a new generated image again, and the authenticity of the image inputted into the generator and the generated image outputted by the generator are determined again using the discriminator. In a case where the generative adversarial network with the network parameter value adjusted satisfies the training end condition, the generative adversarial network with the network parameter value adjusted may be used as the trained generative adversarial network.

[0065] Here, the training end condition may be that the number of iterations of the training process of the generative adversarial network reaches a set number of times, or the image processing of the generative adversarial network with the network parameter value adjusted satisfies a set accuracy requirement. Here, the set number of times may be a value set empirically. The set accuracy requirement is related to the loss of the generative adversarial network. For example, the set accuracy requirement may be that the loss of the generative adversarial network is less than a set loss, and the set loss may be a loss value set empirically.

[0066] In the related art, in the process of training the generative adversarial network, the discriminator generally discriminates two types of images. The two types of images are the image inputted into the generator and the generated image obtained by the generator. The image inputted into the generator is generally considered to be a real image. That is, the discriminator may obtain a discrimination result of the real image and a discrimination result of the generated image. However, in the embodiments of the disclosure, after the generated image set is obtained using the generator, the second generated image may be selected from the generated image set, and the second generated image is inputted into the generator as the real image. That is, compared with the solution of training the generative adversarial network in the related art, there is no need to add a real image as standard data. Instead, the generated image may be inputted into the generator as a real image to continue training the generative adversarial network.

[0067] After the trained generative adversarial network is obtained, the original image

may be processed with the generator in the trained generative adversarial network, to obtain a first generated image.

[0068] In practical applications, steps 201 to 202 may be implemented by a processor in an electronic device. The processor may be at least one of an Application Specific Integrated Circuit (ASIC), a Digital Signal Processor (DSP), a Digital Signal Processing Device (DSPD), a Programmable Logic Device (PLD), a Field-Programmable Gate Array (FPGA), a Central Processing Unit (CPU), a controller, a microcontroller, or a microprocessor.

[0069] It can be understood that in the related art, in the case of limited training data, the overfitting problem of the discriminator may occur in the process of training the generative adversarial network. the overfitting problem of the discriminator indicates that the discriminator determines the authenticity of the generated image with an excessive accuracy. The requirement of the generative adversarial network on the discriminator is that the probability of determining the authenticity of the generated image is around 0.5. Therefore, the overfitting problem of the discriminator may cause the trained generative adversarial network to be unable to stably obtain high-quality generated images. In the embodiments of the disclosure, at least part of the generated images may be inputted into a generator as a real image for training the generative adversarial network. The training process of the generative adversarial network is obtained based on the discrimination results of the discriminator for the image inputted into the generator and the generated image outputted by the generator. Since the generated image is a fake image, and the goal of the generator in the training process of the generative adversarial network is to generate a fake image that approximates the real image to deceive the discriminator, the accuracy of the discriminator to discriminate between real images and fake images can be reduced to a certain extent, thereby facilitating alleviating the overfitting problem of the discriminator, so that the trained generative adversarial network has a better image generation performance.

[0070] Further, the embodiments of the disclosure do not need to add additional standard data to increase the diversity of training data, but can take at least part of the generated image of the generator as the real image, and add at least part of the generated

image to the training data of the generative adversarial network. Although the training process of the generative adversarial network in the embodiments of the disclosure needs to introduce a certain computational cost, compared with the solution 1 described above, the introduced computational cost is lower and can be ignored.

[0071] In combination with the foregoing content, the embodiments of the disclosure also provide a neural network training method. FIG. 3 is a flowchart of a neural network training method according to an embodiment of the disclosure. As shown in FIG. 3, the process may include the following steps.

[0072] In step 301, a sample image set is inputted into a generative adversarial network, and the sample image set is processed using the generative adversarial network, to obtain a generated image set.

[0073] In step 302, a second generated image is obtained, the second generated image including at least part of images in the generated image set.

[0074] In step 303, the image sample set and the second generated image are taken as training data of the generative adversarial network, and the generative adversarial network is trained according to the training data.

[0075] The implementation of step 301 to step 303 is described in the foregoing embodiments, and details are not repeated here.

[0076] In the embodiments of the disclosure, the training process of the generative adversarial network may also be illustrated by FIG. 4. As shown in FIG. 4, G represents a generator, D represents a discriminator, $p_z(z)$ represents a set of input noise variables, the generator G may output a generated image $G(z)$ based on an inputted real image x and a noise variable z , x is an image in the training data, the discriminator D may discriminate the inputted real image x to obtain the discrimination result $D(x)$ of the real image x , and the discriminator D may also discriminate the generated image $G(z)$ to obtain the discrimination result $D(G(z))$ of the generated image $G(z)$.

[0077] In the embodiments of the disclosure, after the generated image $G(z)$ is obtained, the generated image $G(z)$ may be added to the training data with a certain probability, so as to continue the training of the generative adversarial network.

[0078] The implementation of obtaining the second generated image is described with two examples below.

[0079] In the first example, a preset selection probability is obtained, and the second generated image is selected from the generated image set according to the preset selection probability.

[0080] Here, the preset selection probability represents the probability of selecting any image in the generated image set. The preset selection probability is a fixed selection probability. In the process of training the generative adversarial network, after the generated image set of the generator is obtained each time, the second generated image may be selected from the generated image set obtained each time according to the fixed selection probability.

[0081] In practical applications, the preset selection probability may be a value set empirically. For example, the preset selection probability is 0.4, 0.5, or 0.6. The preset selection probability can also be determined by trying values. That is, the selection probability may be set to a plurality of values. The generative adversarial network may be trained for each value of the selection probability, and then the image generation quality of the trained generative adversarial network may be tested, to obtain a test result. Finally, the value of the preset selection probability is determined according to the test result corresponding to each value of the selection probability.

[0082] It can be understood that the second generated image is selected by the preset selection probability. Since the preset selection probability is fixed, each time the generated image set of the generator is obtained, the second generated image may be selected from the generated image set according to the fixed selection probability, i.e., there is no need to select the second generated image according to different selection probabilities from the generated image set obtained each time according to the

dynamically changed selection probability, which is simple and easy to implement.

[0083] In the second example, the probability of selecting the second generated image from the generated image set dynamically changes with the training progress of the generative adversarial network, which is illustrated below.

[0084] An overfitting parameter is first obtained, the overfitting parameter represents a degree of overfitting of a discriminator of the generative adversarial network; and the second generated image matching the overfitting parameter in number is obtained from the generated image set.

[0085] Here, the larger the overfitting parameter is, the higher the degree of overfitting of the discriminator of the generative adversarial network is. For example, the value range of the overfitting parameter is 0 to 1. In a case where the value of the overfitting parameter is 0, it is indicated that the overfitting problem does not occur in the discriminator of the generative adversarial network. In a case where the value of the overfitting parameter is 1, it is indicated that the discriminator of the generative adversarial network is in a complete overfitting state.

[0086] It can be seen that in the embodiments of the disclosure, the generated image is not blindly used as training data, and the probability of selecting any image in the generated image set may be adaptively adjusted according to the current degree of overfitting of the discriminator of the generative adversarial network. Therefore, according to the current degree of overfitting of the discriminator of the generative adversarial network, the second generated image may be adaptively selected according to the corresponding image selection probability.

[0087] In order to accurately obtain the overfitting parameter, at least one of the first discrimination result or the second discrimination result is first obtained, the first discrimination result represents a discrimination result corresponding to the sample image set, and the second discrimination result represents a discriminant result corresponding to the generated image set. Then the overfitting parameter is obtained according to the obtained at least one of the first discriminant result or the second discriminant result.

[0088] Referring to FIG. 4, the first discrimination result includes the discrimination result $D(x)$ of the real image x , and the second discrimination result includes the discrimination result $D(G(z))$ of the generated image $G(z)$.

[0089] It can be understood that, since the discrimination result corresponding to the sample image set and the discrimination result corresponding to the generated image set are the results both obtained by the same discriminator, a degree of overfitting of the discriminator may be reflected by at least one of the discrimination result corresponding to the sample image set or the discrimination result corresponding to the generated image set, so that the embodiments of the disclosure can accurately obtain the overfitting parameter based on the discrimination result corresponding to the sample image set and the discrimination result corresponding to the generated image set.

[0090] The following exemplarily describes several implementations of obtaining the overfitting parameter according to the obtained at least one of the first discrimination result or the second discrimination result.

[0091] In the first implementation, a first average value is taken as the overfitting parameter. The first average value represents an average value of a sign function of a logarithmic output of the first discrimination result.

[0092] In the first implementation, the overfitting parameter λ may be obtained according to formula (1) and formula (2):

$$\lambda = E(\text{sign}(D_{real})) \quad (1)$$

$$D_{real} = \text{logit}(D(x)) \quad (2)$$

where $\text{logit}(\cdot)$ represents the logarithmic output, $\text{sign}(\cdot)$ represents the sign function value, and $E(\cdot)$ represents the average value.

[0093] In the second implementation, an opposite number of a second average value is taken as the overfitting parameter. The second average value represents an average value

of a sign function of a logarithmic output of the second discrimination result.

[0094] In the second implementation, the overfitting parameter λ may be obtained according to formula (3) and formula (4):

$$\lambda = -E(\text{sign}(D_{fake})) \quad (3)$$

$$D_{fake} = \text{logit}(D(G(z))) \quad (4).$$

[0095] In the third implementation, half of a difference between the first average value and the second average value is taken as the overfitting parameter.

[0096] In the third implementation, the overfitting parameter λ may be obtained according to formula (5):

$$\lambda = \frac{E(\text{sign}(D_{real})) - E(\text{sign}(D_{fake}))}{2} \quad (5).$$

[0097] It can be seen that the embodiments of the disclosure can accurately obtain the overfitting parameter based on the discrimination result corresponding to the sample image set and the discrimination result corresponding to the generated image set.

[0098] For the implementation of obtaining the second generated image matching the overfitting parameter in number from the generated image set, for example, the selection probability may be first determined, and the selection probability represents a probability of selecting any image in the generated image set. Then, the value of the selection probability is updated according to the value of the overfitting parameter, to obtain the updated selection probability. The value of the overfitting parameter is positively correlated with the updated selection probability. Finally, the second generated image matching the overfitting parameter in number is selected from the generated image set according to the updated selection probability.

[0099] In the embodiments of the disclosure, the initial value of the selection probability may be set to 0. After each overfitting parameter is obtained, the current

selection probability may be updated according to the size of the overfitting parameter. If the value of the overfitting parameter is larger, the updated selection probability is greater, and more images can be selected from the generated image set as the second generated image. If the value of the overfitting parameter is smaller, the updated selection probability is smaller, and less images can be selected from the generated image set as the second generated image.

[00100] It can be seen that in the embodiments of the disclosure, the second generated image can be accurately and reasonably selected according to the value of the overfitting parameter. That is, the training data can be adaptively adjusted according to the current degree of overfitting of the discriminator of the generative adversarial network.

[00101] For the implementation of updating the value of the selection probability according to the value of the overfitting parameter, for example, in a case where the value of the overfitting parameter is greater than a set threshold, the value of the selection probability is increased to obtain the updated selection probability. In a case where the value of the overfitting parameter is less than or equal to a set threshold, the value of the selection probability is decreased to obtain the updated selection probability.

[00102] In the embodiments of the disclosure, the set threshold may be data set empirically. For example, the set threshold may be 0.5, 0.6, or 0.7. The set threshold may also be determined according to the number of images in the sample image set, and the set threshold is positively correlated with the number of images in the sample image set. In the case of a large number of images in the sample image set, it can be considered that there is no need to add too many generated images to the training data. In this case, the set threshold may be set to a larger value. Otherwise, in the case of a small number of images in the sample image set, it can be considered that more generated images need to be added to the training data. In this case, the set threshold may be set to a smaller value.

[00103] In an actual scenario, the selection probability is expressed as P , and the set threshold is expressed as t . In the case where the value of the overfitting parameter λ is greater than the set threshold t , it can be considered that the discriminator of the generative adversarial network has a higher degree of overfitting. The selection

probability P is increased by a certain step size to obtain the updated selection probability P . Otherwise, in a case where the value of the overfitting parameter λ is less than or equal to the set threshold t , it can be considered that a degree of overfitting of the discriminator of the generative adversarial network is lower. The selection probability P can be reduced by a certain step size to obtain the updated selection probability P .

[00104] After the updated selection probability P is obtained, the generated image $G(z)$ may be sent to the training data of the generative adversarial network with a probability P , so as to adaptively deceive the discriminator to alleviate the overfitting problem of the discriminator in the case of training a generative adversarial network based on limited training data, which is beneficial to improvement of the image generation quality of the trained generative adversarial network.

[00105] It can be seen from the content above that the embodiments of the disclosure do not need to process the generative adversarial network through additional regularization terms, but instead adaptively select images from the generated images according to the current degree of overfitting of the discriminator, and use the selected image as training data to continue training the generative adversarial network, which can realize the adaptive adjustment of the training data. Therefore, there is no need to finely manually adjust the parameters of the generative adversarial network. The process of selecting the image from the generated images is irrelevant to a weight parameter of the generative adversarial network. That is, the training process of the generative adversarial network is not sensitive to the weight parameter. Furthermore, for any image generation scenario and any training state, the training data is adaptively enhanced according to the current degree of overfitting of the discriminator, to realize the training of the generative adversarial network, so that the embodiments of the disclosure can be applied to various image generation scenarios and various training states.

[00106] Those skilled in the art can understand that in the foregoing method of the specific implementation, the writing sequence of the steps does not mean a strict execution sequence but constitutes any limitation on the implementation process. The

specific execution sequence of the steps should be determined by its function and possible inherent logic.

[00107] On the basis of the image generation method provided in the foregoing embodiments, embodiments of the disclosure provide an image generation apparatus.

[00108] FIG. 5 is a schematic diagram of a composition structure of an image generation apparatus according to an embodiment of the disclosure. As shown in FIG. 5, the apparatus may include a first obtaining module 501 and a first processing module 502.

[00109] The first obtaining module 501 is configured to obtain an original image.

[00110] The first processing module 502 is configured to input the original image into a trained generative adversarial network, and process the original image using the trained generative adversarial network to obtain a first generated image. Training data of the generative adversarial network includes a sample image set and a second generated image. The second generated image includes at least part of images in a generated image set. The generated image set represents generated images obtained by processing the sample image set using the generative adversarial network.

[00111] In some embodiments, the first obtaining module 501 is further configured to:

 obtain an overfitting parameter, the overfitting parameter representing a degree of overfitting of a discriminator of the generative adversarial network; and

 obtain the second generated image matching the overfitting parameter in number from the generated image set.

[00112] In some embodiments, the first obtaining module 501 is specifically configured to:

 obtain at least one of a first discrimination result or a second discrimination result, the first discrimination result representing a discrimination result corresponding to the sample image set, and the second discrimination result representing a discrimination result corresponding to the generated image set; and

obtain the overfitting parameter according to the obtained at least one of the first discrimination result or the second discrimination result.

[00113] In some embodiments, the first obtaining module 501 is configured to obtain the overfitting parameter according to the obtained at least one of the first discrimination result or the second discrimination result, including one of the follow items:

taking a first average value as the overfitting parameter, the first average value representing an average value of a sign function of a logarithmic output of the first discrimination result;

taking an opposite number of a second average value as the overfitting parameter, the second average value representing an average value of a sign function of a logarithmic output of the second discrimination result; or

taking half of a difference between the first average value and the second average value as the overfitting parameter.

[00114] In some embodiments, the first obtaining module 501 is specifically configured to:

determine a selection probability, the selection probability representing a probability of selecting an image from the generated image set;

update a value of the selection probability according to a value of the overfitting parameter, to obtain an updated selection probability, the value of the overfitting parameter being positively correlated with the updated selection probability; and

select the second generated image matching the overfitting parameter in number from the generated image set according to the updated selection probability.

[00115] In some embodiments, the first obtaining module 501 is configured to update a value of the selection probability according to a value of the overfitting parameter, to obtain an updated selection probability, including one of the following items:

in a case where the value of the overfitting parameter is greater than a set threshold, increasing the value of the selection probability to obtain the updated selection probability; or

in a case where the value of the overfitting parameter is less than or equal to a set threshold, decreasing the value of the selection probability to obtain the updated selection probability.

[00116] In some embodiments, the first processing module 502 is further configured to obtain a preset selection probability, and select the second generated image from the generated image set according to the preset selection probability.

[00117] In practical applications, both the first obtaining module 501 and the first processing module 502 may be implemented by a processor in a computer device. The processor can be at least one of an ASIC, a DSP, a DSPD, a PLD, a FPGA, a CPU, a controller, a microcontroller, or a microprocessor.

[00118] On the basis of the neural network training method provided in the foregoing embodiments, embodiments of the disclosure provide a neural network training apparatus.

[00119] FIG. 6 is a schematic diagram of a composition structure of a neural network training apparatus according to an embodiment of the disclosure. As shown in FIG. 6, the apparatus may include a second processing module 601, a second obtaining module 602, and a training module 603.

[00120] The second processing module 601 is configured to input a sample image set into a generative adversarial network, and process the sample image set using the generative adversarial network, to obtain a generated image set.

[00121] The second obtaining module 602 is configured to obtain a second generated image, the second generated image including at least part of images in the generated image set.

[00122] The training module 603 is configured to take the image sample set and the second generated image as training data of the generative adversarial network, and train

the generative adversarial network according to the training data.

[00123] In some embodiments, the second obtaining module 602 is specifically configured to:

obtain an overfitting parameter, the overfitting parameter representing a degree of overfitting of a discriminator of the generative adversarial network; and

obtain the second generated image matching the overfitting parameter in number from the generated image set.

[00124] In some embodiments, the second obtaining module 602 is specifically configured to:

obtain at least one of a first discrimination result or a second discrimination result, the first discrimination result representing a discrimination result corresponding to the sample image set, and the second discrimination result representing a discrimination result corresponding to the generated image set; and

obtain the overfitting parameter according to the obtained at least one of the first discrimination result or the second discrimination result.

[00125] In some embodiments, the second obtaining module 602 is configured to obtain the overfitting parameter according to the obtained at least one of the first discrimination result or the second discrimination result, including one of the following items:

taking a first average value as the overfitting parameter, the first average value representing an average value of a sign function of a logarithmic output of the first discrimination result;

taking an opposite number of a second average value as the overfitting parameter, the second average value representing an average value of a sign function of a logarithmic output of the second discrimination result; or

taking half of a difference between the first average value and the second average value as the overfitting parameter.

[00126] In some embodiments, the second obtaining module 602 is specifically configured to:

determine a selection probability, the selection probability representing a probability of selecting an image from the generated image set;

update a value of the selection probability according to a value of the overfitting parameter, to obtain an updated selection probability, the value of the overfitting parameter being positively correlated with the updated selection probability; and

select the second generated image matching the overfitting parameter in number from the generated image set according to the updated selection probability.

[00127] In some embodiments, the second obtaining module 602 is configured to update a value of the selection probability according to a value of the overfitting parameter, to obtain an updated selection probability, including one of the following items:

in a case where the value of the overfitting parameter is greater than a set threshold, increasing the value of the selection probability to obtain the updated selection probability; and in a case where the value of the overfitting parameter is less than or equal to a set threshold, decreasing the value of the selection probability to obtain the updated selection probability.

[00128] In some embodiments, the second obtaining module 602 is specifically configured to obtain a preset selection probability, and select the second generated image from the generated image set according to the preset selection probability.

[00129] In addition, functional units in this embodiment may be integrated into one processing unit, or each of the units may be physically separated, or two or more units may be integrated into one unit. The integrated unit may be implemented in the form of

hardware, or may be implemented in a form of a software functional module.

[00130] If the integrated unit is implemented in the form of a software function module and is not sold or used as an independent product, it can be stored in a computer-readable storage medium. On the basis of such an understanding, the technical solution of this embodiment essentially or the part that contributes to the existing technology, or all or part of the technical solution can be embodied in the form of a software product. The computer software product is stored in a storage medium, including several instructions that cause a computer device (which can be a personal computer, a server, or a network device, etc.) or a processor to execute all or part of the steps of the method described in this embodiment. The foregoing storage medium includes: a USB flash drive, a mobile hard disk drive, a Read-Only Memory (ROM), a Random Access Memory (RAM), a magnetic disk, or an optical disk and other media that may store program codes.

[00131] Specifically, the computer program instructions corresponding to an image generation method or a neural network training method in this embodiment can be stored on storage media such as optical disks, hard disks, and USB flash drives. In a case where the computer program instructions in the storage media corresponding to the generation method or the neural network training method are read or executed by an electronic device, any one of the image generation method or the neural network training method in the foregoing embodiments is implemented.

[00132] Based on the same technical concept of the foregoing embodiments, FIG. 7 shows an electronic device 70 provided by an embodiment of the disclosure, which may include a memory 701 and a processor 702.

[00133] The memory 701 is configured to store a computer program and data.

[00134] The processor 702 is configured to run the computer program stored in the memory to implement the image generation method or the neural network training method according to any one of the foregoing embodiments.

[00135] In practical applications, the memory 701 may be a volatile memory, such as an RAM; or a non-volatile memory, such as an ROM, a flash memory, a Hard Disk Drive (HDD) or a Solid-State Drive (SSD); or a combination of the foregoing types of

memories, and provides instructions and data to the processor 702.

[00136] The processor 802 can be at least one of an ASIC, a DSP, a DSPD, a PLD, a FPGA, a CPU, a controller, a microcontroller, or a microprocessor. It can be understood that, for different devices, the electronic devices for implementing the processor functions may also be other devices, which is not specifically limited in the embodiments of the disclosure.

[00137] Embodiments of the disclosure also provide a computer program, including a computer-readable code. In a case where the computer-readable code runs in an electronic device, a processor of the electronic device executes the image generation method or the neural network training method according to any one of the embodiments.

[00138] In some embodiments, the functions or modules contained in the apparatus provided in the embodiments of the disclosure can be configured to execute the method described in the foregoing method embodiments. For specific implementation, reference is made to the description of the foregoing method embodiments. For brevity, details are not repeated here.

[00139] The above description of various embodiments tends to emphasize the differences between the various embodiments, the same or similarities can be referred to each other. For brevity, details are not repeated here.

[00140] The methods disclosed in the method embodiments provided in the disclosure can be combined arbitrarily without conflict to obtain new method embodiments.

[00141] The features disclosed in the product embodiments provided in the disclosure can be combined arbitrarily without conflict to obtain new product embodiments.

[00142] The features disclosed in the method or device embodiments provided in the disclosure can be combined arbitrarily without conflict to obtain new method or device embodiments.

[00143] Through the description of the above implementations, those skilled in the art can clearly understand that the method of the above embodiments can be implemented by

means of software and the necessary general hardware platform, and certainly can also be implemented by hardware. However, in many cases, the former is better. Based on such an understanding, the technical solution of the disclosure essentially or the part that contributes to the existing technology can be embodied in the form of a software product, and the computer software product is stored in a storage medium (such as ROM/RAM, magnetic disk, the optical disk), including several instructions that cause a terminal (which can be a mobile phone, a computer, a server, an air conditioner, or a network device, etc.) to execute the method described in each embodiment of the disclosure.

[00144] The embodiments of the disclosure are described above with reference to the accompanying drawings. However, the disclosure is not limited to the foregoing specific embodiments. The foregoing specific embodiments are merely illustrative, rather than restrictive. Under the motivation of the disclosure, those of ordinary skill in the art can make many forms without departing from the purpose of the disclosure and the protection scope of the claims, and these forms all fall within the protection of the disclosure.

CLAIMS

1. An image generation method, comprising:

obtaining an original image; and

inputting the original image into a trained generative adversarial network, and processing the original image using the trained generative adversarial network to obtain a first generated image, wherein training data of the generative adversarial network comprises a sample image set and a second generated image, the second generated image comprises at least part of images in a generated image set, and the generated image set represents generated images obtained by processing the sample image set using the generative adversarial network.

2. The method of claim 1, further comprising:

obtaining an overfitting parameter, the overfitting parameter representing a degree of overfitting of a discriminator of the generative adversarial network; and

obtaining the second generated image matching the overfitting parameter in number from the generated image set.

3. The method of claim 2, wherein the obtaining an overfitting parameter comprises:

obtaining at least one of a first discrimination result or a second discrimination result, the first discrimination result representing a discrimination result corresponding to the sample image set, and the second discrimination result representing a discrimination result corresponding to the generated image set; and

obtaining the overfitting parameter according to the obtained at least one of the first discrimination result or the second discrimination result.

4. The method of claim 3, wherein the obtaining the overfitting parameter according to the obtained at least one of the first discrimination result or the second discrimination result comprises one of following items:

taking a first average value as the overfitting parameter, the first average value representing an average value of a sign function of a logarithmic output of the first discrimination result;

taking an opposite number of a second average value as the overfitting parameter, the second average value representing an average value of a sign function of a logarithmic output of the second discrimination result; or

taking half of a difference between the first average value and the second average value as the overfitting parameter.

5. The method of any one of claims 2 to 4, wherein the obtaining the second generated image matching the overfitting parameter in number from the generated image set comprises:

determining a selection probability, the selection probability representing a probability of selecting an image from the generated image set;

updating a value of the selection probability according to a value of the overfitting parameter, to obtain an updated selection probability, the value of the overfitting parameter being positively correlated with the updated selection probability; and

selecting the second generated image matching the overfitting parameter in number from the generated image set according to the updated selection probability.

6. The method of claim 5, wherein the updating a value of the selection probability according to a value of the overfitting parameter, to obtain an updated selection probability comprises one of following items:

in a case where the value of the overfitting parameter is greater than a set threshold, increasing the value of the selection probability to obtain the updated selection probability; or

in a case where the value of the overfitting parameter is less than or equal to a set threshold, decreasing the value of the selection probability to obtain the updated selection probability.

7. The method of any one of claims 1 to 6, further comprising:

obtaining a preset selection probability; and selecting the second generated image from the generated image set according to the preset selection probability.

8. A neural network training method, comprising:

inputting a sample image set into a generative adversarial network, and processing the sample image set using the generative adversarial network, to obtain a generated image set;

obtaining a second generated image, the second generated image comprising at least part of images in the generated image set; and

taking the image sample set and the second generated image as training data of the generative adversarial network, and training the generative adversarial network according to the training data.

9. The method of claim 8, wherein the obtaining a second generated image comprises:

obtaining an overfitting parameter, the overfitting parameter representing a degree of overfitting of a discriminator of the generative adversarial network; and

obtaining the second generated image matching the overfitting parameter in number from the generated image set.

10. The method of claim 9, wherein the obtaining an overfitting parameter comprises:

obtaining at least one of a first discrimination result or a second discrimination result, the first discrimination result representing a discrimination result corresponding to the sample image set, and the second discrimination result representing a discrimination result corresponding to the generated image set; and

obtaining the overfitting parameter according to the obtained at least one of the first discrimination result or the second discrimination result.

11. The method of claim 10, wherein the obtaining the overfitting parameter according to the obtained at least one of the first discrimination result or the second discrimination result comprises one of following items:

taking a first average value as the overfitting parameter, the first average value representing an average value of a sign function of a logarithmic output of the first discrimination result;

taking an opposite number of a second average value as the overfitting parameter, the second average value representing an average value of a sign function of a logarithmic output of the second discrimination result; or

taking half of a difference between the first average value and the second average value as the overfitting parameter.

12. The method of any one of claims 9 to 11, wherein the obtaining the second generated image matching the overfitting parameter in number from the generated image set comprises:

determining a selection probability, the selection probability representing a probability of selecting an image from the generated image set;

updating a value of the selection probability according to a value of the overfitting parameter, to obtain an updated selection probability, the value of the overfitting parameter being positively correlated with the updated selection probability; and

selecting the second generated image matching the overfitting parameter in number from the generated image set according to the updated selection probability.

13. The method of claim 12, wherein the updating a value of the selection probability according to a value of the overfitting parameter, to obtain an updated selection probability comprises one of the following items:

in a case where the value of the overfitting parameter is greater than a set threshold, increasing the value of the selection probability to obtain the updated selection probability; and in a case where the value of the overfitting parameter is less than or equal to a set threshold, decreasing the value of the selection probability to obtain the updated selection probability.

14. The method of any one of claims 8 to 13, wherein the obtaining a second generated image comprises:

obtaining a preset selection probability; and selecting the second generated image from the generated image set according to the preset selection probability.

15. An electronic device, comprising a processor and a memory configured to store a computer program capable of running in the processor,

wherein the processor is configured to run the computer program to execute an image generation method;

wherein the image generation method comprises:

obtaining an original image; and

inputting the original image into a trained generative adversarial network, and processing the original image using the trained generative adversarial network to obtain a first generated image, wherein training data of the generative adversarial network comprises a sample image set and a second generated image, the second generated image comprises at least part of images in a generated image set, and the generated image set represents generated images obtained by processing the sample image set using the generative adversarial network.

16. An electronic device, comprising a processor and a memory configured to store a computer program capable of running in the processor,

wherein the processor is configured to run the computer program to execute a neural network training method;

wherein the neural network training method comprises:

inputting a sample image set into a generative adversarial network, and processing the sample image set using the generative adversarial network, to obtain a generated image set;

obtaining a second generated image, the second generated image comprising at least part of images in the generated image set; and

taking the image sample set and the second generated image as training data of the generative adversarial network, and training the generative adversarial network according to the training data.

17. A computer storage medium, having a computer program stored thereon, the computer program, when executed by a processor, implementing an image generation method;

wherein the image generation method comprises:

obtaining an original image; and

inputting the original image into a trained generative adversarial network, and processing the original image using the trained generative adversarial network to obtain a first

generated image, wherein training data of the generative adversarial network comprises a sample image set and a second generated image, the second generated image comprises at least part of images in a generated image set, and the generated image set represents generated images obtained by processing the sample image set using the generative adversarial network.

18. A computer storage medium, having a computer program stored thereon, the computer program, when executed by a processor, implementing a neural network training method;

wherein the neural network training method comprises:

inputting a sample image set into a generative adversarial network, and processing the sample image set using the generative adversarial network, to obtain a generated image set;

obtaining a second generated image, the second generated image comprising at least part of images in the generated image set; and

taking the image sample set and the second generated image as training data of the generative adversarial network, and training the generative adversarial network according to the training data.

19. A computer program, comprising a computer-readable code, wherein in a case where the computer-readable code runs in an electronic device, a processor of the electronic device executes an image generation method;

wherein the image generation method comprises:

obtaining an original image; and

inputting the original image into a trained generative adversarial network, and processing the original image using the trained generative adversarial network to obtain a first generated image, wherein training data of the generative adversarial network comprises a sample image set and a second generated image, the second generated image comprises at

least part of images in a generated image set, and the generated image set represents generated images obtained by processing the sample image set using the generative adversarial network.

20. A computer program, comprising a computer-readable code, wherein in a case where the computer-readable code runs in an electronic device, a processor of the electronic device executes a neural network training method;

wherein the neural network training method comprises:

obtaining an original image; and

inputting the original image into a trained generative adversarial network, and processing the original image using the trained generative adversarial network to obtain a first generated image, wherein training data of the generative adversarial network comprises a sample image set and a second generated image, the second generated image comprises at least part of images in a generated image set, and the generated image set represents generated images obtained by processing the sample image set using the generative adversarial network.