

METHOD AND DEVICE FOR DETECTING A BONE AGE

[0001] The present application claims the priority of a Chinese patent application with an application number of 201811163210.7 and an application title of “Method and Device for Detecting A Bone Age” filed to the National Intellectual Property Administration, PRC on September 30, 2018. The content disclosed herein is incorporated in full in the present application by reference.

Field

[0002] An embodiment of the present disclosure relates to the technical field of machine learning, in particular to a method and device for detecting a bone age.

Background

[0003] The bone age is the age of bone, which is the developmental age acquired by comparing the bone development level of young children with the bone development standard, and it reflects the physical maturity degree more accurately than age, height and weight and reflects the growth level and maturity degree of an individual more correctly.

[0004] Clinically, the biological age of a child is identified by detecting the bone age, and the development state of the child is evaluated through a difference between the biological age and the calendar age, thereby understanding the trend of the child’s sexual maturity and predicting the adult height of the child and the like. Therefore, it is widely used for treatment and monitoring of diseases affecting growth and development of children and it is of great help for diagnosis of some pediatric endocrine diseases.

[0005] In the prior art, the bone age is estimated by checking the bone age image artificially after taking a bone age image. This method depends on artificial estimation of the bone age according to the bone age image, and thus the precision is greatly influenced by human subjective factors, resulting in low efficiency.

Summary

[0006] In the prior art, due to the problem of low efficiency and great influence of human subjective factors on the precision caused by dependence on artificial estimation of the bone age according to the bone age image, the embodiment of the present application provides a method and device for detecting a bone age.

[0007] In a first aspect, the embodiment of the present application provides a method for detecting a bone age, including:

obtaining a bone age image of a user to be detected and adjusting each bone in the bone age image to a reference position;

determining a carpal region from the bone age image;

5 determining a number of ossification centers in the carpal region by using a classification model, where the classification model is determined after training a depth residual network with bone age images of the carpal region in which the number of the ossification centers is marked in advance, as training samples; and

determining the bone age of the user to be detected according to the number of the ossification centers in the carpal region.

10 **[0008]** In the embodiment of the present application, since the numbers of ossification centers in the carpal region represent different stages of the bone age, the embodiment of the present application, by using the classification model, automatically determines the number of ossification centers in the carpal region, and then, determines the bone age of the user to be detected according to the number of ossification centers in the carpal region, without subjective
15 judgment of the bone age according to the bone age image. Thus on the one hand, the precision of detecting the bone age is improved, and on the other hand, the efficiency of detecting the bone age is enhanced. As compared with a method for determining a bone age by identifying the carpal state, the method for determining a bone age of a user to be detected according to the number of ossification centers in the carpal region is more efficient.

20 **[0009]** Optionally, determining the carpal region from the bone age image includes:

determining coordinates of key points corresponding to the carpal region in the bone age image by using a segmentation model, where the segmentation model is determined after training a depth residual network with a plurality of bone age images in which coordinates of key points are marked in advance, as training samples; and

25 determining the carpal region according to the coordinates of the key points corresponding to the carpal region.

[0010] Optionally, determining the number of ossification centers in the carpal region by using the classification model includes:

30 processing the bone age image of the carpal region via N continuous convolution feature extraction blocks to acquire image features of the carpal region, with N greater than 0, where the convolution feature extraction blocks includes L convolution modules with L greater than 0, and any one of the convolution modules includes a convolution layer, a Batch Normalization (BN) layer and an excitation layer; where regarding any two continuous first convolution feature extraction block and second convolution feature extraction block among the N
35 convolution feature extraction blocks, a result, acquired by adding a second image feature

outputted by the second convolution feature extraction block and a first image feature outputted by the first convolution feature extraction block, is used as an input of a third convolution feature extraction block or an output of the N continuous convolution feature extraction blocks; where the third convolution feature extraction block is a convolution feature extraction block located behind the second convolution feature extraction block and continuous with the second convolution feature extraction block;

inputting the image features of the carpal region into a fully-connected layer and outputting a type of the carpal region; and

determining the number of ossification centers in the carpal region according to the type of the carpal region.

[0011] Since when the number of ossification centers in the carpal region is determined by using a classification model, the segmentation model is firstly adopted to segment the carpal region from the bone age image and narrow a detection scope; then the number of ossification centers is determined from the carpal region and the bone age is determined according to the number of ossification centers in the carpal region, thus improving the precision of detecting the bone age.

[0012] Optionally, adjusting each bone in the bone age image to the reference position includes:

obtaining coordinates of a preset reference point;

determining coordinates of key points in the bone age image by using an adjusting model, where the adjusting model is determined after training a depth residual network with a plurality of bone age images in which the coordinates of the key points are marked in advance, as training samples; and the coordinates of the key points and the coordinates of the preset reference point are in a same coordinate system;

determining a corresponding relationship between a current position and the reference position of each bone in the bone age image according to the coordinates of the preset reference point and the coordinates of the key points; and

adjusting each bone in the bone age image to the reference position according to the corresponding relationship.

[0013] Prior to determining the carpal region, each bone in the bone age image of the user to be detected is firstly adjusted to the reference position, thus improving the precision of determining the carpal region and further enhancing the precision of detecting the bone age.

[0014] In a second aspect, the embodiment of the present application provides a device for detecting a bone age, including:

an obtaining module configured to obtain a bone age image of a user to be detected and

adjusting each bone in the bone age image to a reference position;

a segmentation module configured to determine a carpal region from the bone age image;

a classification module configured to determine a number of the ossification centers in the carpal region by using a classification model, where the classification model is determined after training a depth residual network with bone age images of the carpal region in which the number of the ossification centers is marked in advance, as training samples; and

a detection module configured to determine the bone age of the user to be detected according to the number of the ossification centers in the carpal region.

[0015] Optionally, the segmentation module is specifically configured to:

determine coordinates of key points corresponding to the carpal region in the bone age image by using a segmentation model, where the segmentation model is determined after training a depth residual network with a plurality of bone age images in which coordinates of key points are marked in advance, as training samples; and

determine the carpal region according to the coordinates of the key points corresponding to the carpal region.

[0016] Optionally, the classification module is specifically configured to:

process the bone age image of the carpal region via N continuous convolution feature extraction blocks to acquire image features of the carpal region, with N greater than 0, where the convolution feature extraction blocks includes L convolution modules with L greater than 0, and any one of the convolution modules includes a convolution layer, a BN layer and an excitation layer; where regarding any two continuous first convolution feature extraction block and second convolution feature extraction block among the N convolution feature extraction blocks, a result, acquired by adding a second image feature outputted by the second convolution feature extraction block and a first image feature outputted by the first convolution feature extraction block, is used as an input of a third convolution feature extraction block or an output of the N continuous convolution feature extraction blocks; where the third convolution feature extraction block is a convolution feature extraction block located behind the second convolution feature extraction block and continuous with the second convolution feature extraction block;

input the image features of the carpal region into a fully-connected layer and output a type of the carpal region; and

determine the number of the ossification centers in the carpal region according to the type of the carpal region.

[0017] Optionally, the obtaining module is specifically configured to:

obtain coordinates of a preset reference point;

determine coordinates of key points in the bone age image by using an adjusting model,

where the adjusting model is determined after training a depth residual network with a plurality of bone age images in which the coordinates of the key points are marked in advance, as training samples, and the coordinates of the key points and the coordinates of the preset reference point are in a same coordinate system;

5 determine a corresponding relationship between a current position and the reference position of each bone in the bone age image according to the coordinates of the preset reference point and the coordinates of the key points; and

adjust each bone in the bone age image to the reference position according to the corresponding relationship.

10 **[0018]** In a third aspect, the embodiment of the present application provides equipment for detecting a bone age, including at least one processor and at least one memory, where the memory stores a computer program that, when executed by the processor, causes the processor to perform the steps of the method according to the first aspect.

15 **[0019]** In a fourth aspect, the embodiment of the present application provides a computer-readable medium storing a computer program that is executable by the equipment for detecting a bone age and that, when operated on the equipment for detecting the bone age, causes the equipment for detecting the bone age to perform the steps of the method according to the first aspect.

20 **Brief Description of the Drawings**

[0020] In order to describe the technical solution in the embodiment of the present disclosure more clearly, the figures required for use in description of the embodiments will be described below briefly. Obviously, the figures described below are merely some embodiments of the present disclosure. Under the precondition of not paying creative labor, those skilled in the art
25 can acquire other figures according to these figures described below.

[0021] Fig. 1 is a flow diagram illustrating a method for detecting a bone age provided in the embodiment of the present application.

[0022] Fig. 2 is a schematic diagram illustrating a bone age image provided in the embodiment of the present application.

30 **[0023]** Fig. 3 is a schematic diagram illustrating a carpal region provided in the embodiment of the present application.

[0024] Fig. 4 is a flow diagram illustrating a method for adjusting the bone age image provided in the embodiment of the present application.

35 **[0025]** Fig. 5 is a structural diagram illustrating a depth residual network provided in the embodiment of the present application.

[0026] Fig. 6 is a structural diagram illustrating a convolution feature extraction block provided in the embodiment of the present application.

[0027] Fig. 7 is a flow diagram illustrating a method for detecting the number of ossification centers provided in the embodiment of the present application.

5 **[0028]** Fig. 8 is a structural diagram illustrating a device for detecting a bone age provided in the embodiment of the present application.

[0029] Fig. 9 is a structural diagram illustrating equipment for detecting a bone age provided in the embodiment of the present application.

10 **Detailed Description of the Embodiments**

[0030] In order to describe the purpose, the technical solution and the advantageous effects of the present disclosure more clearly, figures and embodiments are incorporated below to further describe the present disclosure in details. It should be understood that the specific embodiments described herein are merely used for interpreting the present disclosure, without being used for
15 defining the present disclosure.

[0031] A bone age: the age of bone, which needs to be determined by means of a specific image of bone in X-ray photography. Generally, it is necessary to photograph an X-ray image of a wrist portion of a person's left hand, a doctor determines the bone age by observing the development degree of the ossification centers of the lower ends of the metacarpophalangeal
20 bone, carpal bone and radioulna of the left hand through the X-ray image.

[0032] The technical solution for detecting a bone age in the embodiment of the present application is suitable for a hospital to detect the bone age of a teenager, thereby providing a reference for the doctor to determine the growth situation of the teenager and simultaneously helping the doctor to diagnose chromosome abnormality, genetic diseases, endocrine diseases
25 and the like.

[0033] Fig. 1 is a flow diagram illustrating a method for detecting a bone age provided in the embodiment of the present application. The flow can be performed by the device for detecting the bone age, specifically including steps of S101 to S104.

[0034] Step S101, obtaining a bone age image of a user to be detected and adjusting each
30 bone in the bone age image to a reference position.

[0035] The bone age image refers to a specific image photographed by using X-ray. Generally, an X-ray image of a person's left hand is photographed as the bone age image, as shown in Fig. 2.

[0036] After obtaining the bone age image of the user to be detected, the bone age image is
35 preprocessed and a preprocessing process mainly includes hand bone segmentation and image

normalization.

[0037] hand bone segmentation includes the following steps: firstly, performing Gaussian filtering for the entire bone age image, binarizing a filtering result, and acquiring a binarization threshold through a maximum class spacing method of solving an image gray histogram; then
5 after expanding a binarization result, acquiring independent regional blocks through flood fill and counting the area of each regional block; reserving the regional block having the maximum area and segmenting a hand bone image; and pasting the segmented hand bone image to a pure black image matching the width and length of the hand bone image.

[0038] Image normalization includes the following steps: processing the bone age image into
10 an image in a dicom-format, selecting window width and window level firstly according to dicom information and converting it into a bone age image in a png format; and by adding black edge(s) to an upper side or two sides of the bone age image, adjusting the length-width ratio of the bone age image into 1:1, and finally scaling the bone age image to a size of 512 * 512.

[0039] Step S102, determining a carpal region from the bone age image.

[0040] The carpal region is located at a wrist portion, and consists of 8 small bones, which are
15 lined in two rows. At a near-side row, there is a scaphoid bone, a lunate bone, a triangular bone and a pisiform bone from radius to ulna, all of which participate in composition of a radiocarpal joint except the pisiform bone; and at a far-side row, there is a trapezium bone, a trapezoid bone, a capitate bone, and a unciform bone from radius to ulna, all of which participate in composition
20 of a carpometacarpal joint, as shown in Fig. 3.

[0041] Step S103, determining a number of ossification centers in the carpal region by using a classification model.

[0042] In the bone development process, a part which is firstly ossified is known as an
25 ossification center. The small bones in the carpal region do not grow simultaneously, but grow sequentially. Therefore, the ossification center of each small bone in the carpal region is detected and then the bone age can be judged according to the number of ossification centers.

[0043] The classification model is determined after training a depth residual network with bone age images of the carpal region in which the number of ossification centers is marked in advance, as training samples.

[0044] Step S104, determining the bone age of the user to be detected according to the
30 number of ossification centers in the carpal region.

[0045] Specifically, a cross reference table between the number of ossification centers in the carpal region and the bone age is disposed in advance. After the classification model outputs the number of ossification centers, the bone age of the user to be detected is determined by
35 checking the table.

[0046] Since the numbers of ossification centers in the carpal region represent different stages of the bone age, the embodiment of the present application, by using the classification model, automatically determines the number of ossification centers in the carpal region, and then, determines the bone age of the user to be detected according to the number of ossification centers in the carpal region, without subjective judgment of the bone age according to the bone age image. Thus on the one hand, the precision of detecting the bone age is improved, and on the other hand, the efficiency of detecting the bone age is enhanced. As compared with a method for determining a bone age by identifying the carpal state, the method for determining the bone age of the user to be detected according to the number of ossification centers in the carpal region is more efficient.

[0047] Optionally, in the above step S101, adjusting each bone in the bone age image to a reference position specifically includes steps of S401 to S404, as shown in Fig. 4.

[0048] Step S401, obtaining coordinates of a preset reference point.

[0049] The coordinates of the preset reference point can be the coordinates of a preset part of bone for representing a reference position of the part of bone. For example, the coordinates of the preset reference point can be preset coordinates of a point related to a middle finger for representing the reference position of the middle finger, and the coordinates of the preset reference point can also be preset coordinates of a point related to a little finger for representing the reference position of the little finger.

[0050] Step S402, determining coordinates of key points in the bone age image by using an adjusting model, where the adjusting model is determined after training a depth residual network with a plurality of bone age images in which the coordinates of the key points are marked in advance, as training samples.

[0051] The coordinates of the key points and the coordinates of the preset reference point are in a same coordinate system.

[0052] For example, a plurality of bone age images are obtained; then, the key points around the little fingers in the bone age images are marked artificially; and next, the bone age images marked with the key points are inputted into the depth residual network for training. When a target function of the depth residual network satisfies preset conditions, the adjusting model is determined; and when the bone age image of the user to be detected is obtained, the bone age image is inputted to the adjusting model to determine the key points around the little finger in the bone age image.

[0053] Step S403, determining a corresponding relationship between a current position and the reference position of each bone in the bone age image according to the coordinates of the preset reference point and the coordinates of the key points.

[0054] Step S404, adjusting each bone in the bone age image to the reference position according to the corresponding relationship.

[0055] When the preset reference point and the key points are the points related to the little finger, the corresponding relationship between a current position of the little finger in the bone age image and a reference position of the little finger in the bone age image can be determined according to the coordinates of the preset reference point and the coordinates of the key points; and further, a corresponding relationship between current positions and reference positions of the other bones in the bone age image can also be acquired, where the corresponding relationship includes a translation relationship and a rotation relationship. Then, each bone in the bone age image is adjusted to the reference position according to the corresponding relationship. Prior to determining the carpal region, each bone in the bone age image of the user to be detected is firstly adjusted to the reference position, thus improving the precision of determining the carpal region and further enhancing the precision of detecting the bone age.

[0056] Optionally, in the above step S102, the segmentation model can be adopted for determining the carpal region from an unadjusted bone age image and the segmentation model also can be adopted for determining the carpal region from an adjusted bone age image, where adjusting the bone age image refers to adjusting each bone in the bone age image to the reference position. The segmentation model is determined after training a depth residual network with a plurality of bone age images in which the coordinates of the key points are marked in advance, as training samples. Of course, other neural network models can be further adopted for training to acquire the segmentation model for determining the carpal region from the adjusted bone age image, which is not defined herein.

[0057] A training process of the segmentation model will be specifically described as follows: obtaining a plurality of bone age images as training samples, where for each of the bone age images, the bone age image is preprocessed and each bone in the bone age image is adjusted to the reference position, and the process of adjusting the position of the bone age image and preprocessing the bone age image have been described previously, which is not described herein; marking key points in each bone age image by a marking staff, with the key points as points close to the carpal region in the bone age image; and then performing data enhancement on the training samples and enhancing the amount of data to 10 times of the original amount of data, where a method for the data enhancement includes, but is not limited to:

[0058] 1. Rotating by a certain angle randomly.

[0059] 2. Translating 0-30 pixels up, down, left or right randomly.

[0060] 3. Scaling 0.85-1.15 times randomly.

[0061] 4. Jittering image contrast and brightness a little.

[0062] Afterward, the training samples are inputted to the depth residual network for training. Upon training, a loss function is calculated according to the coordinates of the marked key points and the coordinates of key points predicted by network. Through a back propagation method for training, a training optimization algorithm uses an stochastic gradient descent (sgd) algorithm with momentum and ladder attenuation.

[0063] Further, after training the segmentation model well, the segmentation model is adopted for determining the coordinates of the key points corresponding to the carpal region in the bone age image and determining the carpal region according to the coordinates of the key points corresponding to the carpal region.

[0064] Since when the number of ossification centers in the carpal region is determined by using a classification model, the segmentation model is firstly adopted to segment the carpal region from the bone age image and narrow the detection scope, and then determine the number of ossification centers from the carpal region, the bone age is determined according to the number of ossification centers in the carpal region, thus improving the precision of detecting the bone age.

[0065] Optionally, in the above step S103, a training process of the classification model is provided as follows:

obtaining bone age images of the carpal region segmented from the plurality of bone age images as training samples; regarding the bone age image of each carpal region, marking the number of ossification centers in the bone age image of each carpal region by a marking staff; and then performing data enhancement on the training samples, where a method for the data enhancement includes, but is not limited to:

[0066] 1. Rotating by a certain angle randomly.

[0067] 2. Translating 0-30 pixels up, down, left or right randomly.

[0068] 3. Scaling 0.85-1.15 times randomly.

[0069] 4. Jittering image contrast and brightness a little.

[0070] Afterward, the training samples are inputted to the depth residual network for training. Upon training, a loss function is calculated according to the number of the marked ossification centers and the number of ossification centers predicted by the network. Through back propagation training, a training optimization algorithm uses an sgd algorithm with momentum and ladder attenuation.

[0071] Optionally, the structure of the depth residual network as shown in Fig. 5 includes N continuous convolution feature extraction blocks and a fully-connected layer, and regarding any two continuous first convolution feature extraction block and second convolution feature extraction block among the N convolution feature extraction blocks, a result, acquired by

adding a second image feature outputted by the second convolution feature extraction block and a first image feature outputted by the first convolution feature extraction block, is used as an input of a third convolution feature extraction block or an output of the N continuous convolution feature extraction blocks. The third convolution feature extraction block is a convolution feature extraction block located behind the second convolution feature extraction block and continuous with the second convolution feature extraction block. The convolution feature extraction block includes L convolution modules with L greater than 0, and any one of the convolution modules includes a convolution layer, a BN layer and an excitation layer, as shown in Fig. 6 specifically.

[0072] Further, after training the classification model well, the classification model is adopted for determining the number of ossification centers in the carpal region, including steps S701 to S703, as shown in Fig. 7.

[0073] Step S701, processing the bone age image of the carpal region via N continuous convolution feature extraction blocks to acquire image features of the carpal region.

[0074] Step S702, inputting the image features of the carpal region into a fully-connected layer and outputting a type of the carpal region.

[0075] Step S703, determining the number of ossification centers in the carpal region according to the type of the carpal region.

[0076] For example, the types of the carpal region outputted by the fully-connected layer are nine types of 0 to 8, where type 0 represents that the number of ossification centers in the carpal region is 0, and type 1 represents that the number of ossification centers in the carpal region is 1, and so on. Then, the bone age of the user to be detected is determined by referring a comparison table according to the number of ossification centers in the carpal region.

[0077] Since the numbers of ossification centers in the carpal region represent different stages of the bone age, the embodiment of the present application, by using the classification model, automatically determines the number of ossification centers in the carpal region, and then, determines the bone age of the user to be detected according to the number of ossification centers in the carpal region, without subjective judgment of the bone age according to the bone age image. Thus on the one hand, the precision of detecting the bone age is improved, and on the other hand, the efficiency of detecting the bone age is enhanced. As compared with a method for determining a bone age by identifying the carpal state, the method for determining the bone age of the user to be detected according to the number of ossification centers in the carpal region is more efficient.

[0078] Based on the same technical concept, the embodiment of the present application provides a device for detecting a bone age, as shown in Fig. 8, the device 800 including:

an obtaining module 801 configured to obtain a bone age image of a user to be detected and adjusting each bone in the bone age image to a reference position;

a segmentation module 802 configured to determine a carpal region from the bone age image;

5 a classification module 803 configured to determine a number of ossification centers in the carpal region by using a classification model, where the classification model is determined after training a depth residual network with bone age images of the carpal region in which the number of ossification centers is marked in advance, as training samples; and

10 a detection module 804 configured to determine the bone age of the user to be detected according to the number of ossification centers in the carpal region.

[0079] Optionally, the segmentation module 802 is specifically configured to:

determine coordinates of key points corresponding to the carpal region in the bone age image by using a segmentation model, where the segmentation model is determined after training a depth residual network with a plurality of bone age images in which coordinates of
15 key points are marked in advance, as training samples; and

determine the carpal region according to the coordinates of the key points corresponding to the carpal region.

[0080] Optionally, the classification module 803 is specifically configured to:

process the bone age image of the carpal region via N continuous convolution feature
20 extraction blocks to acquire image features of the carpal region, with N greater than 0, where the convolution feature extraction blocks includes L convolution modules with L greater than 0, and any one of the convolution modules includes a convolution layer, a BN layer and an excitation layer; where regarding any two continuous first convolution feature extraction block and second convolution feature extraction block among the N convolution feature extraction
25 blocks, a result, acquired by adding a second image feature outputted by the second convolution feature extraction block and a first image feature outputted by the first convolution feature extraction block, is used as an input of a third convolution feature extraction block or an output of the N continuous convolution feature extraction blocks; where the third convolution feature extraction block is a convolution feature extraction block located behind the second convolution
30 feature extraction block and continuous with the second convolution feature extraction block;

input the image features of the carpal region into a fully-connected layer and output a type of the carpal region; and

determine the number of ossification centers in the carpal region according to the type of the carpal region.

35 **[0081]** Optionally, the obtaining module 801 is specifically configured to:

obtain coordinates of a preset reference point;

determine coordinates of key points in the bone age image by using an adjusting model, where the adjusting model is determined after training a depth residual network with a plurality of bone age images in which the coordinates of the key points are marked in advance, as training samples, and the coordinates of the key points and the coordinates of the preset reference point are in a same coordinate system;

determine a corresponding relationship between a current position and the reference position of each bone in the bone age image according to the coordinates of the preset reference point and the coordinates of the key points; and

adjust each bone in the bone age image to the reference position according to the corresponding relationship.

[0082] Based on the same technical concept, the embodiment of the present application provides equipment for detecting a bone age, as shown in Fig. 9, including at least one processor 901 and at least one memory 902 connected to the at least one processor. The embodiment of the present application does not define a specific connection medium between the processor 901 and the memory 902. In Fig. 9, the processor 901 and the memory 902 are connected through a bus as an example. The bus can be an address bus, a data bus or a control bus etc.

[0083] In the embodiment of the present application, the memory 902 stores instructions that are executable by the at least one processor 901. The at least one processor 901 can perform the steps included in the previous method for detecting bone age by performing the instructions stored in the storage 902.

[0084] The processor 901 as a control center of the device for detecting a bone age can utilize various interfaces and lines to connect each part of the device for detecting the bone age, thus realizing detection of the bone age by operating or performing the instructions stored in the memory 902 and calling data stored in the memory 902. Optionally, the processor 901 may include one or more processing units. The processor 901 can integrate an application processor and a modulation-demodulation processor, where the application processor mainly processes an operating system, a user interface and an application program, etc., and the modulation-demodulation processor mainly processes wireless communication. It can be understood that the above modulation-demodulation processor may also not be integrated into the processor 901. In some embodiments, the processor 901 and the memory 902 can be implemented on a same chip. In some embodiments, they can also be respectively implemented on independent chips.

[0085] The processor 901 can be a universal processor, for example, a central processing unit

(CPU), a digital signal processor, an application specific integrated circuit (ASIC), a site programmable gate array, a programmable logic device, a discrete gate or transistor logic device, or a discrete hardware component, which may realize or perform the methods, steps and logic block diagrams disclosed in the embodiment of the present application. The universal processor
5 may be a microprocessor or any conventional processor, etc. By combining with the steps of the method disclosed in the embodiment of the present application, the execution of the hardware processor, or the execution of the hardware and software module combination in the processor can be directly embodied.

[0086] The memory 902, as a non-volatile computer readable storage medium, may be used
10 for storing non-volatile software programs, non-volatile computer-executable programs and modules. The memory 902 may include at least one type of storage medium, e.g. flash memory, hard disk, multimedia card, card-type memory, random accessory memory (RAM), static random access memory (SRAM), programmable read only memory (PROM), read only memory (ROM), electrically erasable programmable read-only memory (EEPROM), magnetic
15 memory, disk, and optical disk, etc. The memory 902 may be any other medium which can be used for carrying or storing the desired program code in the form of an instruction or data structure and being accessible by a computer, but not limited thereto. The memory 902 in the embodiment of the present application may further be a circuit or any other device capable of realizing the storage function, which is used for storing program instructions and/or data.

[0087] Based on the same inventive concept, the embodiment of the present application
20 further provides a computer readable medium storing a computer program that is executable by the equipment for detecting a bone age and that, when operated on the equipment for detecting the bone age, causes the equipment for detecting the bone age to perform the steps of the method for detecting the bone age.

[0088] Those skilled in the art should understand that the embodiment of the present
25 disclosure may be provided as a method or a computer program product. Therefore, the present disclosure may adopt a complete hardware embodiment, a complete software embodiment, or an embodiment in a form of combining software and hardware aspects. Moreover, the present disclosure can adopt the form of the computer program product implemented on one or more
30 computer usable storage media (including but not limited to the disc memory, CD-ROM, and an optical memory, etc.) in which computer usable program codes are included.

[0089] The present disclosure is described by referring to the flow diagrams and/or block
35 diagrams of the method, the equipment (system) and the computer program product in the embodiment of the present disclosure. It should be understood that computer program instructions realize each process and/or block in the flow diagram and/or the block diagram and

a combination of the process and/or block in the flow diagram and/or the block diagram. The computer program instructions can be provided to a general-purpose computer, a special-purpose computer, an embedded processor or a processor of other programmable data processing equipment to generate a machine, so that the instructions executed by the processor of a computer or other programmable data processing equipment can be used to generate a device to realize specified functions in one or more flows in the flow chart and/or one or more blocks in the block diagram.

[0090] The computer program instructions can be further stored in a computer readable memory capable of guiding a computer or other programmable data processing equipment to work in a specific manner, so as to enable the instructions stored in the computer readable memory to generate a manufactured product including an instruction device. The instruction device realizes a function specified in one or more flows in the flow diagram and/or one or more blocks in the block diagram.

[0091] The computer program instructions can also be loaded to a computer or other programmable data processing equipment, so as to perform a series of operation steps on the computer or the other programmable equipment to generate computer implemented processing, such that the instructions performed on the computer or the other programmable equipment provide steps for realizing functions specified in one or more flows in the flow diagram and/or one or more blocks in the block diagram.

[0092] Although preferred embodiments of the present disclosure have been described, those skilled in the art can make additional modifications and amendments to the embodiments once getting to know the basic inventiveness concept. Therefore, the attached claims intend to be interpreted as including the preferred embodiments and all modifications and amendments falling into the scope of the present disclosure.

[0093] Obviously, those skilled in the art can make various modifications and variations to the present disclosure without departing from the spirit and scope of the present disclosure. By doing this, if these modifications and variations to the present disclosure belong to the claims of the present disclosure and equivalent techniques thereof, the present disclosure also intends to include these modifications and variations inside.

CLAIMS

1. A method for detecting a bone age, comprising:

obtaining a bone age image of a user to be detected and adjusting each bone in the bone
age image to a reference position;

determining a carpal region from the bone age image;

determining a number of ossification centers in the carpal region by using a classification
model, wherein the classification model is determined after training a depth residual network
with bone age images of the carpal region in which the number of the ossification centers is
marked in advance, as training samples; and

determining the bone age of the user to be detected according to the number of the
ossification centers in the carpal region.

2. The method according to claim 1, wherein determining the carpal region from the bone age
image comprises:

determining coordinates of key points corresponding to the carpal region in the bone age
image by using a segmentation model, wherein the segmentation model is determined after
training a depth residual network with a plurality of bone age images in which coordinates of
key points are marked in advance, as training samples; and

determining the carpal region according to the coordinates of the key points corresponding
to the carpal region.

3. The method according to claim 1, wherein determining the number of ossification centers in
the carpal region by using the classification model comprises:

processing the bone age image of the carpal region via N continuous convolution feature
extraction blocks to acquire image features of the carpal region, with N greater than 0, wherein
the convolution feature extraction block comprises L convolution modules with L greater than 0,
and any one of the convolution modules comprises a convolution layer, a Batch Normalization
(BN) layer and an excitation layer; wherein regarding any two continuous first convolution
feature extraction block and second convolution feature extraction block among the N
convolution feature extraction blocks, a result, acquired by adding a second image feature
outputted by the second convolution feature extraction block and a first image feature outputted
by the first convolution feature extraction block, is used as an input of a third convolution
feature extraction block or an output of the N continuous convolution feature extraction blocks;

wherein the third convolution feature extraction block is a convolution feature extraction block located behind the second convolution feature extraction block and continuous with the second convolution feature extraction block;

5 inputting the image features of the carpal region into a fully-connected layer and outputting a type of the carpal region; and

determining the number of ossification centers in the carpal region according to the type of the carpal region.

4. The method according to any one of claims 1 to 3, wherein adjusting each bone in the bone age image to the reference position comprises:

10 obtaining coordinates of a preset reference point;

determining coordinates of key points in the bone age image by using an adjusting model, wherein the adjusting model is determined after training a depth residual network with a plurality of bone age images in which the coordinates of the key points are marked in advance, as training samples; and the coordinates of the key points and the coordinates of the preset
15 reference point are in a same coordinate system;

determining a corresponding relationship between a current position and the reference position of each bone in the bone age image according to the coordinates of the preset reference point and the coordinates of the key points; and

20 adjusting each bone in the bone age image to the reference position according to the corresponding relationship.

5. A device for detecting a bone age, comprising:

an obtaining module configured to obtain a bone age image of a user to be detected and adjusting each bone in the bone age image to a reference position;

a segmentation module configured to determine a carpal region from the bone age image;

25 a classification module configured to determine a number of the ossification centers in the carpal region by using a classification model, wherein the classification model is determined after training a depth residual network with bone age images of the carpal region in which the number of the ossification centers is marked in advance, as training samples; and

30 a detection module configured to determine the bone age of the user to be detected according to the number of the ossification centers in the carpal region.

6. The device according to claim 5, wherein the segmentation module is specifically configured

to:

determine coordinates of key points corresponding to the carpal region in the bone age image by using a segmentation model, wherein the segmentation model is determined after training a depth residual network with a plurality of bone age images in which coordinates of key points are marked in advance, as training samples; and

determine the carpal region according to the coordinates of the key points corresponding to the carpal region.

7. The device according to claim 5, wherein the classification module is specifically configured to:

process the bone age image of the carpal region via N continuous convolution feature extraction blocks to acquire image features of the carpal region, with N greater than 0, wherein the convolution feature extraction blocks comprises L convolution modules with L greater than 0, and any one of the convolution modules comprises a convolution layer, a Batch Normalization (BN) layer and an excitation layer; wherein regarding any two continuous first convolution feature extraction block and second convolution feature extraction block among the N convolution feature extraction blocks, a result, acquired by adding a second image feature outputted by the second convolution feature extraction block and a first image feature outputted by the first convolution feature extraction block, is used as an input of a third convolution feature extraction block or an output of the N continuous convolution feature extraction blocks; wherein the third convolution feature extraction block is a convolution feature extraction block located behind the second convolution feature extraction block and continuous with the second convolution feature extraction block;

input the image features of the carpal region into a fully-connected layer and output a type of the carpal region; and

determine the number of the ossification centers in the carpal region according to the type of the carpal region.

8. The device according to any one of claims 5 to 7, wherein the obtaining module is specifically configured to:

obtain coordinates of a preset reference point;

determine coordinates of key points in the bone age image by using an adjusting model, wherein the adjusting model is determined after training a depth residual network with a plurality of bone age images in which the coordinates of the key points are marked in advance,

as training samples, and the coordinates of the key points and the coordinates of the preset reference point are in a same coordinate system;

determine a corresponding relationship between a current position and the reference position of each bone in the bone age image according to the coordinates of the preset reference point and the coordinates of the key points; and

adjust each bone in the bone age image to the reference position according to the corresponding relationship.

9. Equipment for detecting a bone age, comprising at least one processor and at least one memory, wherein the memory stores a computer program that, when executed by the processor, causes the processor to perform the steps of the method according to any one of claims 1 to 4.

10. A computer-readable medium, storing a computer program that is executable by the equipment for detecting a bone age and that, when operated on the equipment for detecting the bone age, causes the equipment for detecting the bone age to perform the steps of the method according to any one of claims 1 to 4.