

IMAGE RESTORATION METHOD AND APPARATUS, ELECTRONIC DEVICE, AND STORAGE MEDIUM

CROSS-REFERENCE TO RELATED APPLICATION

[0001] The application is based upon and claims priority to Chinese Patent Application No. 201910117782.X filed on February 15, 2019, the disclosure of which is hereby incorporated by reference in its entirety.

TECHNICAL FIELD

[0002] Embodiments of the present disclosure relate to the technical field of image restoration, and relate to, but are not limited to an image restoration method and apparatus, an electronic device and a storage medium.

BACKGROUND

[0003] Image restoration is a process that degraded images are reconstructed or restored by means of computers. There are many reasons for degradation of the images, for example, distortions caused by noise exposure and on-blur obscureness of cameras, image compression and so on. The image restoration process in reality is very complicated, because the degradation process of the images may include a variety of distortions at different degrees, and the distortions vary from each other in type and degree between different images and even are not uniformly distributed in the same image. For instance, the exposure noise is large in dark portions of an image, while small in bright portions of the image.

[0004] Generally, all regions of each image are subjected to the same processing during image restoration, which is usually complex in order that the image including different contents and distortions can be restored, such as using a deep neural network.

Such complex algorithm operates slowly, and cannot meet the requirements in actual applications.

[0005] As a matter of fact, different image regions vary from each other in contents and distortions, which causes that some image regions may be restored in a simpler manner. For example, the sky background in the image has a simple texture and a high brightness, such that the noise included is relatively small, and thus these regions can be easily restored. However, concerning the non-uniform distribution of the contents and distortions of the image, some simple regions are also subjected to complex calculation, resulting in a slow speed of image restoration.

SUMMARY

[0006] Embodiments of the present disclosure are intended to provide an image restoration method and apparatus, an electronic device and a storage medium, so as to improve the speed of image restoration.

[0007] The technical solutions in the embodiments of the present disclosure are implemented as follows.

[0008] An embodiment of the present disclosure provides an image restoration method, which may include the following operations.

[0009] Region division is performed on an acquired image to obtain at least one sub-image; and each of the at least one sub-image is input to a multi-path neural network, and each sub-image is restored by using a restoration network determined for each sub-image to obtain and output a restored image of each sub-image, thereby obtaining a restored image of the acquired image.

[0010] In the above solutions, the operation that each of the at least one sub-image is input to the multi-path neural network, and each sub-image is restored by using the restoration network determined for each sub-image to obtain and output the restored image of each sub-image may include the following operations. Each sub-image is

encoded to obtain features of each sub-image; the features of each sub-image are input to sub-networks of the multi-path neural network, a restoration network is selected for each sub-image by using path selection networks in the sub-networks, and each sub-image is processed according to the restoration network of each sub-image to obtain and output processed features of each sub-image; and the processed features of each sub-image are decoded to obtain the restored image of each sub-image.

[0011] In the above solutions, the operation that the features of each sub-image are input to the sub-networks of the multi-path neural network, the restoration network is selected for each sub-image by using the path selection networks in the sub-networks, and each sub-image is processed according to the restoration network of each sub-image to obtain and output the processed features of each sub-image may include the following operations. When the number of sub-networks is N and the N sub-networks are sequentially connected to each other, an i -th level of features of each sub-image are input to an i -th sub-network, and an i -th restoration network is selected for each sub-image from M restoration networks in the i -th sub-network by using an i -th path selection network in the i -th sub-network. The i -th level of features of each sub-image are processed according to the i -th restoration network to obtain and output an $(i+1)$ -th level of features of each sub-image. The i is updated to $i+1$, and the processing returns to the operation that the i -th level of features of each sub-image are input to the i -th sub-network, and the i -th restoration network is selected for each sub-image from the M restoration networks in the i -th sub-network by using the i -th path selection network in the i -th sub-network. Until an N -th level of features of each sub-image are obtained and output, the N -th level of features of each sub-image are determined as the processed features of each sub-image. When $i=1$, the i -th level of features of each sub-image are the features of each sub-image, where N is a positive integer not less than 1, M is a positive integer not less than 2, and i is a positive integer, i is greater than or equal to 1 and i is less than or equal to N .

[0012] In the above solutions, when the number of obtained restored images of the sub-images is greater than or equal to a preset number, the method may further include the following operations. Restored images of the preset number of sub-images are acquired, and reference images corresponding to the restored images of the preset

number of sub-images are acquired. Based on the restored images of the preset number of sub-images and the corresponding reference images, networks except for the path selection networks in the multi-path neutral network are trained by an optimizer according to a loss function between the restored images of the preset number of sub-images and the corresponding reference images, and parameters of the networks except for the path selection networks in the multi-path neutral network are updated. Based on the restored images of the preset number of sub-images and the corresponding reference images, the path selection networks are trained by the optimizer using a reinforcement learning algorithm according to a preset reward function, and parameters in the path selection networks are updated.

[0013] In the above solutions, after the restored images of the preset number of sub-images are acquired and the reference images corresponding to the restored images of the preset number of sub-images are acquired, and before the networks except for the path selection networks in the multi-path neutral network are trained by the optimizer according to the loss function between the obtained restored images of the preset number of sub-images and the corresponding reference images, and the parameters of the networks except for the path selection networks in the multi-path neutral network are updated, the method may further include the following operations. Based on the restored images of the preset number of sub-images and the corresponding reference images, the networks except for the path selection networks in the multi-path neutral network are trained by the optimizer according to the loss function between the restored images of the preset number of sub-images and the corresponding reference images, and parameters in the multi-path neutral network are updated.

[0014] In the above solutions, the reward function is formulated as follows:

$$r_i = \begin{cases} -p(1 - 1_{\{1\}}(a_i)), & 1 \leq i \leq N \\ -p(1 - 1_{\{1\}}(a_i)) + d, & i = N \end{cases} \quad (1)$$

[0015]

[0016] where r_i is a reward function for an i -th level of sub-networks, p is a preset penalty, $1_{\{1\}}(a_i)$ is an indicator function, and d is a coefficient of difficulty; and when a_i

=1, a value of the indicator function is 1, and when $a_i \neq 1$, the value of the indicator function is 0.

[0017] In the above solutions, the coefficient of difficulty d is formulated as follows:

$$[0018] \quad d = \begin{cases} L_d/L_0, & 0 \leq L_d \leq L_0 \\ 1, & L_d \geq L_0 \end{cases} \quad (2)$$

[0019] where L_d is the loss function between the restored images of the preset sub-images and the corresponding reference images, and L_0 is a threshold.

[0020] An embodiment of the present disclosure provides an image restoration apparatus, which may include: a division module and a restoration module. The division module is configured to perform region division on an acquired image to obtain at least one sub-image. The restoration module is configured to input each of the at least one sub-image to a multi-path neural network, and restore each sub-image by using a restoration network determined for each sub-image to obtain and output a restored image of each sub-image, thereby obtaining a restored image of the acquired image.

[0021] In the above image restoration apparatus, the restoration module may include: an encoding sub-module, a restoration sub-module and a decoding sub-module. The encoding sub-module is configured to encode each sub-image to obtain features of each sub-image. The restoration sub-module is configured to input the features of each sub-image to sub-networks of the multi-path neural network, select a restoration network for each sub-image by using path selection networks in the sub-networks, and process, according to the restoration network of each sub-image, each sub-image to obtain and output processed features of each sub-image. The decoding sub-module is configured to decode the processed features of each sub-image to obtain the restored image of each sub-image.

[0022] In the above image restoration apparatus, the restoration sub-module is specifically configured to: input, when the number of sub-networks is N and the N sub-networks are sequentially connected to each other, an i-th level of features of each sub-image to an i-th sub-network, and select an i-th restoration network for each sub-image

from M restoration networks in the i-th sub-network by using an i-th path selection network in the i-th sub-network; process, according to the i-th restoration network, the i-th level of features of each sub-image to obtain and output an (i+1)-th level of features of each sub-image; update the i to i+1, and return to the operation of inputting the i-th level of features of each sub-image to the i-th sub-network, and select the restoration network for each sub-image from the M restoration networks in the i-th sub-network by using the i-th path selection network in the i-th sub-network; and determine, until an N-th level of features of each sub-image are obtained and output, the N-th level of features of each sub-image as the processed features of each sub-image. When i=1, the i-th level of features of each sub-image are the features of each sub-image, where N is a positive integer not less than 1, M is a positive integer not less than 2, and i is a positive integer greater than or equal to 1 and less than or equal to N.

[0023] In the above image restoration apparatus, when the number of obtained restored images of the sub-images is greater than or equal to a preset number, the apparatus may further include: an acquisition module and a first training module. The acquisition module is configured to acquire restored images of the preset number of sub-images, and acquire reference images corresponding to the restored images of the preset number of sub-images. The first training module is configured to: train, based on the restored images of the preset number of sub-images and the corresponding reference images, networks except for the path selection networks in the multi-path neutral network by an optimizer according to a loss function between the restored images of the preset number of sub-images and the corresponding reference images, and update parameters of the networks except for the path selection networks in the multi-path neutral network; and train, based on the restored images of the preset number of sub-images and the corresponding reference images, the path selection networks by the optimizer using a reinforcement learning algorithm according to a preset reward function, and update parameters in the path selection networks.

[0024] In the above image restoration apparatus, the apparatus may further include: a second training module. After the restored images of the preset number of sub-images are acquired and the reference images corresponding to the restored images of the preset number of sub-images are acquired, and before the networks except for the path selection

networks in the multi-path neutral network are trained by the optimizer according to the loss function between the obtained restored images of the preset number of sub-images and the corresponding reference images, and the parameters of the networks except for the path selection networks in the multi-path neutral network are updated, the second training module is configured to: train, based on the restored images of the preset number of sub-images and the corresponding reference images, the networks except for the path selection networks in the multi-path neutral network by the optimizer according to the loss function between the restored images of the preset number of sub-images and the corresponding reference images, and the parameters except for the path selection networks in the multi-path neutral network are updated.

[0025] In the above image restoration apparatus, the reward function is formulated as follows:

$$[0026] \quad r_i = \begin{cases} -p(1 - 1_{\{1\}}(a_i)), & 1 \leq i \leq N \\ -p(1 - 1_{\{1\}}(a_i)) + d, & i = N \end{cases} \quad (1)$$

[0027] where r_i is a reward function for an i -th level of sub-networks, p is a preset penalty, $1_{\{1\}}(a_i)$ is an indicator function, and d is a coefficient of difficulty; and when $a_i = 1$, the value of the indicator function is 1, and when $a_i \neq 1$, the value of the indicator function is 0.

[0028] In the above image restoration apparatus, the coefficient of difficulty d is formulated as follows:

$$[0029] \quad d = \begin{cases} L_d/L_0, & 0 \leq L_d \leq L_0 \\ 1, & L_d \geq L_0 \end{cases} \quad (2)$$

[0030] where L_d is the loss function between the preset restored images of the sub-image and the corresponding reference image, and L_0 is a threshold.

[0031] An embodiment of the present disclosure provides an electronic device, which may include: a processor, a memory and a communication bus. The communication bus

is configured to implement connection and communication between the processor and the memory; and the processor is configured to execute an image restoration program stored in the memory to implement the image restoration method as described above.

[0032] The present disclosure provides a computer readable storage medium, which stores one or more programs; where the one or more programs may be executed by one or more processors to implement the image restoration method as described above.

[0033] Therefore, according to the image restoration method and apparatus, the electronic device and the storage medium provided by the embodiments of the present disclosure, the image restoration apparatus performs region division on the acquired image to obtain at least one sub-image, inputs each of the at least one sub-image to the multi-path neural network, and restores each sub-image by using the restoration network determined for each sub-image to output and obtain the restored image of each sub-image, thereby obtaining the restored image of the acquired image. That is, in the technical solutions provided by the embodiments of the present disclosure, the region division is first performed on the acquired image to obtain the at least one sub-image, each of the at least one sub-image is then input to the multi-path neural network, and each sub-image is restored by using the restoration network determined for each sub-image. Hence, the corresponding restoration network is determined for each sub-image in the multi-path neural network, such that the restoration network used by each sub-image is not completely the same, and different restoration networks are used for different sub-images. In this way, different sub-images are restored by using different restoration networks, so that some sub-images may be restored in a simple manner, and some sub-images are restored in a complex manner. Consequently, using the region-based image restoration method enables the complexity of image restoration to be reduced, thereby improving the speed of image restoration.

BRIEF DESCRIPTION OF THE DRAWINGS

[0034] FIG. 1 is a flowchart schematic diagram of an image restoration method according to an embodiment of the present disclosure.

- [0035] FIG. 2 is a flowchart schematic diagram of another image restoration method according to an embodiment of the present disclosure.
- [0036] FIG. 3 is a structural schematic diagram of an optional multi-path neural network according to an embodiment of the present disclosure.
- [0037] FIG. 4 is a structural schematic diagram of an optional dynamic block according to an embodiment of the present disclosure.
- [0038] FIG. 5 is a structural schematic diagram of another optional dynamic block according to an embodiment of the present disclosure.
- [0039] FIG. 6 is a structural schematic diagram of an image restoration apparatus according to an embodiment of the present disclosure.
- [0040] FIG. 7 is a structural schematic diagram of an electronic device according to an embodiment of the present disclosure.

DETAILED DESCRIPTION

- [0041] To make the objectives, technical solutions, and advantages of the present disclosure clearer, the specific technical solutions of the present disclosure are described below in detail with reference to the accompanying drawings in the embodiments of the present disclosure. The following embodiments are used for illustrating the present disclosure, but are not to limit the scope of the present disclosure.
- [0042] An embodiment of the present disclosure provides an image restoration method. FIG. 1 is a flowchart schematic diagram of an image restoration method provided by an embodiment of the present disclosure. As shown in FIG. 1, the image restoration method may include the following operations.
- [0043] In S101, region division is performed on an acquired image to obtain at least one sub-image.
- [0044] At present, due to distortions of images caused by noise exposure and on-blur

obscurity of cameras, image compression and so on, restoration of the images is necessary. However, since the degradation process of the images may have a variety of distortions with different degrees, and a type and degree of distortion vary from each other between different images. As a result, if all regions of each image are subjected to the same processing through a very deep neural network, the speed of image restoration will be affected.

[0045] In order to improve the speed of image restoration, after an image is acquired, the region division is first performed on the image to obtain at least one sub-image.

[0046] In actual applications, if an image having a resolution of 63×63 is acquired, the image is divided into multiple regions, each of which is the above sub-image. Each sub-image overlaps with a neighboring image at 10 pixels in a horizontal abscissa direction and a vertical ordinate direction. After each sub-image is restored through a multi-path neural network, the restored sub-images are spliced into an integrated image; and overlapping regions are averaged, so that the restored image can be obtained.

[0047] In S102, each of the at least one sub-image is input to a multi-path neural network, and each sub-image is restored by using a restoration network determined for each sub-image to obtain and output a restored image of each sub-image, thereby obtaining a restored image of the acquired image based on the obtained restored image of each sub-image.

[0048] After at least one sub-image is obtained, in order to restore each of the at least one sub-image, each sub-image may be sequentially input to the multi-path neural network. In the multi-path neural network, the restoration network is determined for each sub-image. Each sub-image is restored by using the restoration network determined for each sub-image, and the restored image of each sub-image is output and obtained from the multi-path neural network. Finally, the restored images of all sub-images are spliced to obtain the restored image of the acquired image.

[0049] In order to obtain the restored image of each sub-image by inputting each sub-image to the multi-path neural network, in an optional embodiment, FIG. 2 is a flowchart schematic diagram of another image restoration method according to an embodiment of

the present disclosure. As shown in FIG. 2, S102 may include the following operations.

- [0050] In S201, each sub-image is encoded to obtain features of each sub-image.
- [0051] In S202, the features of each sub-image are input to sub-networks of the multi-path neural network, a restoration network is selected for each sub-image by using path selection networks in the sub-networks, and each sub-image is processed according to the restoration network of each sub-image to output and obtain processed features of each sub-image.
- [0052] In S203, the processed features of each sub-image are decoded to obtain the restored image of each sub-image.
- [0053] Specifically, the multi-path neural network includes three processing portions. The first processing portion is to encode each sub-image, which may be implemented by an encoder. For instance, the sub-image is a color image region, and may be represented as a tensor of $63*63*3$. After the sub-image is encoded by an encoder, features of the sub-image are output and obtained, and may be represented as a tensor of $63*63*64$.
- [0054] In this way, each sub-image is first encoded in the multi-path neural network to obtain the features of the sub-image.
- [0055] The second processing portion is to input the features of each sub-image to the sub-networks of the multi-path neural network. The sub-networks may be dynamic blocks correspondingly. The number of the dynamic blocks may be N , N being a positive integer greater than or equal to 1. In other words, the sub-networks may be one dynamic block, or may also be two or more dynamic blocks, which is not specifically limited in the embodiment of the present disclosure.
- [0056] Each dynamic block includes a pathfinder (equivalent to the path selection network as described above), configured to determine the restoration network for each sub-image, such that each image may be processed in different dynamic blocks by adoption of a different restoration network. Therefore, the purpose of selecting different processing manners for different sub-images is achieved; and the obtained processed features are a tensor of $63*63*64$.

- [0057] The third processing portion is to decode each sub-image. After the processed features of each sub-image are obtained, the processed features of each sub-image are decoded, which may be implemented by a decoder herein. For instance, the above processed features are decoded to obtain the restored image of the sub-image, and the restored image may be represented as a tensor of $63*63*3$.
- [0058] In order to implement the processing on the features of the sub-images in the sub-networks of the multi-path neural network, in an optional embodiment, S202 may include the following operations.
- [0059] When the number of sub-networks is N and the N sub-networks are sequentially connected to each other,
- [0060] an i -th level of features of each sub-image are input to an i -th sub-network, and an i -th restoration network is selected for each sub-image from M restoration networks in the i -th sub-network by using an i -th path selection network in the i -th sub-network.
- [0061] According to the i -th restoration network, the i -th level of features of each sub-image are processed to output and obtain an $(i+1)$ -th level of features of each sub-image.
- [0062] The i is updated to $i+1$, and the operation returns to the operation that the i -th level of features of each sub-image are input to the i -th sub-network, and the i -th restoration network is selected for each sub-image from the M restoration networks in the i -th sub-network by using an i -th path selection network in the i -th sub-network.
- [0063] Until an N -th level of features of each sub-image are output and obtained, the N -th level of features of each sub-image are determined as the processed features of each sub-image.
- [0064] When $i=1$, the i -th level of features of each sub-image are the features of each sub-image.
- [0065] The N is a positive integer not less than 1, the M is a positive integer not less than 2, and i is a positive integer, i is greater than or equal to 1 and i is less than or equal to N .

[0066] In a case that the sub-networks are dynamic blocks, when the multi-path neutral network includes N dynamic blocks and the N dynamic blocks are sequentially connected to each other, the obtained features of each sub-image are input to the first dynamic block. Each dynamic block includes a pathfinder, a shared path and M dynamic paths.

[0067] Upon receiving features of a sub-image, the first dynamic block takes the received features of the sub-image as the first level of features of the sub-image; the first pathfinder determines the first restoration network for the sub-image from M dynamic paths according to the first level of features of the sub-image, such that a shared path and a dynamic path that is selected from the M dynamic paths constitute the first restoration network. Then, the first level of features of the sub-image are processed according to the first level of restoration networks to obtain the second level of features of the sub-image. Then i is updated as 2, the second level of features of the sub-image are input to the second dynamic block, and the third level of features of the sub-image are obtained according to the same processing method as that for the first dynamic block; and so on until the N-th level of features of the sub-image are obtained, thereby obtaining the processed feature of each sub-image.

[0068] In the multi-path neutral network, both the size of each feature of the sub-image and the number of restoration networks are variable. In actual applications, the size of the feature of the sub-image may have a tensor of $63*63*64$, or may also have a tensor of $32*32*16$, the tensor of $96*96*48$, etc. The number N of dynamic blocks and the number M of dynamic paths are variable, for example, $N=6, M=2$; $N=5, M=4$, which is not specifically limited in the embodiment of the present disclosure.

[0069] Herein, it is to be noted that when the distortion problem to be solved is complex during selection of the parameters N and M as described above, both the N and the M may be increased appropriately; or otherwise, the N and the M may be decreased.

[0070] The structure for the shared path and the (2-M)-th dynamic path is not limited to a residual block, or may also be a dense block or another structure.

[0071] It is to be noted that the network structure of the pathfinder in each dynamic

block may be identical, or may also be different, which is not specifically limited in the embodiment of the present disclosure.

[0072] In actual applications, the input of the pathfinder is a tensor of $63*63*64$, and the output is a serial number a_i of the selected path; and the structure of the path selector, from input to output, respectively includes C convolutional layers, a fully connected layer (where the output dimension is 32), a Long-Short Term Memory (LSTM) module (the number of states is 32) and a fully connected layer (where the output dimension is M). The activation function for the last layer is Softmax or Rectified Linear Unit (ReLU); and the serial number of the maximum element in the activated M-dimensional vector is the serial number of the selected dynamic path.

[0073] The number of C may be adjusted according to the difficulty of the restoration tasks; and the output dimension of the first fully connected layer and the number of states of the LSTM module are not limited to 32, and may also be 16, 64, etc.

[0074] In order to update the parameters in the multi-path neural network, in an optional embodiment, when the number of obtained restored images of the sub-images is greater than or equal to a preset number, the method may further include the following operations.

[0075] Restored images of the preset number of sub-images are acquired, and reference images corresponding to the restored images of the preset number of sub-images are acquired.

[0076] Based on the restored images of the preset number of sub-images and the corresponding reference images, networks except for the path selection networks in the multi-path neural network are trained by an optimizer according to a loss function between the restored images of the preset number of sub-images and the corresponding reference images, and parameters of the networks except for the path selection networks in the multi-path neural network are updated.

[0077] Based on the restored images of the preset number of sub-images and the corresponding reference images, the path selection networks are trained by the optimizer

by use of a reinforcement learning algorithm according to a preset reward function, and update parameters of the path selection networks are updated.

[0078] Specifically, the reference images are pre-stored, for example, the preset number of the reference images is 32. After restored images of the 32 sub-images are obtained, by taking the restored images of the 32 sub-images and their corresponding reference images as samples, based on the sample data, the networks except for the path selection networks in the multi-path neutral network are trained by using the optimizer according to the loss function between the restored images of the sub-images and the corresponding reference images, and the parameters of the networks except for the path selection networks in the multi-path neutral network are updated.

[0079] At the meantime, the restored images of the 32 sub-images and the corresponding reference images are still taken as the samples. In order to train the path selection networks, a reinforcement learning algorithm is used herein. For use of the reinforcement learning algorithm, reward functions are preset, and the optimization objective of the reinforcement learning algorithm is to maximize an expectation of a sum of all reward functions. Therefore, based on the sample data, according to the preset reward functions, the path selection networks are trained by the optimizer by use of the reinforcement learning algorithm, thereby updating the parameters of the path selection networks.

[0080] In other words, the networks except for the path selection networks in the multi-path neutral network, and the path selection networks are trained simultaneously in different processing manners to update the parameters of the networks.

[0081] A loss function between the restored images of the sub-images and the corresponding reference images are preset. The loss function may be L2 loss function, and may also be Visual Geometry Group (VGG) loss function, which is not specifically limited in the embodiment of the present disclosure.

[0082] In order to better update the parameters of the networks except for the path selection networks in the multi-path neutral network, in an optional embodiment, after the restored images of the preset number of sub-images are acquired and the reference

images corresponding to the restored images of the preset number of sub-images are acquired, and before the networks except for the path selection networks in the multi-path neutral network are trained by the optimizer according to the loss function between the obtained restored images of the preset number of sub-images and the corresponding reference images, and the parameters of the networks except for the path selection networks in the multi-path neutral network are updated, the method may further include the following operation.

[0083] Based on the restored images of the preset number of sub-images and the corresponding reference images, the networks except for the path selection networks in the multi-path neutral network are trained by the optimizer according to the loss function between the restored images of the preset number of sub-images and the corresponding reference images, and the parameters of the networks except for the path selection networks in the multi-path neutral network are updated.

[0084] In other words, before the networks except for the path selection networks in the multi-path neutral network, and the path selection networks are simultaneously trained in different processing manners, the networks except for the path selection networks in the multi-path neutral network may be first trained based on the samples. Then, the networks except for the path selection networks in the multi-path neutral network, and the path selection networks are simultaneously trained in different processing manners. In this way, the parameters of the networks except for the path selection networks in the multi-path neutral network, and the path selection networks may be better optimized.

[0085] In an optional embodiment, the reward function is as shown in the formula (1):

[0086]
$$r_i = \begin{cases} -p(1 - 1_{\{i\}}(a_i)), & 1 \leq i \leq N \\ -p(1 - 1_{\{i\}}(a_i)) + d, & i = N \end{cases} \quad (1)$$

[0087] where r_i is a reward function for an i -th level of sub-networks, p is a preset penalty, $1_{\{i\}}(a_i)$ is an indicator function, and d is a coefficient of difficulty.

[0088] When $a_i=1$, the value of the indicator function is 1, and when $a_i \neq 1$, the value of the indicator function is 0.

[0089] The penalty is a set value. The value of the penalty is associated with the degree of distortion of the sub-image, and represents complexity of the network. When $a_i=1$, i.e., a simple connection path is selected, the penalty is 0 because no additional computation overhead is introduced. When $a_i \neq 1$, i.e., one complex path is selected, the reward function has a penalty (deduced by P).

[0090] The reward function is a reward function based on a coefficient of difficulty of the sub-image. The coefficient of difficulty may be a constant 1, or may also be a value associated with the loss function, which is not be specifically limited in the embodiment of the present disclosure.

[0091] Herein, when the coefficient of difficulty is the value associated with the loss function, in an optional embodiment, the coefficient of difficulty d is as shown in the formula (2):

[0092]
$$d = \begin{cases} L_d/L_0, & 0 \leq L_d \leq L_0 \\ 1, & L_d \geq L_0 \end{cases} \quad (2)$$

[0093] Where, L_d represents a loss function between the restored images of the preset sub-images and the corresponding reference images, and L_0 is a threshold.

[0094] The above loss function may be mean-square error L2 loss function, or may also be VGG loss function, which is not be specifically limited in the embodiment of the present disclosure.

[0095] It is to be noted that the form of the loss function used in the coefficient of difficulty may be the same as that of the loss function used in the network training, or may also be different from that of the loss function used in the network training, which is not be specifically limited in the embodiment of the present disclosure.

[0096] For example, when the coefficient of difficulty is the independent variable and

is a distance L2 between the restored image of the sub-image and the corresponding reference image, where L2 represents restoration effect; and the value of the distance becomes larger as the restoration effect is better, and thus the reward function is larger. The coefficient of difficulty d represents difficulty of restoration of one image region. The larger the difficulty is, the larger the value of d will be, which encourages that the network performs finer restoration on the region; and the less the difficulty is, the less the value of the d will be, and it is not advocated that the network performs excessively fine restoration on the region.

[0097] Examples are given below to illustrate the image restoration method in the above one or more embodiments.

[0098] FIG. 3 is a structural schematic diagram of an optional multi-path neural network according to an embodiment of the present disclosure. As shown in FIG. 3, an image is acquired, region division is performed on the image to obtain multiple sub-images x , the sub-images x (denoted by the tensor of $63*63*3$) are input to an encoder of the multi-path neural network, the encoder being a convolutional layer Conv. The sub-images x are encoded by the convolutional layer to obtain features of the sub-images x (denoted by the tensor of $63*63*64$).

[0099] Then, the features of the sub-images x are input to the first dynamic block that includes the number of N dynamic blocks (Dynamic Block 1...Dynamic Block i...Dynamic Block N). As can be seen from FIG. 3, each dynamic block includes a shared path f_s^i , a pathfinder f_{PF} and M dynamic paths $f_1^i, f_2^i \dots f_M^i$. For the first dynamic block, the first level of features x_1 of the sub-images are received, and the pathfinder processes the x_1 to obtain a_1 . In the embodiment, the a_1 may select f_1^i . One dynamic path is determined for the x_1 from the M dynamic paths by the a_1 , and the shared path and the dynamic path determined by the a_1 constitute a restoration network to process x_1 , so as to obtain the first level of features x_2 of the sub-images. The features x_2 are input to the second level of dynamic blocks; and with the same processing as the x_1 , x_3 is obtained, and so on until x_n is obtained to serve as the processed features of the sub-images.

- [00100] At last, the x_n is input to a decoder, and the decoder is the convolutional layer Conv. By decoding the x_n with the convolutional layer Conv, the restored images of the sub-images (represented by the tensor of $63*63*64$, and as illustrated by the picture below output in FIG. 3) are obtained.
- [00101] The input of the pathfinder is the tensor of $63*63*64$, and the output is a serial number a_i of the selected path. As shown in FIG. 3, the structure of the path selector, from the input to output, respectively includes C convolutional layers (Conv 1 to Conv C), a fully connected layer FC (where the output dimension is 32), an LSTM module (where the number of states is 32) and a fully connected layer FC (where the output dimension is M). The activation function for the last layer is Softmax or Rectified Linear Unit (ReLU); and the serial number of the maximum element in the activated M-dimensional vector is the serial number of the selected dynamic path.
- [00102] If the preset number is 32, after the restored images of the 32 sub-images are obtained, reference images corresponding to the 32 sub-images are first acquired from reference images GT (represented by y) to obtain a training sample. Then, according to the loss function L2 loss between the restored images of the preset number of sub-images and the reference images, networks except for the pathfinders in FIG. 3 are trained by using optimizer Adam, to update parameters of the network except for the path finders, thereby achieving optimization of network parameters.
- [00103] Meanwhile, based on the above training sample, according to a preset reward function Reward associated with the coefficient of difficulty, the pathfinder in FIG. 3 is also trained by the optimizer Adam using a reinforcement learning algorithm, to update parameters of the pathfinder, thereby achieving optimization of the network parameters.
- [00104] The algorithm used by the optimizer may be Stochastic Gradient Descent (SGD). The reinforcement learning algorithm may be REINFORCE, or may also be other algorithms such as actor-critic, which is not specifically limited in the embodiment of the present disclosure.
- [00105] It is to be noted that the solid arrow in FIG. 3 represents Forward, the short dotted arrow represents Backward, and the long dotted arrow represents Path Selection.

[00106] FIG. 4 is a structural schematic diagram of an optional dynamic block according to an embodiment of the present disclosure. As shown in FIG. 4, the dynamic block includes a shared path. The shared path is composed of two convolutional layers (two Conv (3, 64, 1)), a pathfinder and two dynamic paths. One of the dynamic paths has the same input and output, i.e., the features of the sub-images are not processed on the dynamic path; and the other dynamic path is provided with two convolutional layers (two Conv (3, 64, 1)), and the result of the pathfinder is synthesized by the shared path and the dynamic path. The pathfinder includes two convolutional layers (Conv (5, 4, 4) and Conv (5, 24, 4)), a fully connected layer Fc (32), an LSTM (32) and an Fc (32).

[00107] FIG. 5 is a structural schematic diagram of another optional dynamic block according to an embodiment of the present disclosure. As shown in FIG. 5, the dynamic block includes a shared path. The shared path is composed of two convolutional layers (Conv (3, 24, 1) and Conv (3, 32, 1)), a pathfinder and four dynamic paths. One dynamic path has the same input and output, i.e., the features of the sub-images are not processed on the dynamic path; and one dynamic path is provided with two convolutional layers (two Conv (3, 32, 1)), and the result of the pathfinder is synthesized by the shared path and the dynamic path. The pathfinder includes four convolutional layers (one Conv (3, 8, 2), two Conv (3, 16, 2) and one Conv (3, 24, 2)), a fully connected layer Fc (32), an LSTM (32) and an Fc (32).

[00108] By means of the above embodiments, the degraded image containing single or more distortions can be restored, and the distortions include but not limited to one or more of: Gaussian noise, Gaussian blur and Joint Photographic Experts Group (JPEG) compression. In the embodiment of the present disclosure, the speed may be increased by 4 times while achieving the same image restoration effect, and the specific proportion of speed-up is associated with the restoration tasks, where the speed-up becomes faster as the restoration task is more complex. Therefore, a better restoration effect is achieved under the premise of the same computational burden, and the restoration effect may be evaluated by a Peak Signal to Noise Ratio (PSNR) and a Structural Similarity Index (SSIM).

[00109] In addition, the present disclosure may quickly improve the image quality of

pictures in the mobile phones, which includes removing or weakening the exposure noise, on-blur obscureness, compression distortion, etc. The content of a picture of the mobile phone can be various, and may have a larger portion of smooth sky region or virtualized background, which can be easily processed and quickly restored by the embodiment of the present disclosure. In this case, the computational burden is mainly focus on the main body region of the picture, thereby implementing image restoration in a sound and good manner.

[00110] According to the image restoration method and apparatus, electronic device and storage medium according to the embodiments of the present disclosure, the image restoration apparatus performs region division on an acquired image to obtain at least one sub-image, inputs each of the at least one sub-image to the multi-path neural network, and restores each sub-image by using a restoration network determined for each sub-image to output and obtain a restored image of each sub-image, thereby obtaining the restored image of the acquired image. That is, in the technical solutions provided by the embodiments of the present disclosure, the region division is first performed on the acquired image to obtain at least one sub-image, each sub-image is then input to the multi-path neural network, and each sub-image is restored by using the restoration network determined for each sub-image. Hence, the corresponding restoration network is determined for each sub-image in the multi-path neural network, such that the restoration network used by each sub-image is not all the same, but instead different restoration networks are used for different sub-images. By using different restoration networks for different sub-images for restoration, some sub-images may be restored in a simple manner, and some sub-images are restored in a complex manner. Therefore, adoption of such region-customized image restoration method reduces the complexity of image restoration, thereby improving the speed of image restoration.

[00111] FIG. 6 is a structural schematic diagram of an image restoration apparatus according to an embodiment of the present disclosure. As shown in FIG. 6, the image restoration apparatus may include: a division module 61 and a restoration module 62.

[00112] The division module 61 is configured to perform region division on an acquired image to obtain at least one sub-image.

- [00113] The restoration module 62 is configured to input each of the at least one sub-image to a multi-path neural network, and restore each sub-image by using a restoration network determined for each sub-image to output and obtain a restored image of each sub-image, thereby obtaining a restored image of the acquired image.
- [00114] In some examples, the restoration module 62 may include: an encoding sub-module, a restoration sub-module and a decoding sub- module.
- [00115] The encoding sub-module is configured to encode each sub-image to obtain features of each sub-image.
- [00116] The restoration sub-module is configured to input the features of each sub-image to sub-networks of the multi-path neural network, select a restoration network for each sub-image by using path selection networks in the sub-networks, and process each sub-image according to the restoration network of each sub-image to output and obtain processed features of each sub-image.
- [00117] The decoding sub-module is configured to decode the processed features of each sub-image to obtain the restored image of each sub-image.
- [00118] In some examples, the restoration sub-module is specifically configured to:
- [00119] when the number of sub-networks is N and the N sub-networks are sequentially connected to each other,
- [00120] input an i -th level of features of each sub-image to an i -th sub-network, and select an i -th restoration network for each sub-image from M restoration networks in the i -th sub-network by using an i -th path selection network in the i -th sub-network;
- [00121] process, according to the i -th restoration network, the i -th level of features of each sub-image to output and obtain an $(i+1)$ -th level of features of each sub-image;
- [00122] update the i to $i+1$, and return to the operation of inputting the i -th level of features of each sub-image to the i -th sub-network, and select the i -th restoration network for each sub-image from the M restoration networks in the i -th sub-network by using the i -th path selection network in the i -th sub-network;

- [00123] until an N-th level of features of each sub-image are output and obtained, determine the N-th level of features of each sub-image as the processed features of each sub-image.
- [00124] When $i=1$, the i-th level of features of each sub-image are the features of each sub-image.
- [00125] The N is a positive integer not less than 1, M is a positive integer not less than 2, and i is a positive integer greater than or equal to 1 and less than or equal to N.
- [00126] In some examples, when the number of obtained restored images of the sub-images is greater than or equal to a preset number, the apparatus may further include: an acquisition module and a first training module.
- [00127] The acquisition module is configured to acquire restored images of the preset number of sub-images, and acquire reference images corresponding to the restored images of the preset number of sub-images.
- [00128] The first training module is configured to:
- [00129] train, based on the restored images of the preset number of sub-images and the corresponding reference images, networks except for the path selection networks in the multi-path neural network by an optimizer according to the loss function between the restored images of the preset number of sub-images and the corresponding reference images, and update parameters of the networks except for the path selection networks in the multi-path neural network; and
- [00130] train, based on the restored images of the preset number of sub-images and the corresponding reference images, the path selection networks by the optimizer by use of a reinforcement learning algorithm according to preset reward functions, and update parameters of the path selection networks.
- [00131] In some examples, the apparatus may further include: a second training module.
- [00132] The second training module is configured to:

[00133] after the restored images of the preset number of sub-images are acquired and the reference images corresponding to the restored images of the preset number of sub-images are acquired, and before the networks except for the path selection networks in the multi-path neutral network are trained by the optimizer according to the loss functions between the obtained restored images of the preset number of sub-images and the corresponding reference images, and update the parameters of the networks except for the path selection networks in the multi-path neutral network, train, based on the restored images of the preset number of sub-images and the corresponding reference images, the networks except for the path selection networks in the multi-path neutral network by the optimizer according to the loss functions between the restored images of the preset number of sub-images and the corresponding reference images, and update the parameters except for the path selection networks in the multi-path neutral network.

[00134] In some examples, the reward function is as shown in the formula (1):

$$[00135] \quad r_i = \begin{cases} -p(1 - 1_{\{1\}}(a_i)), & 1 \leq i \leq N \\ -p(1 - 1_{\{1\}}(a_i)) + d, & i = N \end{cases} \quad (1)$$

[00136] where r_i is a reward function of the i -th level of sub-networks, p is a preset penalty, $1_{\{1\}}(a_i)$ is an indicator function, and d is a coefficient of difficulty.

[00137] When $a_i=1$, the value of the indicator function is 1, and when $a_i \neq 1$, the value of the indicator function is 0.

[00138] In some examples, the coefficient of difficulty d is as shown in the formula (2):

$$[00139] \quad d = \begin{cases} L_d/L_0, & 0 \leq L_d \leq L_0 \\ 1, & L_d \geq L_0 \end{cases} \quad (2)$$

[00140] where L_d is the loss function between the restored images of the preset sub-images and the corresponding reference images, and L_0 is a threshold.

- [00141] FIG. 7 is a structural schematic diagram of an electronic device according to an embodiment of the present disclosure. As shown in FIG. 7, the electronic device may include: a processor 71, a memory 72, and a communication bus 73.
- [00142] The communication bus 73 is configured to implement connection and communication between the processor 71 and the memory 72.
- [00143] The processor 71 is configured to execute an image restoration program stored in the memory 72 to implement the image restoration method as described above.
- [00144] An embodiment of the present disclosure further provides a computer readable storage medium, which stores one or more programs; and the one or more programs may be executed by one or more processors to implement the image restoration method as described above. The computer readable storage medium may be a transitory memory such as a Random-Access Memory (RAM), or a non-transitory memory such as a Read-Only Memory (ROM), a flash memory, a Hard Disk Drive (HDD) or a Solid-State Drive (SSD), or may be a device including any one or combination of the above memories, such as a mobile phone, a computer, a tablet and a Personal Digital Assistant (PDA).
- [00145] Those skilled in the art should understand that the embodiments of the present disclosure can provide a method, a system or a computer program product. Thus, the present disclosure can take the form of hardware embodiments, software embodiments or software-hardware combined embodiments. Moreover, the present disclosure can take the form of the computer program product implemented on one or more computer available storage media (including, but not limited to, disk memory, optical memory etc.) containing computer-usable program codes.
- [00146] The present disclosure is described with reference to flowcharts and/or block diagrams of the method, apparatus (system) and computer program product according to the embodiments of the present disclosure. It should be understood that each flow and/or block in the flowcharts and/or the block diagrams and a combination of the flows and/or the blocks in the flowcharts and/or the block diagrams can be realized by computer program instructions. These computer program instructions can be provided for a general computer, a dedicated computer, an embedded processor or processors of other

programmable data processing devices to generate a machine, so that an apparatus for realizing functions designated by one or more processes in a flowchart and/or one or more blocks in a block diagram is generated via instructions executed by the computers or the processors of the other programmable data processing devices.

[00147] These computer program instructions can also be stored in a computer readable memory capable of guiding the computers or the other programmable data processing devices to operate in a specific manner, so that the instructions stored in the computer readable memory product an article of manufacture including an instruction apparatus, and the instruction apparatus realizes the functions designated by one or more processes in a flowchart and/or one or more blocks in a block diagram.

[00148] These computer program instructions can also be loaded on computers or other programmable data processing devices so as to carry out a series of operation operations on the computers or other programmable devices to generate the process to be achieved by the computer, so that the instructions executed by the computers or other programmable devices provide steps for implementing the functions designated by one or more processes in a flowchart and/or one or more blocks in a block diagram.

[00149] The above are merely preferred embodiments of the present disclosure, and are not intended to limit the protective scope of the present disclosure.

CLAIMS

1. An image restoration method, comprising:

performing region division on an acquired image to obtain at least one sub-image; and
inputting each of the at least one sub-image to a multi-path neural network, and
restoring each sub-image by using a restoration network determined for the sub-image to
obtain and output a restored image of each sub-image, thereby obtaining a restored image of
the acquired image.

2. The method of claim 1, wherein inputting each of the at least one sub-image to the multi-path neural network, and restoring each sub-image by using the restoration network determined for the sub-image to obtain and output the restored image of each sub-image comprises:

encoding each sub-image to obtain features of the sub-image;
inputting the features of each sub-image to sub-networks of the multi-path neural network, selecting a restoration network for each sub-image by using path selection networks in the sub-networks, and processing, according to the restoration network of each sub-image, the sub-image to obtain and output processed features of the sub-image; and
decoding the processed features of each sub-image to obtain the restored image of the sub-image.

3. The method of claim 2, wherein inputting the features of each sub-image to the sub-networks of the multi-path neural network, selecting the restoration network for each sub-image by using the path selection networks in the sub-networks, and processing, according to the restoration network of each sub-image, the sub-image to obtain and output the processed features of the sub-image comprises:

when a number of the sub-networks is N and the N sub-networks are sequentially connected,

inputting an i -th level of features of each sub-image to an i -th sub-network, and
selecting an i -th restoration network for each sub-image from M restoration networks in the i -th sub-network by using an i -th path selection network in the i -th sub-network;

processing, according to the i -th restoration network, the i -th level of features of each sub-image to obtain and output an $(i+1)$ -th level of features of the sub-image;

updating the i to $i+1$, and returning to the inputting the i -th level of features of each sub-image to the i -th sub-network, and selecting the i -th restoration network for each sub-image from the M restoration networks in the i -th sub-network by using the i -th path selection network in the i -th sub-network;

until an N -th level of features of each sub-image are obtained and output, determining the N -th level of features of each sub-image as the processed features of the sub-image,

wherein when $i=1$, the i -th level of features of each sub-image are the features of the sub-image, and

wherein the N is a positive integer not less than 1, M is a positive integer not less than 2, and i is a positive integer, i is greater than or equal to 1 and i is less than or equal to N .

4. The method of claim 1, wherein when a number of obtained restored images of sub-images is greater than or equal to a preset number, the method further comprises:

acquiring restored images of the preset number of sub-images, and acquiring reference images corresponding to the restored images of the preset number of sub-images;

training, based on the restored images of the preset number of sub-images and the corresponding reference images, networks except for the path selection networks in the multi-path neutral network by an optimizer according to a preset loss function between the restored images of the preset number of sub-images and the corresponding reference images, and updating parameters of the networks except for the path selection networks in the multi-path neutral network; and

training, based on the restored images of the preset number of sub-images and the corresponding reference images, the path selection networks by the optimizer using a reinforcement learning algorithm according to a preset reward function, and updating parameters of the path selection networks.

5. The method of claim 4, wherein after acquiring the restored images of the preset number of sub-images and acquiring the reference images corresponding to the restored images of the preset number of sub-images, and before training the networks except for the path selection networks in the multi-path neutral network by the optimizer according to the loss function

between the obtained restored images of the preset number of sub-images and the corresponding reference images, and updating the parameters of the networks except for the path selection networks in the multi-path neutral network, the method further comprises:

training, based on the restored images of the preset number of sub-images and the corresponding reference images, the networks except for the path selection networks in the multi-path neutral network by the optimizer according to the loss function between the restored images of the preset number of sub-images and the corresponding reference images, and updating parameters in the multi-path neutral network.

6. The method of claim 4, wherein the reward function is formulated as follows:

$$r_i = \begin{cases} -p(1 - 1_{\{1\}}(a_i)), & 1 \leq i \leq N \\ -p(1 - 1_{\{1\}}(a_i)) + d, & i = N \end{cases}$$

where the r_i is a reward function for an i -th level of sub-networks, p is a preset penalty, $1_{\{1\}}(a_i)$ is an indicator function, and d is a coefficient of difficulty; and

when $a_i=1$, a value of the indicator function is 1, and when $a_i \neq 1$, the value of the indicator function is 0.

7. The method of claim 6, wherein the coefficient of difficulty d is formulated as follows:

$$d = \begin{cases} L_d/L_0, & 0 \leq L_d \leq L_0 \\ 1, & L_d \geq L_0 \end{cases}$$

where the L_d is the preset loss function between the restored images of the preset sub-images and the corresponding reference images, and L_0 is a threshold.

8. An image restoration apparatus, comprising:

a division module configured to perform region division on an acquired image to obtain at least one sub-image; and

a restoration module, configured to input each of the at least one sub-image to a multi-path neural network, and restore each sub-image by using a restoration network determined for the sub-image to obtain and output a restored image of each sub-image, thereby obtaining a restored image of the acquired image.

9. The apparatus of claim 8, wherein the restoration module comprises:

an encoding sub-module, configured to encode each sub-image to obtain features of the sub-image;

a restoration sub-module, configured to input the features of each sub-image to sub-networks of the multi-path neural network, select a restoration network for each sub-image by using path selection networks in the sub-networks, and process, according to the restoration network of each sub-image, the sub-image to obtain and output processed features of the sub-image; and

a decoding sub-module, configured to decode the processed features of each sub-image to obtain the restored image of the sub-image.

10. The apparatus of claim 9, wherein the restoration sub-module is further configured to:

when the number of sub-networks is N and the N sub-networks are sequentially connected,

input an i -th level of features of each sub-image to an i -th sub-network, and select an i -th restoration network for each sub-image from M restoration networks in the i -th sub-network by using an i -th path selection network in the i -th sub-network;

process, according to the i -th restoration network, the i -th level of features of each sub-image to obtain and output an $(i+1)$ -th level of features of each sub-image;

update the i to $i+1$, and return to the inputting the i -th level of features of each sub-image to the i -th sub-network, and selecting the i -th restoration network for each sub-image from the M restoration networks in the i -th sub-network by using the i -th path selection network in the i -th sub-network; and

until an N -th level of features of each sub-image are obtained and output, determine the N -th level of features of each sub-image as the processed features of the sub-image,

wherein when $i=1$, the i -th level of features of each sub-image being the features of the sub-image, and

wherein the N is a positive integer not less than 1, M is a positive integer not less than 2, and i is a positive integer, i is greater than or equal to 1 and i is less than or equal to N .

11. The apparatus of claim 8, wherein when a number of obtained restored images of sub-

images is greater than or equal to a preset number, the apparatus further comprises:

- an acquisition module, configured to acquire restored images of the preset number of sub-images, and acquire reference images corresponding to the restored images of the preset number of sub-images; and

- a first training module, configured to:

- train, based on the restored images of the preset number of sub-images and the corresponding reference images, networks except for the path selection networks in the multi-path neutral network by an optimizer according to a preset loss function between the restored images of the preset number of sub-images and the corresponding reference images, and update parameters of the networks except for the path selection networks in the multi-path neutral network; and

- train, based on the restored images of the preset number of sub-images and the corresponding reference images, the path selection networks by the optimizer by use of a reinforcement learning algorithm according to a preset reward function, and update parameters of the path selection networks.

12. The apparatus of claim 11, further comprising:

- a second training module, configured to:

- after the restored images of the preset number of sub-images are acquired and the reference images corresponding to the restored images of the preset number of sub-images are acquired, and before the networks except for the path selection networks in the multi-path neutral network are trained by the optimizer according to the loss function between the obtained restored images of the preset number of sub-images and the corresponding reference images, and the parameters of the networks except for the path selection networks in the multi-path neutral network are updated,

- train, based on the restored images of the preset number of sub-images and the corresponding reference images, the networks except for the path selection networks in the multi-path neutral network by the optimizer according to the loss function between the restored images of the preset number of sub-images and the corresponding reference images, and update the parameters except for the path selection networks in the multi-path neutral network.

13. The apparatus of claim 11, wherein the reward function is formulated as follows:

$$r_i = \begin{cases} -p(1 - l_{\{i\}}(a_i)), & 1 \leq i \leq N \\ -p(1 - l_{\{i\}}(a_i)) + d, & i = N \end{cases}$$

where the r_i is a reward function for an i -th level of sub-networks, p is a preset penalty, $l_{\{i\}}(a_i)$ is an indicator function, and d is a coefficient of difficulty; and

when $a_i=1$, a value of the indicator function is 1, and when $a_i \neq 1$, the value of the indicator function is 0.

14. The apparatus of claim 13, wherein the coefficient of difficulty d is formulated as follows:

$$d = \begin{cases} L_d/L_0, & 0 \leq L_d \leq L_0 \\ 1, & L_d \geq L_0 \end{cases}$$

where the L_d is the preset loss function between the restored images of the preset sub-images and the corresponding reference images, and L_0 is a threshold.

15. An electronic device, comprising a processor, a memory and a communication bus, wherein

the communication bus is configured to implement connection and communication between the processor and the memory; and

the processor is configured to execute an image restoration program stored in the memory to implement the image restoration method of any one of claims 1 to 7.

16. A computer readable storage medium, having stored therein one or more programs, wherein the one or more programs are capable of being executed by one or more processors to implement the image restoration method of any one of claims 1 to 7.