A method for defect inspection on arc surfaces and its device

FIELD OF INVENTION

The present invention relates to the field of image processing and deep learning. More particularly, it relates to an automatic method for defect detection on arc surfaces and the device.

BACKGROUND

At present, the automatic detection of small arc surface defects is mainly based on the following algorithms:

1. Feature extraction and image processing. The image features are usually designed by experts according to the characteristics of the defects and then are used to match those in the online images.

2. Back-propagation neural networks. The image features extracted artificially are used to feed into the neural networks and separate the images into ones with defects and others without, and to classify the defect types.

3. Support vector machines or other classifiers are used to classify the features extracted manually.

The above methods have the following disadvantages:

1. The artificial features may result in the loss of some useful information and decrease the recognition accuracy, due to the inaccuracy of subjective judgment.

2. Feature extraction methods rely too much on parameter setting which restricts them to large scale applications. The parameters often have to be reset to follow changing defect types.

3. The classifiers like normal neural networks can only classify the whole image but can’t accurately locate the defect position, which makes it difficult to support on-line usage.

It is of great practical value to find an automatic surface defect detection method with high adaptability, real-time performance and high recognition accuracy.

SUMMARY OF THE INVENTION

The main purpose of the present invention is to overcome the shortcomings and the insufficiencies of existing technologies, and to provide an automatic arc surface defect detection method. This method has the advantages of high adaptability, high

real-time performance and high recognition accuracy.

Another purpose of the invention is to provide a device for realizing the above defect detection method for arc surfaces automatically. This device is easy to operate, simple and stable in its structure.

The purpose of the invention is realized by the following technical scheme: an automatic arc surface defect detection method comprises of the following steps:

(1) Training stage: collect sample images to build the training set, and manually mark all defect regions on these sample images;

The defect pre-targeting process for each image in the training set comprising:

(1-1) Each pixel in the image is regarded as a single region. Calculate the Euclidean distance in RGB space between each pixel and its 8 adjacent pixels in three color channels. Take this Euclidean distance as the weight, each weight represents the dissimilarity of the two adjacent region at this edge. Merge each edge to get the initial segmented region set R: if the inter-class difference between two adjacent regions is smaller than the intra-class difference of each region, merge them into a new region; otherwise, leave it.

(1-2) Initialize the set S of region similarity into an empty set.

(1-3) Calculate the similarity of every two adjacent regions in the segmented region set R and add the result to the set S.

(1-4) Find the largest value of similarity in the set S, and merge the corresponding two adjacent regions and put it into the set R. Delete the similarity values of these two regions in the set S. And recalculate the similarities in the set R. Repeat the above operations until the set S is empty, and the obtained set R is all the possible regions of defects.

Compare the regions obtained from each image in the training set in set R with the manually marked defect regions, and divide them into negative and positive samples according to their coincidence degree.

Use both positive and negative samples as inputs to train the deep neural networks offline. The stochastic gradient descent method is adopted in the training process, and the outputs are the defect categories and the coordinates of the defect region.

A trained deep neural network model is obtained.

(2)Online testing stage: collect the arc surface image for detection, and find the pre-targeting defect regions to get set R. Input set R into the trained deep neural network model and obtain the defect categories and coordinates of the defect regions.

Preferably, when building the training set from sample images, use the following methods at least once to increase the number of samples: rotation with a random angle, translation, scaling, flipping, stretching, or clipping. Thus, the image samples can be expanded by 6 times to prevent over fitting in training.

Further, the said rotation is randomly selected from 0 to 360 degrees, the said translation is randomly offset - 8 to 8 pixels, the said scaling factor is randomly selected between 1/1.5 to 1.5, the said flipping includes two directions at horizontal and at vertical, the said stretching is stretching the short edge, and the stretching factor is randomly selected between 1/1.2 to 1.2, the said clipping is manually selecting the target region. Using the above parameters to increase the number of samples, the obtained training model will be more accurate.

Preferably, before defect pre-targeting, calculate the average of grey value of each channel of all the images in the training set, and then in each image the average grey value is subtracted from the grey values of each pixel of three channels to get a new sample image. The convergence speed can be improved by the above treatment.

Further, before defect pre-targeting, the sequence of new sample images is randomly disrupted in the training set to make the network training more accurate.

Specifically, the said inter-class difference is defined as the minimum weight of all edges connecting two regions, the said intra-class difference is defined as the maximum weight of all edges in the region plus a restriction coefficient $\frac{k}{s}$, where s is the number of pixels in the region, k is the segmentation threshold.

Preferably, in step (1-2), the said similarity values in set S should comprise of three similarities: color similarity, texture similarity and size similarity, wherein:

Color similarity $S_{color}(C_a, C_b) = \sum_{i=1}^{3M} \min(C_a^i, C_b^i)$. Divide the range of the color grayscale into M sub-intervals, called M bins. In region a and region b, calculate the M bins histograms of each color channel, then 3M dimension vectors C_a and C_b are obtained from region a and region b respectively.

The texture similarity $S_{texture}(T_a,T_b)=\sum_{i=1}^{N}\min(T_a^i,T_b^i)$. Transform the image into a grayscale image, and in region *a* and region *b*, calculate the N bins gradient histograms, then N dimension vectors T_a and T_b are obtained from region *a* and region *b* respectively.

Size similarity $S_{size}=1-\frac{s(a)-s(b)}{s(im)}$, where $s(a)$ is the number of pixels in region *a*, $s(b)$ is the number of pixels in region *b*, $s(im)$ is the number of pixels in the whole image.

Preferably, the procedure of dividing the negative sample and the positive sample according to their degree of coincidence is:

Calculate the coincidence degree $O=\frac{S_o}{S_p+S_t-S_o}$, where S_p is the area of the pre-targeting region, S_t is the area of the real target box, S_o is the overlap area of S_p and S_t. The regions with a coincidence degree between 0 and 50% are negative samples, the regions with a coincidence degree above 70% are positive samples, and the rest of the regions are ignored.

Preferably, after obtaining the categories and coordinates of the defect regions in step (2), the non-maximum suppression algorithm is used to eliminate the redundant object boxes and to determine the optimal location of the defect region.

The device for realizing the above automatic arc surface defect detection method comprises cameras, a sliding table, a base plate, a motor, a motor controller, a light source, a light source controller and a host computer. Each camera is fixed on a three degrees of freedom camera holder. The three degrees of freedom camera holders, sliding table, light source and the light source controller are fixed on the base plate. The motor is fixed and connected to the sliding table through the coupling, and the camera is connected with the host computer through the RJ45 network interface. During defect inspection, the work piece is placed horizontally on the sliding table, and the host computer sends motion instructions to the motor controller. The motor controller controls the motion of the work piece on the sliding table in the area of the camera's shooting field. The light source, with the light source controller, provides illumination for the cameras. In this way a clear arc surface image of the work piece is obtained for defect inspection.

Preferably, the device comprises two industrial cameras. The first industrial

camera is fixed 20 cm~30 cm above the horizontal plane of the work piece, and the angle between the first industrial camera and the horizontal surface is -30° ~ -45° . The second industrial camera is fixed 20 cm~30 cm below the horizontal plane of the work piece, and the angle between the second industrial camera and the horizontal plane is 30° ~ 45° . The use of the first and second industrial cameras with different angles is to ensure that the field of view completely covers all the inspection arc surfaces.

Compared to prior arts, the present invention has the following advantages and beneficial effects:

1. The images of the arc surface defects collected by the proposed invention device are clear and high quality.
2. The method used in the present invention increases the number of images by performing multiple transformations on the image samples in the sample preparation process and prevents the over-fitting of the training.
3. First, the defect region is pre-targeted based on graph theory, then all the pre-targeted defect regions are identified using an off-line training network model. Compared with classification of the whole image, it improves the recognition accuracy, and the network model can locate the defect position in the area more accurately.
4. The defect detection process of the present invention is automatically carried out without manual parameter setting, and is suitable for different image acquisition environments and different types of defects.

BRIEF DESCRIPTION OF THE DRAWINGS

Fig. 1 is a schematic diagram of the hardware structure for this embodiment of the device.

Fig. 2 is a frame diagram for this embodiment of the device.

Fig. 3 is a flow schematic diagram for this embodiment of the method.

Fig. 4 is a flow chart for the sample preparation for the training phase in this embodiment of the method.

Fig. 5 is a flow chart of the defect pre-targeting algorithm in this embodiment.

Fig. 6 is a flow chart of the network training algorithm in this embodiment of the method.

Fig. 7 is a flow chart of the on-line detection process in this embodiment of the method.

DETAILED DESCRIPTION

The present method will be described further in greater detail by referring to the following embodiment and drawings. However, the said method can be employed in terms of other embodiments.

Embodiment 1

As shown in Fig. 1, the present embodiment of an automatic device for defect detection on arc surfaces comprises two industrial cameras with micro focus lenses, two three degrees of freedom camera holders and two light sources, a sliding table, a base plate and a motor. Wherein the three degrees of freedom camera holder 3 and the slide table 6 are fixed on the base plate 9, and the motor 7 is fixed and connected to the slide table 6 through the coupling. The work piece 5 is placed horizontally on the sliding table 6. When the work piece 5 is in position, AB, its image is captured by the industrial camera 1 fixed in camera holder 3. When the work piece 5 moves to position BC, its image is captured by the industrial camera 2. The plane light source 4, with the light source controller 10, provides light for the camera. The industrial cameras 1 and 2 are connected to the PC (host computer) through the RJ45 network interface, and the motor 7 is connected with the PC. The objective part of work piece 5 is an arc surface with a small curvature. In order to cover the arc surface that is close to being semicircular, the industrial camera 1 is fixed 20 cm above the horizontal plane of work piece 5, and the angle between the first industrial camera and the horizontal surface is -30° . The industrial camera 2 is fixed 20 cm below the horizontal plane of work piece 5, and the angle between the second industrial camera and the horizontal plane is 30° . The industrial cameras take pictures of the work piece in both positions AB and BC to ensure that the field of view completely covers

the arc surface to be inspected.

When the length of the section AB is longer than the radius r of the clear focusing area of the lens, n shots are taken in section AB, and n=AB/r. In addition, the static exposure time for the work piece is 100ms.

The inspection process is as follows: the PC sends motion instructions to the motor controller, which controls the motion of the work piece on the sliding table in section AB and BC. When the work piece in section AB is detected as stationary, camera 1 starts to take pictures and transmits them to the computer through the RJ45 interface. When the workpiece is detected as stationary in section BC, camera 2 starts to take pictures and transmits them to the computer through the R.J.45 interface.

Fig. 2 illustrates that the device in the present embodiment composes of, according to their function, lighting and imaging component 1, mechanical transmission component 2 and PC 3. The lighting and imaging component 1 comprises a plane light source, a light source controller, industrial cameras and three degrees of freedom camera holders. Every camera is fixed on a three degrees of freedom camera holder. The three degrees of freedom camera holder, sliding table, light source and light source controller are fixed onto the base plate. The light source controller is connected to the plane light source by a connecting wire to control the intensity of the light source. The mechanical transmission component 2 comprises: a motor, a motor controller, a sliding table and a motion control card. The motor is fixed and connected to the sliding table through a coupling. The motor controller is connected to the motor by a connecting wire. The motion control card is connected with the motor controller by a wire, and again connected with the PC through a PCI interface.

PC 3 is installed with the automatic inspection system for defects, which comprises of two offline modules: sample preparation and network training, and four on-line modules: motion control module, image acquisition module, defect pre-targeting module and defect inspection module. The industrial camera in the component 1 for lighting and imaging is connected to the PC through the RJ45 network interface to take online pictures. The PC commands and manages the motion control card in the mechanical transmission component 2 through the motion control module to control the motor starting and stopping, speed adjustment, direction transformation and the motion of the work piece on the sliding table.

Fig. 3 is the main flow chart of the method described in this embodiment, comprising two main steps: off-line deep neural network model for training and on-line automatic defect inspection. At the training stage, samples are prepared and initially the defect pre-targeting algorithm is implemented. Then, the image samples with multiple pre-targeting boxes are input to the deep neural network for off-line training. Finally, the trained network model is used for on-line inspection. At the on-line inspection stage, the images of small arc surfaces of the work piece are captured on-line, the same defect pre-targeting algorithm as in the off-line training is executed. Then, a single image with multiple pre-targeting boxes is input to the deep neural network. Each pre-targeted region in the image is identified and classified in turn to obtain the coordinates and defect classes of the final defect regions, followed by displaying and outputting the inspection results.

Fig. 4 is a flow chart of the algorithm for sample preparation described in this embodiment, comprising the following steps:

S1. Capture 20,000 images; but in practical applications the technicians in the field can decide the number of images themselves.

S2.The following methods are used to enlarge the sample set and manually increase the number of training samples: rotation (randomly rotate from 0 to 360 degrees), translation (randomly offset - 8 to 8 pixels), scaling (scaling factor is randomly selected between 1/1.5 to 1.5), flipping (includes two directions at horizontal and at vertical), stretching (stretching factor is randomly selected between 1/1.2 to 1.2 for short edge stretching), and clipping (manually selecting the target region). Thus, the image samples can be increased by 6 times to effectively prevent over fitting of the training.

S3. Label the images in the above sample set. Locate and label manually all the defects on each image, and save the categories and coordinates of all defects of one image to a text file and give them the same name in each image.

S4. In order to improve the convergence speed, calculate the average grey value of each channel for all the images in the training set, and then in each image the average grey value is subtracted from the grey values of each pixel of three channels.

S5. The sequence of all images in the sample set is randomly disrupted without repetition.

Fig. 5 is a flow chart of the defect pre-targeting algorithm described in this embodiment, comprising the following steps:

S1. Each pixel in the image is regarded as a single region. Calculate the Euclidean distance between each pixel and its 8 adjacent pixels for the three channels of RGB space. Take this Euclidean distance as the weight which represents the dissimilarity of the two adjacent regions at this edge. Merge each edge to get the initial segmented region set R: if the inter-class difference between two adjacent regions is bigger than the intra-class difference of each region, merge them into a new region; otherwise, leave it. The said inter-class difference is defined as the minimum weight of all edges connecting two regions, the said intra-class difference is defined as the maximum weight of all edges in the region plus a restriction coefficient $\frac{k}{s}$, where s is the number of pixels in the region, k is the segmentation threshold and set to 500.

S2. Initialize the set S of similarity values among regions to an empty set. The said similarity values in set S comprise of: color similarity, texture similarity and size similarity, wherein: Color similarity $S_{color}(C_a, C_b) = \sum_{i=1}^{3M} \min(C_a^i, C_b^i)$. For region a and region b, the 25 bin histograms of each color channel are calculated, then 75 dimension vectors C_a and C_b are obtained from region a and region b respectively. Texture similarity $S_{texture}(T_a, T_b) = \sum_{i=1}^{N} \min(T_a^i, T_b^i)$. Transform the image into a grayscale image, and for region a and region b, the 8 bin gradient histograms are calculated, then 8 dimension vectors T_a and T_b are obtained from region a and region b respectively. Size similarity $S_{size} = 1 - \frac{s(a) - s(b)}{s(im)}$, where $s(a)$ is the number of pixels in region a, $s(b)$ is the number of pixels in region b, $s(im)$ is the number of pixels in the whole image.

S3. Calculate the similarity of every two adjacent regions in the region set R and add them to set S.

S4. Find the largest value s_{max} of similarity in the set S, and merge the two corresponding adjacent regions and put it into the set R. Delete all similarity values related to these two regions in set S. And recalculate the new region similarities in set R. Repeat the above operations until the set S is empty, and the obtained set R

includes all the possible defect regions.

Fig. 6 is a flow chart of the offline network training algorithm of this embodiment, comprising the following steps:

S1. Use the defect pre-targeting algorithm on the prepared sample set to obtain multiple defect pre-targeting regions in each image sample.

S2. Calculate the coincidence degree O of these pre-targeted regions and the true defect target boxes marked manually. $O=\frac{S_o}{S_p+S_t-S_o}$, where S_p is the area of the pre-targeted region, S_t is the area of the true target box, S_o is the overlap area of S_p and S_t. The regions with a degree of coincidence between 0 and 50% are negative samples, the regions with a degree of coincidence above 70% are positive samples, and the remaining regions are ignored.

S3. The maximum number of iterations is 40000, the learning rate is 0.001, and the number of images per batch is 128. Taking both positive samples and negative samples as inputs, the deep neural network model is trained offline, and the output is the categories and coordinates of the defect region.

S4. The training process adopts a stochastic gradient descent method to reduce the gap between the network output and the expected one.

Fig. 7 is a flow chart of the online inspection system of the embodiment, comprising the following steps:

S1. Initialize the camera and mechanical transmission component, calibrate the light intensity, and focus the camera.

S2. Control the motor to stop at a fixed position, and capture images.

S3. Execute the same defect pre-targeting algorithm as with the off-line training to obtain multiple defect pre-targeting regions in each online image.

S4. Use the deep neural network model to classify and identify the pre-targeting regions, and the outputs are the categories and coordinates of the defect regions.

S5. Adopt the non-maximum suppression algorithm to eliminate the redundant object boxes and determine the optimal location of the defect regions.

While certain features of the invention have been illustrated and described herein, many modifications, substitutions, changes, and equivalents will now occur to those of ordinary skill in the art. It is, therefore, to be understood that the appended claims are intended to cover all such modifications and changes as fall within the true

spirit of the invention.

What is claimed is:

1. An automatic method of defect inspection for an arc surface is characterized in following steps:

(1) Training stage: collect sample images to build training set, and manually mark all defect regions on these sample images.

The defect pre-targeting process for each image in the training set comprising:

(1-1) Calculate the Euclidean distance between each pixel and its 8 adjacent pixels in three channels in RGB space. Take this Euclidean distance as the weight which represents the dissimilarity of the two adjacent region at this edge. Merge each edge to get the initial segmented region set R: if the inter-class difference between two adjacent regions is bigger than the intra-class difference of each region, merge them into a new region; otherwise, leave it.

(1-2) Initialize the region similarity set S into an empty set.

(1-3) Calculate the similarity of every two adjacent regions in the segmented region set R and add the result to the set S.

(1-4) Find the largest value of similarity in the set S, and merge the two corresponding adjacent regions and put it into the set R. Delete all similarity values related to these two regions in set S. And recalculate the new region similarities in set R. Repeat the above operations until the set S is empty, and the obtained set R contains all the possible regions of defects.

Compare the regions in set R obtained from each image in the training set with the manually marked defect regions, and divide them into negative and positive samples according to their degree of coincidence.

The regions in set R, which is obtained from each image in the training set, are compared with the manually marked defect regions and divided into negative samples and positive samples according to the degree of coincidence.

Use both positive and negative samples as inputs to train the deep neural networks offline. The stochastic gradient descent method is used in the training process, and the outputs are the defect categories and coordinates of the defect regions.

The trained deep neural network model is thus obtained.

(2) Online testing stage: collect the arc surface image for detection, and find the pre-targeting defect regions to get set R. Input set R into the trained deep neural network model and obtain the defect categories and coordinates of the defect regions.

2. The method of claim 1 is characterized in that, when building the training set from sample images, use the following methods at least once to increase the number of samples: rotation with a random angle, translation, scaling, flipping, stretching, or clipping.

3. The method of claim 2 is characterized in that the said rotation is randomly selected from 0 to 360 degrees, the said translation is randomly offset - 8 to 8 pixels, the said scaling factor is randomly selected between 1/1.5 to 1.5, the said flipping includes two directions at horizontal and at vertical, the said stretching is stretching the short edge, and the stretching factor is randomly selected between 1/1.2 to 1.2, the said clipping is manually selecting the target region.

4. The method of claim 1: the said automatic method of defect inspection for arc surfaces, is characterized in that, before defect pre-targeting, calculate the average of the grey value of each channel of all the images in the training set, and then in each image the grey value is subtracted from the grey values of each pixel of three channels to get a new sample image.

Before defect pre-targeting, the sequence of new sample images is randomly disordered in the training set.

5. The method of claim 1: the said automatic method of defect inspection for arc surfaces, is characterized in that, the said inter-class difference is defined as the minimum weight of all edges connecting two regions, the said intra-class difference is defined as the maximum weight of all edges in the region plus a restriction coefficient $\frac{k}{s}$, where s is the number of pixels in the region, k is the segmentation threshold.

6. The method of claim 1: the said automatic method of defect inspection for arc surfaces, wherein said steps (1-2) are characterized in that the said similarity values in set S comprise of three similarities: color similarity, texture similarity and size similarity, wherein:

Color similarity $S_{color}(C_a, C_b) = \sum_{i=1}^{3M} \min(C_a^i, C_b^i)$. Divide the range of color grayscale

into M sub-intervals, called M bins. In region *a* and region *b*, calculate the M bin histograms of each color channel, then 3M dimension vectors C_a and C_b are obtained from region *a* and region *b* respectively.

Texture similarity $S_{texture}(T_a,T_b)=\sum_{i=1}^{N}\min(T_a^i,T_b^i)$. Transform the image into a grayscale image, and in region *a* and region *b*, calculate the N bin gradient histograms, then N dimension vectors T_a and T_b are obtained from region *a* and region *b* respectively.

Size similarity $S_{size}=1-\frac{s(a)-s(b)}{s(im)}$, where $s(a)$ is the number of pixels in region *a*, $s(b)$ is the number of pixels in region *b*, $s(im)$ is the number of pixels in the whole image.

7. The method of claim 1: the said automatic method of defect inspection for arc surfaces, wherein said the procedure of dividing negative and positive samples according to the degree of coincidence is characterized in these sub steps:

Calculate coincidence degree $O=\frac{S_o}{S_p+S_t-S_o}$, where S_p is the area of the pre-targeting region, S_t is the area of the real target box, S_o is the overlap area of S_p and S_t. The regions with a degree of coincidence between 0 and 50% are negative samples, the regions with a degree of coincidence above 70% are positive samples, and the remaining regions are ignored.

8. The method of claim 1: the said automatic method of defect inspection for arc surfaces, wherein the said step (2) is characterized in that, after obtaining the categories and coordinates of the defect regions, the non-maximum suppression algorithm is used to eliminate the redundant object boxes and determine the optimal location of the defect region.

9. A device for realizing the method of claims 1-8, the said automatic method of defect inspection for arc surfaces, is characterized in comprising: cameras, a sliding table, a base plate, a motor, a motor controller, a light source, a light source controller and a host computer. Each camera is fixed on a three degrees of freedom camera holder. The three degrees of freedom camera holders, sliding table, light source and the light source controller are fixed on the base plate. The motor is fixed and connected to the sliding table through the coupling, and the camera is connected to

the host computer through the RJ45 network interface. During defect inspection, the work piece is placed horizontally on the sliding table, and the host computer sends motion instructions to the motor controller. The motor controller controls the motion of the work piece on the sliding table in the area of the camera's field of view. The light source, with the light source controller, provides illumination for the cameras. So in this way a clear image of the work piece arc surface for defect inspection can be obtained.

10. The device of claim 9 is characterized as comprising two industrial cameras. The first industrial camera is fixed 20 cm~30 cm above the horizontal plane of the work piece, and the angle between the first industrial camera and the horizontal surface is -30° ~ -45° . The second industrial camera is fixed 20 cm~30 cm below the horizontal plane of the work piece, and the angle between the second industrial camera and the horizontal plane is 30° ~ 45° .