CLAIMS

What is claimed is:

1. A method for image super-resolution, comprising:

obtaining an image to be processed;

inputting the image to be processed into a first super-resolution network model and a second super-resolution network model trained in advance, respectively; wherein the first super-resolution network model is a convolutional neural network trained using a plurality of original sample images and corresponding target sample images; the second super-resolution network model is a generative network included in a generative adversarial network trained using a plurality of original sample images and corresponding target sample images; network structures of the first super-resolution network model and the second super-resolution network model are the same; resolutions of the target sample images are greater than resolutions of the original sample images;

obtaining a first image output from the first super-resolution network model and a second image output from the second super-resolution network model; wherein a resolution of the first image and a resolution of the second image are both greater than a resolution of the image to be processed; and

fusing the first image and the second image to obtain a target image, wherein a resolution of the target image is greater than the resolution of the image to be processed.

2. The method of claim 1, wherein a training process of the first super-resolution network model comprises:

obtaining a training sample set containing a plurality of training samples; wherein each training sample comprises an original sample image and a corresponding target sample image, a resolution of the target sample image is greater than a resolution of the original sample image;

inputting a first preset number of first original sample images in the training

sample set into a current convolutional neural network to obtain first reconstruction target images corresponding to the first original sample images;

calculating a loss value based on the first reconstruction target images, first target sample images corresponding to the first original sample images and a preset first loss function; and

determining whether the current convolutional neural network converges based on the loss value of the preset first loss function; if the current convolutional neural network converges, taking the current convolutional neural network as a trained first super-resolution network model; and if the current convolutional neural network does not converge, adjusting network parameters of the current convolutional neural network, and returning to perform a step of inputting the first preset number of first original sample images in the training sample set into the current convolutional neural network to obtain first reconstruction target images corresponding to the first original sample images.

3. The method of claim 2, wherein a training process of the second super-resolution network model comprises:

taking network parameters of the first super-resolution network model as initial parameters of the generative network in the generative adversarial network to obtain a current generative network; and setting initial parameters of a discrimination network in the generative adversarial network to obtain a current discrimination network;

inputting a second preset number of second original sample images in the training sample set into the current generative network to obtain second reconstruction target images corresponding to the second original sample images;

inputting the second reconstruction target images into the current discrimination network to obtain, for each second reconstruction target image, a first current prediction probability value of the second reconstruction target image being a second target sample image; and inputting second target sample images corresponding to the second original sample images into the current discrimination network to obtain, for each second target sample image, a second current prediction probability value of the

second target sample image being a second target sample image;

calculating a loss value based on first current prediction probability values, second current prediction probability values, a real result of whether it is a second target sample image and a preset second loss function;

adjusting network parameters of the current discrimination network according to the loss value of the preset second loss function to obtain a current intermediate discrimination network;

inputting a third preset number of third original sample images in the training sample set into the current generative network to obtain third reconstruction target images corresponding to the third original sample images;

inputting the third reconstruction target images into the current intermediate discrimination network to obtain, for each third reconstruction target image, a third current prediction probability value of the third reconstruction target image being a third target sample image;

calculating a loss value based on third current prediction probability values, a real result of whether it is a third target sample image, third target sample images corresponding to the third original sample images, the third reconstruction target images, and a preset third loss function; and

adjusting network parameters of the current generative network according to the loss value of the third loss function, increasing the number of iterations by one, returning to perform a step of inputting the second preset number of second original sample images in the training sample set into the current generative network to obtain second reconstruction target images corresponding to the second original sample images until the preset number of iterations is reached, and taking the trained current generative network as the second super-resolution network model.

4. The method of claim 1, wherein fusing the first image and the second image to obtain a target image comprises:

fusing pixel values of pixels in the first image and pixel values of pixels in the

second image according to weights to obtain the target image; wherein the weights are preset or determined based on the resolution of the first image and the resolution of the second image.

5. The method of claim 4, wherein fusing pixel values of pixels in the first image and pixel values of pixels in the second image according to weights to obtain the target image comprises:

fusing pixel values of pixels in the first image and pixel values of pixels in the second image according to weights using a following equation to obtain a fused image as a target image:

$$img3=alpha1*img1+(1-alpha1)*img2;$$

wherein, alpha1 is a weight of a pixel value for each pixel in the first image respectively, img1 is the pixel value for each pixel in the first image respectively, img2 is a pixel value for each pixel in the second image respectively, and img3 is a pixel value for each pixel in the target image respectively; a value range of alpha1 is [0,1].

6. A method for image super-resolution, comprising:

obtaining an image to be processed;

inputting the image to be processed into a pre-trained super-resolution reconstruction model; wherein the super-resolution reconstruction model is obtained by training a preset convolutional neural network and a generative adversarial network comprising a generative network and a discrimination network respectively using a plurality of training samples and then performing parameter fusion on network parameters of the trained preset convolutional neural network and network parameters of the trained generative network; network structures of the super-resolution reconstruction model, the preset convolutional neural network and the generative network are the same; wherein each training sample comprises an original sample image and a corresponding target sample image, a resolution of the target sample image is greater than a resolution of the original sample image; and

obtaining a target image corresponding to the image to be processed output from the super-resolution reconstruction model, wherein a resolution of the target image is greater than a resolution of the image to be processed.

7. The method of claim 6, wherein a training process of the super-resolution reconstruction model comprises:

obtaining a training sample set containing a plurality of training samples, wherein each training sample includes an original sample image and a corresponding target sample image, the resolution of the target sample image is greater than the resolution of the original sample image;

training a preset convolutional neural network based on the training sample set, and taking the trained preset convolutional neural network as a target convolutional neural network model;

training the generative adversarial network based on the training sample set, and taking a generative network in the trained generative adversarial network as a target generative network model;

performing weighted fusion on network parameters of each layer of the target convolutional neural network model and network parameters of each layer of the target generative network model respectively to obtain fused network parameters; and

creating the super-resolution reconstruction model; wherein the network structure of the super-resolution reconstruction model is the same as the network structures of the preset convolutional neural network and the generative network, and network parameters of the super-resolution reconstruction model are the fused network parameters.

8. The method of claim 7, wherein training a preset convolutional neural network based on the training sample set and taking the trained preset convolutional neural network as a target convolutional neural network model comprises:

inputting a first preset number of first original sample images in the training sample set into a current preset convolutional neural network to obtain first

reconstruction target images corresponding to the first original sample images;

calculating a loss value based on the first reconstruction target images, first target sample images corresponding to the first original sample images and a preset first loss function;

determining whether the current preset convolutional neural network converges based on the loss value of the preset first loss function; if the current convolutional neural network converges, obtaining a trained target convolutional neural network model; and if the current convolutional neural network does not converge, adjusting network parameters of the current preset convolutional neural network, and returning to perform a step of inputting the first preset number of first original sample images in the training sample set into the current preset convolutional neural network to obtain first reconstruction target images corresponding to the first original sample images.

9. The method of claim 8, wherein training the generative adversarial network based on the training sample set and taking a generative network in the trained generative adversarial network as a target generative network model comprises:

taking network parameters of the target convolutional neural network model as initial parameters of the generative network in the generative adversarial network to obtain a current generative network; and setting initial parameters of the discrimination network in the generative adversarial network to obtain a current discrimination network;

inputting a second preset number of second original sample images in the training sample set into the current generative network to obtain second reconstruction target images corresponding to the second original sample images;

inputting the second reconstruction target images into the current discrimination network to obtain, for each second reconstruction target image, a first current prediction probability value of the second reconstruction target image being a second target sample image; and inputting second target sample images corresponding to the second original sample images into the current discrimination network to obtain, for each second target sample image, a second current prediction probability value of the

second target sample image being a second target sample image;

calculating a loss value based on first current prediction probability values, second current prediction probability values, a real result of whether it is a second target sample image and a preset second loss function;

adjusting network parameters of the current discrimination network according to the loss value of the preset second loss function to obtain a current intermediate discrimination network;

inputting a third preset number of third original sample images in the training sample set into the current generative network to obtain third reconstruction target images corresponding to the third original sample images;

inputting the third reconstruction target images into the current intermediate discrimination network to obtain, for each third reconstruction target image, a third current prediction probability value of the third reconstruction target image being a third target sample image;

calculating a loss value based on third current prediction probability values, a real result of whether it is a third target sample image, third target sample images corresponding to the third original sample images, the third reconstruction target images, and a preset third loss function; and

adjusting network parameters of the current generative network according to the loss value of the third loss function, increasing the number of iterations by one, returning to perform a step of inputting the second preset number of second original sample images in the training sample set into the current generative network to obtain second reconstruction target images corresponding to the second original sample images until the preset number of iterations is reached, and taking the trained current generative network as the target generative network model.

10. The method of claim 7, wherein performing weighted fusion on network parameters of each layer of the target convolutional neural network model and network parameters of each layer of the target generative network model respectively to obtain fused network parameters comprises:

performing weighted fusion on the network parameters of each layer of the target convolutional neural network model and the network parameters of each layer of the target generative network model according to a following equation to obtain fused network parameters:

$$\theta_{NET3}^{n}=alpha1*\theta_{NET1}^{n}+(1-alpha1)*\theta_{NET2}^{n};$$

wherein, alpha1 is a weight coefficient of a network parameter of the target convolutional neural network model, NET1 represents the target convolutional neural network model, θ_{NET1}^{n} is a network parameter of a n-th layer of the target convolutional neural network model, NET2 represents the target generative network model, θ_{NET2}^{n} is a network parameter of a n-th layer of the target generative network model, NET3 represents a super-resolution reconstruction model, and θ_{NET3}^{n} is a network parameter of a n-th layer of the super-resolution reconstruction model; a value range of the alpha1 is [0,1].

11. A method for training a super-resolution reconstruction model, wherein the method comprises:

obtaining a training sample set containing a plurality of training samples; wherein each training sample comprises an original sample image and a corresponding target sample image, a resolution of the target sample image is greater than a resolution of the original sample image;

training a preset convolutional neural network based on the training sample set and taking the trained preset convolutional neural network as a target convolutional neural network model;

training a generative adversarial network based on the training sample set and taking a generative network in the trained generative adversarial network as a target generative network model;

performing weighted fusion on network parameters of each layer of the target convolutional neural network model and network parameters of each layer of the target generative network model respectively to obtain fused network parameters;

creating the super-resolution reconstruction model; wherein a network structure of the super-resolution reconstruction model is the same as network structures of the preset convolutional neural network and the generative network, and network parameters of the super-resolution reconstruction model are the fused network parameters.

12. The method of claim 11, wherein training a preset convolutional neural network based on the training sample set and taking the trained preset convolutional neural network as a target convolutional neural network model comprises:

inputting a first preset number of first original sample images in the training sample set into a current preset convolutional neural network to obtain first reconstruction target images corresponding to the first original sample images;

calculating a loss value based on the first reconstruction target images, first target sample images corresponding to the first original sample images and a preset first loss function;

determining whether the current convolutional neural network converges based on the loss value of the preset first loss function; if the current convolutional neural network converges, obtaining a trained target convolutional neural network model; and if the current convolutional neural network does not converge, adjusting network parameters of the current preset convolutional neural network, and returning to perform a step of inputting the first preset number of first original sample images in the training sample set into the current preset convolutional neural network to obtain first reconstruction target images corresponding to the first original sample images.

13. The method of claim 12, wherein training the generative adversarial network based on the training sample set and taking a generative network in the trained generative adversarial network as a target generative network comprises:

taking network parameters of the target convolutional neural network model as initial parameters of the generative network in the generative adversarial network to obtain a current generative network; and setting initial parameters of the discrimination network in the generative adversarial network to obtain a current

discrimination network;

inputting a second preset number of second original sample images in the training sample set into the current generative network to obtain second reconstruction target images corresponding to the second original sample images;

inputting the second reconstruction target images into the current discrimination network to obtain, for each second reconstruction target image, a first current prediction probability value of the second reconstruction target image being a second target sample image; and inputting second target sample images corresponding to the second original sample images into the current discrimination network to obtain, for each second target sample image, a second current prediction probability value of the second target sample image being a second target sample image;

calculating a loss value based on first current prediction probability values, second current prediction probability values, a real result of whether it is a second target sample image and a preset second loss function;

adjusting network parameters of the current discrimination network according to the loss value of the preset second loss function to obtain a current intermediate discrimination network;

inputting a third preset number of third original sample images in the training sample set into the current generative network to obtain third reconstruction target images corresponding to the third original sample images;

inputting the third reconstruction target images into the current intermediate discrimination network to obtain, for each third reconstruction target image, a third current prediction probability value of the third reconstruction target image being a third target sample image;

calculating a loss value based on third current prediction probability values, a real result of whether it is a third target sample image, third target sample images corresponding to the third original sample images, the third reconstruction target images, and a preset third loss function;

adjusting network parameters of the current generative network according to the loss value of the third loss function, increasing the number of iterations by one, returning to perform a step of inputting the second preset number of second original sample images in the training sample set into the current generative network to obtain second reconstruction target images corresponding to the second original sample images until the preset number of iterations is reached, and taking the trained current generative network as the second super-resolution network model.

14. The method of claim 11, wherein performing weighted fusion on network parameters of each layer of the target convolutional neural network model and network parameters of each layer of the target generative network model respectively to obtain fused network parameters comprises:

performing weighted fusion on the network parameters of each layer of the target convolutional neural network model and the network parameters of each layer of the target generative network model according to a following equation to obtain fused network parameters:

$$\theta_{NET3}^{n}=alpha1*\theta_{NET1}^{n}+(1-alpha1)*\theta_{NET2}^{n};$$

wherein, alpha1 is a weight coefficient of a network parameter of the target convolutional neural network model, NET1 represents the target convolutional neural network model, θ_{NET1}^{n} is a network parameter of a n-th layer of the target convolutional neural network model, NET2 represents the target generative network model, θ_{NET2}^{n} is a network parameter of a n-th layer of the target generative network model, NET3 represents a super-resolution reconstruction model, and θ_{NET3}^{n} is a network parameter of a n-th layer of the super-resolution reconstruction model; a value range of the alpha1 is [0,1].

15. An electronic device, comprising a processor, a communication interface, a memory and a communication bus, wherein the processor, the communication interface and the memory are communicated with each other through the communication bus;

the memory is configured to store a computer program;

the processor is configured to implement the method of any one of claims 1 to 5, or the method of any one of claims 6 to 10, or the method of any one of claims 11 to 14 when executing the computer program stored in the memory.

16. A computer-readable storage medium storing a computer program thereon, wherein the computer program implements the method of any one of claims 1 to 5, or the method of any one of claims 6 to 10, or the method of any one of claims 11 to 14 when executed by a processor.