

DEFECT SAMPLE SYNTHESIS METHOD, TRAINING METHOD OF DEFECT INSPECTION NETWORK, COMPUTER-READABLE MEDIUM, COMPUTING SYSTEM, AND IMAGE INSPECTION APPARATUS

CROSS-REFERENCE TO RELATED APPLICATION

[0001] This application claims priority to Singapore Patent Application No. 10202013262U, filed on December 31, 2020, the entire contents of which are incorporated herein by reference for all purposes.

FIELD OF THE INVENTION

[0002] The present invention relates to a defect sample synthesis method, and more particularly to a defect sample synthesis method, a training method of a defect inspection network, a computer-readable medium, a computing system, and an image inspection apparatus.

BACKGROUND OF THE INVENTION

[0003] Deep Convolutional Neural Networks (DCNNs) have extensive applications in computer vision tasks like image recognition and object detection. DCNNs based models have achieved state-of-the-art performances. However, training of such models requires abundant amounts of annotated data, which restricts extensive applications of such deep learning based models in industrial automatic defect inspection, as defect samples are very scarce and difficult to collect in general. On the other hand, normal samples are usually abundant and much easier to collect.

[0004] In cases where defect samples are very scarce, data augmentation is a widely adopted strategy to train deep learning based models. Simple affine transformations and blending operations can generate some extra samples for training. However, it is still challenging to create samples that are beneficial to model training due to easy and limited transformation operations. Generative Adversarial Networks (GANs) are able to perform image synthesis in an unsupervised way. One way to achieve data augmentation is to sample from latent space and generate images of defects directly. Nevertheless, this image synthesis method has limited capacity in generating defect images with complex textures and irregular patterns. Another way is to deem defects as a style and add such style to normal images. Existing methods for style transfer like CycleGAN and StarGAN can synthesize somewhat realistic defect images in this way, but they all fail to preserve its original background. Therefore, existing methods are generating both defects and their backgrounds together, lacking the ability to simulate cannot simulate the interactions between defects and normal backgrounds, i.e., cannot simulate defects on different kinds of backgrounds. Such synthesis cannot provide unseen information to the defect inspection models, therefore is not an effective way to augment data for improving CNNs-based models for defect inspection.

[0005] Therefore, there is a need of providing a defect sample synthesis method distinct from prior art in order to solve the above drawbacks.

SUMMARY OF THE INVENTION

[0006] Some embodiments of the present invention are to provide a defect sample synthesis method, a training method of a defect inspection network, a computer-readable medium, a computing system, and an image

inspection apparatus in order to overcome at least one of the above-mentioned drawbacks encountered by prior art.

[0007] The present invention provides a defect sample synthesis method, a training method of a defect inspection network, a computer-readable medium, a computing system, and an image inspection apparatus. By inputting a normal sample to a synthesizer and allowing the synthesizer to generate a synthesized defect sample, synthesized defect samples which are realistic and diverse can be generated for training accurate and robust defect inspection networks.

[0008] The present invention also provides a defect sample synthesis method, a training method of a defect inspection network, a computer-readable medium, a computing system, and an image inspection apparatus. Through the encoder-decoder module with the addition of noise, defacement and restoration processes with randomness are mimicked. Meanwhile, by controlling locations and categories of defects with the control map, a flexible control of defect generation is implemented.

[0009] In accordance with an aspect of the present invention, there is provided a defect sample synthesis method. The defect sample synthesis method includes steps of providing a normal sample and a synthesizer, inputting the normal sample to the synthesizer, and allowing the synthesizer to generate a synthesized defect sample.

[0010] In accordance with another aspect of the present invention, there is provided a training method of a defect inspection network. The training method includes steps of providing a network backbone and a defect inspection model, inputting a real dataset and a synthesized dataset to the network backbone, and training the defect inspection model with the real dataset and the synthesized dataset.

[0011] In accordance with another aspect of the present invention, there is provided a computer-readable medium. The computer-readable medium has a computer program configured to perform at least one of a defect sample synthesis method and a training method.

[0012] In accordance with another aspect of the present invention, there is provided a computing system. The computing system is configured to perform at least one of a defect sample synthesis method and a training method.

[0013] In accordance with another aspect of the present invention, there is provided an image inspection apparatus for performing automatic defect inspection. The image inspection apparatus includes a computer-readable medium having a computer program configured to perform at least one of a defect sample synthesis method and a training method.

[0014] The above contents of the present invention will become more readily apparent to those ordinarily skilled in the art after reviewing the following detailed description and accompanying drawings, in which:

BRIEF DESCRIPTION OF THE DRAWINGS

[0015] FIG. 1 schematically illustrates a flow chart of a defect sample synthesis method according to an embodiment of the present invention;

[0016] FIG. 2 schematically illustrates a configuration of the defect sample synthesis method of FIG. 1;

[0017] FIG. 3 schematically illustrates a partial flow chart of a defect sample synthesis method according to another embodiment of the present invention;

[0018] FIG. 4 schematically illustrates a configuration of the defect sample synthesis method of FIG. 3;

[0019] FIG. 5 schematically illustrates a partial flow chart of a defect sample synthesis method according to another embodiment of the present invention;

[0020] FIG. 6 schematically illustrates a configuration of the defect sample synthesis method of FIG. 5;

[0021] FIG. 7 schematically illustrates a flow chart of a defect sample synthesis method according to another embodiment of the present invention;

[0022] FIG. 8 schematically illustrates defacement and restoration processes performed by a defect sample synthesis method and synthesized defect samples added into a defect inspection network;

[0023] FIG. 9 schematically illustrates a flow chart of a training method of a defect inspection network according to an embodiment of the present invention;

[0024] FIG. 10 schematically illustrates a configuration of a training method of a defect inspection network according to an embodiment of the present invention; and

[0025] FIG. 11 schematically illustrates a flow chart of a training method of a defect inspection network according to another embodiment of the present invention.

DETAILED DESCRIPTION OF THE PREFERRED EMBODIMENT

[0026] The present invention will now be described more specifically with reference to the following embodiments. It is to be noted that the following descriptions of preferred embodiments of this invention are presented herein for purpose of illustration and description only. It is not intended to be exhaustive or to be limited to the precise form disclosed.

[0027] Please refer to FIGs. 1 and 2. FIG. 1 schematically illustrates a flow chart of a defect sample synthesis method according to an embodiment of the present invention. FIG. 2 schematically illustrates a configuration of the defect sample synthesis method of FIG. 1. According to an embodiment of the present invention, a defect sample synthesis method includes steps S100, S200, S300, 400 and S500. In S100, a normal sample 1 and a synthesizer 2 are provided. In S200, the normal sample 1 is inputted to the synthesizer 2. In step S300, the synthesizer 2 is allowed to generate a synthesized defect sample 3. In brief, by inputting a normal sample 1 to a synthesizer 2 and allowing the synthesizer 2 to generate a synthesized defect sample 3, synthesized defect samples which are realistic and diverse can be generated for training accurate and robust defect inspection networks. In step S400, the synthesized defect sample 3 is inputted to the synthesizer 2. In step S500, the synthesizer 2 is allowed to generate a restored normal sample 5.

[0028] Based on the defect sample synthesis method of the embodiment of the present invention, defect-generative adversarial networks (Defect-GANs) generating defect samples by mimicking the defacement and restoration processes can be implemented. Defacement refers to adding defects over normal samples while restoration refers to removing defects from defect samples.

[0029] In an embodiment, the synthesizer 2 of the present invention employs an encoder-decoder architecture to generate defects over normal samples and remove defects from defect samples. Please refer to FIGs. 1, 3 and 4. FIG. 3 schematically illustrates a partial flow chart of a defect sample synthesis method according to another embodiment of the present invention. FIG. 4 schematically illustrates a configuration of the defect sample synthesis method of FIG. 3. The elements of FIGs. 3 and 4 that

are similar with those of FIGs. 1 and 2 are represented by the same reference numerals, and the detailed description thereof is omitted herein. As shown in FIGs. 1, 3 and 4, the synthesizer 2 includes an encoder-decoder module 21, and the normal sample 1 is inputted to the encoder-decoder module 21 in the step S200. The step S300 of a defect sample synthesis method of FIG. 1 further includes steps S310, S330 and S350. In step S310, a noise 25 is inserted to the encoder-decoder module 21 for increasing randomness. In step S330, the encoder-decoder 21 is allowed to generate a defect spatial distribution 22 and a defect foreground 23. In S350, a layer composition 24 is performed according to the normal sample 1, the defect spatial distribution 22, and the defect foreground 23 to generate the synthesized defect sample 3. It should be noted that the layer composition 24 generates defects over the normal sample 1 while preserving the appearance of the normal sample, which allows the flexible generation of defects over specified regions while keeping contexts of the normal sample 1 natural. In addition, through the encoder-decoder module 21 with the addition of noise 25, the defacement process with randomness is mimicked. In particular, the noise 25 may be generated by a noise generating module, but not limited herein. The noise 25 introduces stochastic variations into the generated defects to improve the diversity of the generated defects. Therefore, the synthesized defect sample 3 generated by the defect sample synthesis method can be generalized to lots types of defect inspection networks.

[0030] Please refer to FIGs. 2, 5 and 6. FIG. 5 schematically illustrates a partial flow chart of a defect sample synthesis method according to another embodiment of the present invention. FIG. 6 schematically illustrates a configuration of the defect sample synthesis method of FIG. 5. The elements of FIGs. 5 and 6 which are similar with those of FIG. 2 are

represented by the same reference numerals, and the detailed description thereof is omitted herein. As shown in FIGs. 5 and 6, the synthesizer 2 includes an encoder-decoder module 21, in the step S400, the synthesized defect sample 3 is inputted to the encoder-decoder module 21, but not limited herein. The step S500 of a defect sample synthesis method of the present invention of FIG. 1 further includes steps S510, S530 and S550. In step S510, a noise 25 is inserted to the encoder-decoder module 21 for increasing randomness. In step S530, the encoder-decoder module 21 is allowed to generate a repaint spatial distribution 26 and a repaint foreground 27. In step S550, a layer composition is performed according to the synthesized defect sample 3, the repaint spatial distribution 26, and the repaint foreground 27 to generate the restored normal sample 5.

[0031] In particular, the Defect-GANs based on the defect sample synthesis method of the present invention is different from existing image-to-image translation GANs since the final generation of defects is a composition of at least two layers. Specifically, in the defacement process, the synthesized defects sample 3 is generated by adding the defect foreground 23 on top of the normal sample 1. Similarly, in the restoration process, the restored normal sample 5 is generated by adding the repaint foreground 27 on top of the synthesized defect sample 3.

[0032] Please refer to FIGS. 3-6 again. In order to control attributes and locations of defects generated by the synthesizer 2, a control map 4 is inputted to the encoder-decoder module 21 for assisting generations of the defect spatial distribution 22 and the defect foreground 23 in the sub-step S330, and generations of the repaint spatial distribution 26 and the repaint foreground 27 in the sub-step S530. By controlling locations and categories of defects with the control map 4, a flexible control of defect generation is implemented.

[0033] Please refer to FIG.2 again. The Defect-GAN includes a generator and a discriminator. During the training stage, Defect-GAN performs image translation using generator in two cycles: $n \rightarrow d \rightarrow \hat{n}$ and $d \rightarrow n \rightarrow \hat{d}$, where $n \in R^{H \times W \times 3}$ denotes a normal sample, $d \in R^{H \times W \times 3}$ denotes a defect sample, and $\hat{n}, \hat{d} \in R^{H \times W \times 3}$ denote restored normal and defect samples, respectively. Since the two cycles are identical and simultaneously conducted, only the cycle $n \rightarrow d \rightarrow \hat{n}$ is described in the following sections for simplicity.

[0034] The generator is shown in FIG. 4 that employs an encoder-decoder architecture (i.e., the encoder-decoder module 21 of the synthesizer 2). The major architecture of the generator mainly follows the commonly used image-to-image translation networks, which first encodes the input image by a stride of 4, and then decodes it to its original size. To improve synthesis realism and diversity for defect generation, one embodiment of the present invention further includes specifically designed spatial and categorical control, stochastic variation, and layer-based composition for generator. The network architecture of discriminator is the same as StarGAN, which includes a D_{src} to distinguish faked samples from real ones using PatchGAN and a D_{cls} to predict the categories of generated defects.

[0035] Different types of defects can exist on different locations of normal samples. To provide better attribute (spatial and categorical) control over the generated defects, an attribute control map $A \in R^{H \times W \times C}$ is fed into generator to add specific kind of defects to specific location, where $A_{x,y} \in R^C$ represents the presence of defects at the corresponding location, and C denotes the number of defect categories. The attribute

control map A is imposed into the network via SPADE normalization and is fed into every block in the decoder part of generator.

[0036] The control map 4 defines the generation target for each generation process (“from normal sample to defect sample” or “from defect sample to normal sample”). The control map 4 is a tensor of $R^{H \times W \times C}$, where H and W are the spatial sizes, and C is the number of defect types including “normal”. The control map 4 feeds into the generation process via SPADE as described in the previous paragraphs. The embodiment takes “from normal sample to the defect sample” as example, and it may also apply to “from defect sample to normal sample”. Specifically, the control map 4 defines where to generate defects (spatial locations) and which type of defects to be generated (e.g., crack or spallation or both of them). It operates slightly different during training and inference and is described below.

[0037] In one embodiment, during training of the control map 4, since the embodiment just has image-level label for each image patch and do not have pixel-level annotations, the control map 4 is the same for all spatial locations. Therefore, during training stage it guides Defect-GAN to add certain type(s) of defects to all spatial locations of the input normal samples.

[0038] In one embodiment, during inference of the control map 4, the control map 4 has better flexibility. The control map 4 can perform whole-image transformation as during the training stage, and it can also control where to add certain types of defects. Concretely, in the embodiment, a 2-D Gaussian map is generated and multiplied on the whole-image control map. The 2-D Gaussian map would also be applied

to the generated defect foregrounds and the defect spatial distributions. Thus, the control map 4 can generate defects roughly on specific places.

[0039] Note that since the embodiment only assumes image-level annotations available, during training stage, the attribute control map A should be constant for all locations of the image, i.e., the attribute control map A is acquired by spatial-wisely repeating the target defect label $C \in R^C$. This restriction can be lifted during inference stage, which enables Defect-GAN to add defects at different location(s) in a context-compatible manner.

[0040] Unlike general objects, defects are known to possess complex and irregular patterns with extremely high stochastic variations that are extremely challenging to model using GANs. To mitigate this issue, the embodiment employs an adaptive noise insertion module in each block of the encoder-decoder architecture, which explicitly injects Gaussian noise into the feature maps after each convolutional block. For each noise injection, it learns an exclusive scalar to adjust the intensity of the injected noise. By explicitly mirroring the stochastic variations within defects, Defect-GAN can generate more realistic defect samples with much higher diversity.

[0041] As illustrated in FIGs. 4 and 6, Defect-GAN is also different from existing image-to-image translation GANs wherein the final generation as composition of two layers is considered in the embodiment. Specifically, in the defacement process, final defects samples are generated by adding a defect foreground layer on top of the provided normal samples. Similarly, in the restoration process, final restored normal samples are generated by adding a repaint foreground layer on top of the defect samples. The defacement process can be formulated as:

$$f_d, m_d = G(n, A_{n \rightarrow d}) \quad (1)$$

$$d = n \odot (1 - m_d) + f_d \odot m_d \quad (2)$$

Where $\odot$ denotes spatial-wise multiplication, f_d denotes generated defect foreground, and $m_d \in [0, 1]$ denotes the corresponding spatial distribution map of f_d . Similarly, the restoration process can be formulated as:

$$f_{\hat{n}}, m_{\hat{n}} = G(d, A_{d \rightarrow \hat{n}}) \quad (3)$$

$$\hat{n} = d \odot (1 - m_{\hat{n}}) + f_{\hat{n}} \odot m_{\hat{n}} \quad (4)$$

Where $\hat{n}$ denotes restored normal sample without defects.

[0042] The intuition behind this layer-wise composition strategy is that defects can be deemed a special kind of foreground composed on the background (normal samples). Similarly, the restoration process that removes defects from the background can also be considered a “repainting” process to cover the defect areas. Instead of generating synthesized images directly, Defect-GAN separately generates defect foregrounds along with the corresponding spatial distribution maps, and then performs a layer-wise composition to produce the synthesized defect samples.

[0043] The novel compositional layer-based synthesis can significantly improve defect synthesis in terms of both realism and diversity. By taking normal samples as background, the model of the embodiment of the present invention may implicitly focus on generation of defects without considering the generation of backgrounds. This feature provides the model of the embodiment of the present invention with more capability to generate more realistic defect samples. Furthermore, defects can potentially exist on various backgrounds. Due to the rarity of defect samples, only specific defects on a very limited number of backgrounds can be collected. As a result, typical image synthesis methods lack defect transferability, i.e., they can only synthesize defect samples under a constrained number of contexts. The embodiment of the present invention

proposed layer-wise composition strategy may mitigate this issue. This is because it is able to sufficiently preserve the identities (appearances, styles, etc.) of backgrounds, which forces the model to simulate how defects would interact with the exact provided backgrounds. This significantly improves the defect transferability, which means the model of the embodiment of the present invention is capable of generating new defect samples within variously different backgrounds.

[0044] To generate visually realistic images, the embodiment adopts adversarial loss to make the generated defect d indistinguishable from real defect sample d_{real} .

$$\mathcal{L}_{adv} = \min_G \max_{D_{src}} \mathbb{E}_{d_{real}} [\log D_{src}(d_{real})] + \mathbb{E}_d [\log(1 - D_{src}(d))] \quad (5)$$

[0045] The Defect-GAN of the embodiment of the present invention aims to generate defects conditioned on target defect label $C \in R^C$. To make the generated defects align with the target category, one embodiment may impose a category classification loss including two terms: $\mathcal{L}_{cls}^r$ to optimize D by classifying real defect sample d_{real} to the corresponding category c' , and $\mathcal{L}_{cls}^f$ to optimize generator to generate defect sample of target category c .

$$\mathcal{L}_{cls}^r = \mathbb{E}_{d_{real}, c'} \left[-\log(D_{cls}(c' | d_{real})) \right] \quad (6)$$

$$\mathcal{L}_{cls}^f = \mathbb{E}_{d, c} [-\log(D_{cls}(c | d))] \quad (7)$$

[0046] Additionally, one embodiment may impose a reconstruction loss $\mathcal{L}_{rec}$ that helps preserve the content of input images as much as possible. L1 loss for the reconstruction loss is adopted.

$$\mathcal{L}_{rec} = \mathbb{E}_{n, \hat{n}} [||n - \hat{n}||_1] \quad (8)$$

[0047] Via the layer-wise composition strategy, spatial distribution maps in both defacement and restoration process to guide the final compositions would be generated. The embodiment may further improve composition by introducing two additional spatial constraints (beyond spatial distribution maps), namely, a cycle-consistency loss and a region constrain loss. To precisely restore the generated defect samples to normal samples, the repaint spatial distribution map may be ideally the same as the defect spatial distribution map. Thus, one embodiment further provides a spatial distribution cycle-consistency loss $\mathcal{L}_{sd-cyc}$ between the defect spatial distribution map and the repaint spatial distribution map.

$$\mathcal{L}_{sd-cyc} = \mathbb{E}_{m_n, m_{\hat{n}}} [||m_n - m_{\hat{n}}||_1] \quad (9)$$

[0048] Meanwhile, in one embodiment, to avoid the defect foreground and the repaint foreground to take over the whole image area, a region constrain loss $\mathcal{L}_{sd-con}$ is introduced to penalize excessively large defect and foreground distribution maps:

$$\mathcal{L}_{sd-con} = \mathbb{E}_{m_n, m_{\hat{n}}} [||m_n - 0||_1 + ||m_{\hat{n}} - 0||_1] \quad (10)$$

[0049] The overall training objectives for generator and discriminator are:

$$\mathcal{L}_D = -\mathcal{L}_{adv} + \lambda_{cls}^r \mathcal{L}_{cls}^r \quad (11)$$

$$\mathcal{L}_G = \mathcal{L}_{adv} + \lambda_{cls}^f \mathcal{L}_{cls}^f + \lambda_{rec} \mathcal{L}_{rec} + \lambda_{con} \mathcal{L}_{sd-cyc} + \lambda_c \mathcal{L}_{sd-con} \quad (12)$$

Where λ_{cls}^r , λ_{cls}^f , λ_{rec} , λ_{sd-cyc} , λ_{sd-con} are hyperparameters that are empirically set as 2.0, 5.0, 5.0, 5.0, 1.0, respectively.

[0050] Please refer to FIGs. 2 and 7. FIG. 7 schematically illustrates a flow chart of a defect sample synthesis method according to another embodiment of the present invention. The steps of FIG. 7 that are similar with those of FIG. 1 are represented by the same reference numerals, and the detailed description thereof is omitted herein. In the embodiment, a

defect sample synthesis method according to an embodiment of the present invention further includes steps S600 and S700. In step S600, the restored normal sample 5 is compared with the normal sample 1 for verification. In step S700, the synthesized defect sample 3 is added into a synthesized dataset of a defect inspection network after the step S600 is performed. In an embodiment, the step S600 is performed after the step S500 is performed, but not limited thereto. In an embodiment, the defect sample synthesis method further includes a step S800, wherein the step S800 is performed after the step S700. In the step S800, the synthesized defect sample 3 is inputted to a defect inspection network. Alternatively, the step S800 may be performed after the step S300, the step S600 or the step S700, but not limited herein.

[0051] In brief, the embodiment of the present invention provides a defect sample synthesis method mimicking the defacement and restoration processes in order to boost defect inspection performance. Please refer to FIG. 8. FIG. 8 schematically illustrates defacement and restoration processes performed by a defect sample synthesis method and synthesized defect samples added into a defect inspection network. By mimicking the defacement processes, the normal samples can be combined with image layers of defects through a layer composition, which is preferably a layer-wise composition, as the synthesized defect samples. Likewise, by mimicking the restoration processes, the synthesized defect samples can be combined with the repaint image layers through a layer composition, which is preferably a layer-wise composition, as the normal samples. Furthermore, the synthesized defect samples can be inputted to a defect inspection network after the synthesized defect samples being synthesized or after the comparison of the synthesized defect sample and the normal samples which are restored through restoration.

[0052] Please refer to FIGs. 9 and 10. FIG. 9 schematically illustrates a flow chart of a training method of a defect inspection network according to an embodiment of the present invention. FIG. 10 schematically illustrates a configuration of a training method of a defect inspection network according to an embodiment of the present invention. According to an embodiment of the present invention, a training method of a defect inspection network includes steps S10, S20 and S30. In step S10, a network backbone 61 and a defect inspection model 62 are provided. Next, in step S20, a real dataset 63 and a synthesized dataset 64 is inputted to the network backbone 61. Then, in step S30, the defect inspection model 62 is trained with the real dataset 63 and the synthesized dataset 64.

[0053] In some embodiments, the defect inspection model 62 learns how to distinguish between synthetic defect samples and real samples. However, the above learning process may affect the accuracy of the model. In order to prevent the defect inspection model 62 to undesirably learn to distinguish synthesized defect samples from real samples, the training method of the embodiment of the present invention attaches an extra classifier to explicitly distinguish such difference and connects the classifier to the network backbone 61 through a gradient reversal layer (GRL). Please refer to FIGs. 10 and 11. FIG. 11 schematically illustrates a flow chart of a training method of a defect inspection network according to another embodiment of the present invention. As shown in FIGs. 10 and 11, a training method of a defect inspection network according to an embodiment of the present invention further includes step S40. In step S40, a source classifier 65 is connected to the network backbone 61 through a gradient reversal layer 66 for letting the real dataset 63 and the synthesized dataset 64 be indistinguishable, and the defect inspection performance can be improved. In the embodiment, via having

the source classifier 65 be connected to the network backbone 61 through a gradient reversal layer 66 to let the real dataset 63 and the synthesized dataset 64 be indistinguishable, the data of the defect samples for training defect inspection networks can be augmented to improve the training of the defect inspection network to enhance the defect inspection performance.

[0054] The embodiment of the present invention provides a computer-readable medium having a computer program configured to perform at least one of the defect sample synthesis method and the training method described in the previous paragraphs.

[0055] The embodiment of the present invention also provides a computing system configured to perform at least one of the defect sample synthesis method and the training method described in the previous paragraphs.

[0056] The embodiment of the present invention also provides an image inspection apparatus for performing automatic defect inspection including a computer-readable medium having a computer program configured to perform at least one of the defect sample synthesis method and the training method described in the previous paragraphs.

[0057] From the above description, the embodiment of the present invention provides a defect sample synthesis method. By inputting a normal sample to a synthesizer and allowing the synthesizer to generate a synthesized defect sample, synthesized defect samples which are realistic and diverse can be generated for training accurate and robust defect inspection networks. In addition, through the encoder-decoder module with the addition of noise, defacement and restoration processes with randomness are mimicked. Meanwhile, by controlling locations and categories of defects with the control map, a flexible control of defect generation is implemented.

[0058] While the invention has been described in terms of what is presently considered to be the most practical and preferred embodiments, it is to be understood that the invention needs not be limited to the disclosed embodiment. On the contrary, it is intended to cover various modifications and similar arrangements included within the spirit and scope of the appended claims which are to be accorded with the broadest interpretation so as to encompass all such modifications and similar structures.

WHAT IS CLAIMED IS:

1. A defect sample synthesis method, comprising steps of:
 - (a) providing a normal sample and a synthesizer;
 - (b) inputting the normal sample to the synthesizer;
 - (c) allowing the synthesizer to generate a synthesized defect sample;
 - (d) inputting the synthesized defect sample to the synthesizer; and
 - (e) allowing the synthesizer to generate a restored normal sample.
2. The defect sample synthesis method according to claim 1, wherein the synthesizer comprises an encoder-decoder module, and the normal sample is inputted to the encoder-decoder module in the step (b).
3. The defect sample synthesis method according to claim 2, wherein the step (c) comprises sub-steps of:
 - (c1) inserting a noise to the encoder-decoder module;
 - (c2) allowing the encoder-decoder module to generate a defect spatial distribution and a defect foreground; and
 - (c3) performing a layer composition according to the normal sample, the defect spatial distribution, and the defect foreground to generate the synthesized defect sample.
4. The defect sample synthesis method according to claim 3, further comprising:

inputting a control map to the encoder-decoder module for assisting generations of the defect spatial distribution and the defect foreground.
5. The defect sample synthesis method according to claim 1, wherein the synthesizer comprises an encoder-decoder module, and the synthesized defect sample is inputted to the encoder-decoder module in the step (d).
6. The defect sample synthesis method according to claim 5, wherein the step (e) comprises sub-steps of:

- (e1) inserting a noise to the encoder-decoder module;
 - (e2) allowing the encoder-decoder module to generate a repaint spatial distribution and a repaint foreground; and
 - (e3) performing a layer composition according to the synthesized defect sample, the repaint spatial distribution, and the repaint foreground to generate the restored normal sample.
7. The defect sample synthesis method according to claim 6, further comprising:
 - inputting a control map to the encoder-decoder module for assisting generations of the defect spatial distribution and the defect foreground.
 8. The defect sample synthesis method according to claim 1, further comprising a step of:
 - (f) comparing the restored normal sample with the normal sample.
 9. The defect sample synthesis method according to claim 8, further comprising:
 - adding the synthesized defect sample into a synthesized dataset of a defect inspection network.
 10. The defect sample synthesis method according to claim 9, further comprising:
 - inputting the synthesized defect sample to a defect inspection network.
 11. A training method of a defect inspection network, comprising steps of:
 - providing a network backbone and a defect inspection model;
 - inputting a real dataset and a synthesized dataset to the network backbone; and
 - training the defect inspection model with the real dataset and the synthesized dataset.
 12. The training method according to claim 11, further comprising:
 - connecting a source classifier to the network backbone through a

gradient reversal layer for letting the real dataset and the synthesized dataset to be indistinguishable.

13. A computer-readable medium having a computer program configured to perform at least one of the defect sample synthesis method of the claims 1-10 and the training method of the claim 11.
14. A computing system configured to perform at least one of the defect sample synthesis method of the claims 1-10 and the training method of the claim 11.
15. An image inspection apparatus for performing automatic defect inspection comprising a computer-readable medium having a computer program configured to perform at least one of the defect sample synthesis method of the claims 1-10 and the training method of the claim 11.