Weld Defect Detection Based on Deep Learning Method

Haodong Zhang, Zuzhi Chen, Chaoqun Zhang, Juntong Xi, and Xinyi Le

Abstract— **Welding is an important joining technology but the defects in welds wreck the quality of the product evidently. Due to the variety of weld defects' characteristics, weld defect detection is a complex task in industry. In this paper, we try to explore a possible solution for weld defect detection and a novel image-based approach is proposed using small X-ray image data sets. An image-processing based data augmentation approach and a WGAN based data augmentation approach are applied to deal with imbalanced image sets. Then we train two deep convolutional neural networks (CNNs) on the augmented image sets using feature-extraction based transfer learning techniques. The two trained CNNs are combined to classify defects through a multi-model ensemble framework, aiming at lower false detection rate. Both of the experiments on augmented images and real world defect images achieve satisfying accuracy, which substantiates the possibility that the proposed approach is promising for weld defect detection.**

I. INTRODUCTION

A. Motivation

Welding is an important joining technology in industrial production. For instance, there are 3000 spot welds in one vehicle at least. Weld defects can affect the quality of the product such as damaging strength, stiffness and toughness. How to improve the efficiency and accuracy of weld defect detection is a key issue in the quality control of industrial production. X-ray detection is an important nondestructive testing technology which can record both inner and exterior defects. Traditionally, visual inspections are performed by experienced human inspectors in industrial welding. However, quality control by manual visual methods are usually exhausting, error-prone, inefficient, and expensive. Besides, the defects recorded in X-ray images are complex, diversified, and unconspicuous, which are very difficult to detect using traditional image-based methods. Therefore, it is essential and necessary to find a new defect detection method with high efficiency, good accuracy and low cost.

In fact, the problem of defect detection is not only bothering industrial welding. It exists in a wide range of manufacturing industries and has caught a major attention from researchers, such as textile industry [1], steel industry [2], and civil infrastructure [3]. With the rapid development of machine vision and digital image processing techniques, image-based defect inspection has drawn increasing attention and gradually displaced the traditional manual inspection. Early methods tend to extract some specific hand-crafted image features according to defect conditions [4], [5], [6].

However, three main challenges exist in the image-based defect detection approaches. First, there may exist a broad range of different defects in one detection task, which usually exhibit varied characteristics. The variability of defects greatly increases the complexity of the defect detection problem, making it difficult to develop a generalized method. Second, the categories and characteristics of defects are generally varied. Some defects appear as regions of low contrast, nonuniform brightness, or irregular shape, which further contributes to the difficulties. Third, collecting large numbers of defect samples, especially some rare types, is extremely expensive in industry, resulting in a severe imbalanced image data-sets. Thus, during the study of weld defect detection, considering the three problems above, a novel detection method will be our preference rather than image-based approacheMIDs.

Recently, with excellent performance on generic visual recognition, convolutional neural network (CNN) has become one of the most attractive methods for surface detection. It has been successfully applied to a number of defect detection scenarios and show better performance than earlier methods [7], [8]. The great improvement in detection accuracy is remarkable but these methods still require an enormous size of image set for training, which is unrealistic in most circumstances. Besides, they didn't take the training time of neural networks and the false detection rate of defect detection into consideration, which in our opinion are two crucial factors of practical application.

B. Contributions

In this paper, we develop a novel learning-based approach to deal with the challenges of weld defect detection. Aiming at the lack of defective data in industry, we propose two data augmentation techniques to acquire training data sets out of insufficient real data and we apply a special neural network which is able to reduce the required quantities of training data.

We successfully apply the proposed approach, including data augmentation and deep learning networks, to solve the industrial case of weld defect detection. It indicates the potential of the learning-based approach for detection problem with small-scale data sets.

We also visualize the defective area on the origin images for the convenience of further inspection.

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Haodong Zhang, Zuzhi Chen, Chaoqun Zhang, Juntong Xi, and Xinyi Le (corresponding author) are with School of Mechanical Engineering, Shanghai Jiao Tong University, Shanghai 200240, China (zhanghaodong, lexinyi@sjtu.edu.cn). Juntong Xi and Xinyi Le are also with Shanghai Key Laboratory of Advanced Manufacturing Environment.

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C. Organization

Some related work about CNN and GAN will be introduced in Section 2, so as the problem description of weld defects. The proposed methods are presented in Section 3, followed by experiment results in Section 4. Finally conclusion and future work will be given in Section 5.

II. Related Work

A. CNNs

CNNs have been rapidly growing in the pass decades. LeNet [9] as one of CNNs, was first proposed by Y. Le Cun et al. in 1989 for solving handwritten digit recognition. With the development of the computing capability, AlexNet [10] was created in 2012 by Krizhevsky with five convolutional layers and three fully connected layers. AlexNet won ILSVRC (ImageNet Large-Scale Visual Recognition Challenge) in 2012 and made CNN widely known in computer vision field. After that, many researchers use deep convolutional neural network as their main structures in image classification and object detection. Several CNNs were investigated to increase CNNs' performance. VGG [11] deepened the network and proved that the prediction accuracy can be increased with deeper network even in a simple structure. Inception module [12] paralleled the layers to increase the accuracy. In ResNet [13], the network is able to learn the residue information in order to eliminate information loss in very deep network.

With the development of CNN, it performs extremely well in various visual recognition tasks. However, when the training data set is limited, CNNs will meet severe over fitting problems. Inspired by human's capability of accumulating and transferring knowledge, researchers are convinced that prior knowledge of a model can also be utilized for solving a new task even in a new domain, which is known as transfer learning.

In [14], the powerful generic visual features trained on a large visual recognition data set can be transfer to new tasks. The transfer property still works even if the new tasks are significantly different from the original ones. In [15], the transfer learning is further substantiated by numerous experiments pf a wide range including image classification, scene recognition, fine-grained recognition, attribute detection, and image retrieval. Transfer-learning based CNNs greatly reduce the training time and the quantity of training data, leading to many new possible applications.

In spite of the successful applications in many fields, CNN based defect detection has not been widely applied in production line. Although the required amount of training data is reduced using transfer learning method, the defect data is still not enough for training, which makes data augmentation necessary.

There are several data augmentation techniques. [16] proposed several principles for solving imbalanced data problems. [17] proposed some data augmentation approaches based on hypergraph analysis. [18], [19] used human knowledge to generate data for training. Recently, a new promising method to generate similar images is proposed, named Generative Adversarial Nets.

B. Wasserstein GAN

Generative Adversarial Nets, known as GAN and GANs, were proposed by Ian Goodfellow in 2014 [20]. Generative Adversarial Nets are composed by generators and discriminators. Generators capture the distribution of train data and generate similar images and then train the discriminator with the generated images and make the discriminators capable to tell whether the input image is real or generated. Discriminators output "1" for real and "0" for generated and then update the parameters of generators to maximize the outputs of discriminators and repeat the procedure. GAN is capable of generating images with high similarities based on training data, which have been proved by a number of successful tests.

Although GAN has a potential for data augmentation, the training process of GAN is difficult to control. Problems remained unsolved such as the abate for loss functions of generators or discriminators and the lack of variety for generated images. In 2016, Alec Radford proposed deep convolutional generative adversarial networks(DCGAN) [21]. DCGAN combines convolutional neural network and generative adversarial networks and makes the training process more stable than the original GAN. The training process of generators and discriminators has to be well-balanced to avoid the unstable situation. Later in 2017, an improved GAN, known as Wasserstein GAN and WGAN, was proposed by Martin Arjovsky [22], [23]. WGAN solves the training instability of GAN with several adjustments on GAN. WGAN shows theoretical integrity and good experimental performance. Some further works have been done by Martin Arjovsky [24] to improve the variety of samples and probability of convergence. The improved WGAN is known as WGAN-GP. Experiments show the advantage of WGAN-GP through quality and quantity. WGAN provides researchers a simple and reliable method to generate training samples for the lack of real data.

C. Problem Description

Weld defects show various kinds of different characters on X-ray image. According to the common characters on image, defects can be mainly divided into three types which are "porosity" type, "crack" type and "burn through" type. Fig. 1 presents X-ray images of typical weld defects of the three kinds.

The defects of "porosity" type are composed by series of single dots. In the X-ray images of the defects of "crack" type, linear shadow can be found vertical or parallel to the edge of welds. Defects of "burn through" type are translated to shadows of anomalous shape on X-ray images.

Classifying the real defect images with the same criteria, data set of each kind can be acquired for data augmentation. In this paper, training data for "porosity" type is augmented via image-processing-based method and data for "burn through" type and "crack" type is augmented via WGAN-based method.

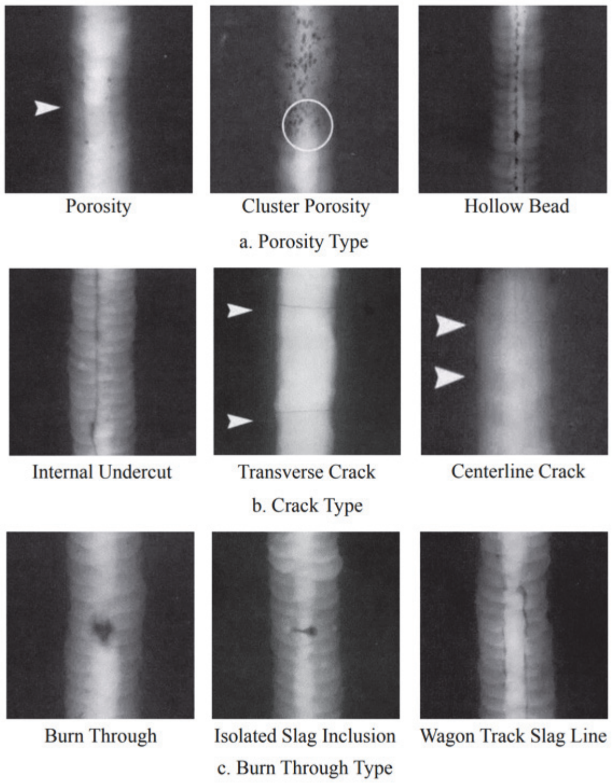


Fig. 1. Various kinds of weld defects.

III. METHODOLOGY

Although CNN is a powerful structure for visual recognition tasks, training for CNN requires a large number of labeled training data to avoid over fitting, which is far beyond the available images of real defects. This dilemma is true for a major number of situations. The difficulty mainly comes from the facts that defective samples of welds are discovered at low frequency.

Images of the defects with specific graphic characters can be augmented by adding artificial defects to same background, such as defects of porosity type.

But some complicate defects such as burn though and crack type are not suitable for this method. Therefore, an algorithm of Wasserstein GAN is applied to generate images with these types of defects.

A. Image-Processing-Based Data Augmentation

In spite of the numerous types of weld defects, we discover that some defects can be decomposed into some basic elements. Take the defects of "porosity" and "crack" in welds as examples, a typical "crack" can be regarded as the formation of irregular line segments. A "porosity" is simply a small circle with specific distribution of gray scale. Using image transforming algorithms, we are able to generate artificial weld defects of certain types which are diversified and quite similar to true defects.

In the generating algorithm, the first step of generating "porosity" is to draw a random shape with unique gray scale. This is achieved by drawing several circles with different diameters whose centers normally distributed around a specific point. We also apply a Gaussian filter in the region of the generated shape. Due to the arbitrary selected position, shape, size and gray scale in our algorithm, generated "porosity" is diversified enough to contain the features of realistic "porosity".

Experiments in Section 4 showed that CNN models trained by generated data achieve equivalent performance compared to the realistic data.

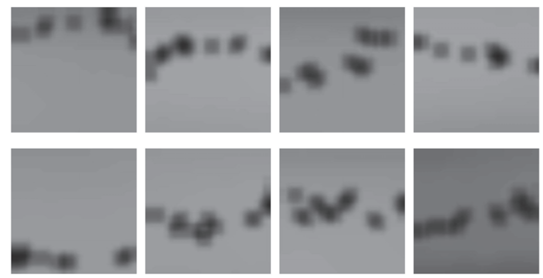


Fig. 2. Generated images of weld defects of "porosity" type via image-processing-based data augmentation

Each image is automatically labeled with the defects' name. Manual labeling of images is no longer needed, increasing algorithm's computational efficiency.

B. Wasserstein GAN Based Data Augmentation

Apparently, generating data using prior human knowledge is an empirical approach which does not take the information of existing defect images into consideration. Thus, some natures of defects may be missed. As for the defects with specific graphic characters, this method can provide good applicability. But certain kinds of defects can not be solved effectively such as burn through and crack of weld defects due to the complexity of the defects.

In order to solve the augmentation problem of complicate defects, burn through and crack type in this paper specifically, a data augmentation technique based on Wasserstein GAN is proposed. It shows a promising capability to augment data of certain types of defects with limited training data.

The WGAN framework is composed of two gaming networks: a generator network that captures random noise and generates fake images, a discriminator network aims at distinguishing real and fake images. The generator network is trained to deceive the discriminator to regard generated images as real ones while the discriminator is trained to discriminate the generated images.

The main framework of WGAN in this paper is shown in Fig. 3.

The generator consists of 6 deconvolutional layers. ReLU is applied for activation function of first 5 layers when the last layer uses tanh as activation function to make sure the value of output is within 0-255 RGB. The discriminator contents 4 convolutional layers using Leaky ReLU as activation function and the Logistic function which tests

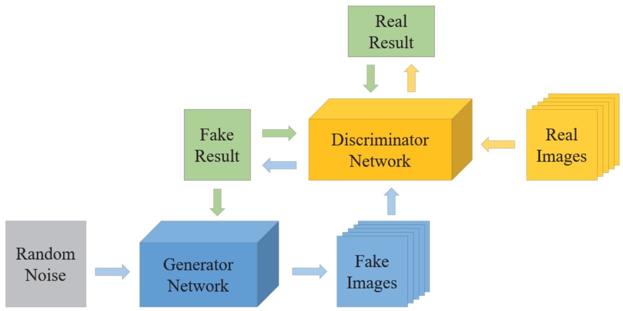


Fig. 3. Framework of WGAN in this paper.

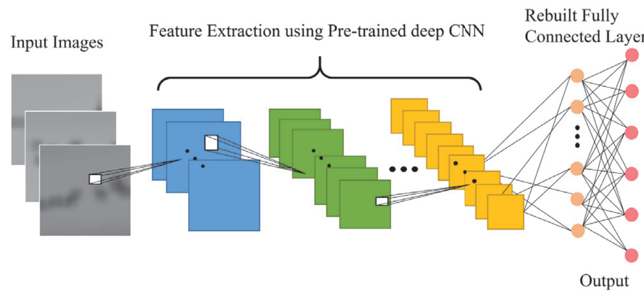


Fig. 5. Overview of the transfer learning method. The pre-trained deep CNN takes an image as input and extracts features, which is followed by a fully connected layer rebuilt for defect classification.

the convolutional results and gives the probability of the authenticity of the input images.

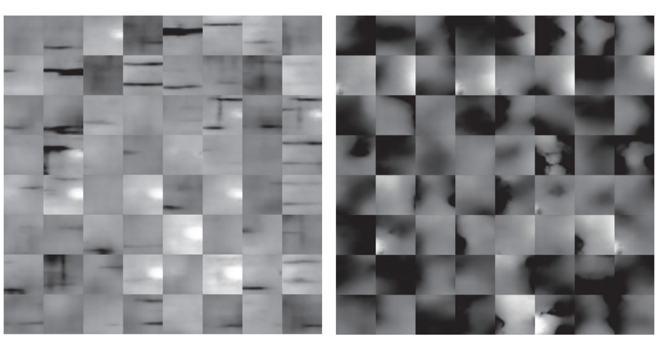
Procedure is also presented in Fig. 3. Some random noise such as random brightness and contrast is put into the generator to generate images. And the generated images will be discriminated by the discriminator where the result is called Fake Result. Real images are also put into the discriminator and the result is called Real Result. Fake Result and Real Result form the loss functions for training the generator and discriminator, as indicated by the green arrows. The RMSProp optimizer of tensorflow is used for optimizing the two networks.

Fig. 4 demonstrates the generated images of "burn through" and "crack" types of weld defects using WGAN algorithm.

C. Transfer Learning of Deep CNNs

After the preparation of labeled training data, training a modern CNN is also computationally expensive and time-consuming. Hence, we employ transfer learning to save training time by using deep pre-trained CNN on augmented image data sets.

According to [14], [15], transfer learning of deep CNN mainly employs the approach of using pre-trained network for feature extraction. These features can then be followed by a generic classifier such as Supported Vector Machine (SVM) for classification. In weld defect detection problem, two CNN models are applied in our main structure. We preserve most parts of the original pre-trained network except the last fully connected layer for extracting features from the welds. The last fully connected layer of the original network is then modified in accordance with our desired outputs. Through the prediction of the models, each image is labeled as defective or normal. Using our training data set, we update the weights of the final layer. The block diagram of our proposed method is shown in Fig. 5.



a. Generated "crack" images b. Generated "burn through" images

Fig. 4. Genetated images of WGAN.

With regard to the CNN architecture, we employ Inception [25] and MobileNet[26] as the source architecture for solving our defect detection problem due to the good accuracy performance on small size and low latency data.

D. Multi-model Ensemble

In the industry, manufacturers are more concerned about the false detection rate than the accuracy of detection. If images containing defects are not detected by the detection system and the product is sold to consumers, the defective product will cause potential risk and damage the company's reputation.

In addition, manual inspection will not be totally abandoned until the image-based method is proved reliable enough in practicality and the corresponding device is widespread. So, we suppose that the questionable images will be checked again by inspectors which is a possible picture of the real situation. Thus, it is acceptable for classifying a "normal" image to a defective image in order to avoid the occurrence of missing defective images as much as possible.

Similar to the decision-making process of human beings, the probability of multiple persons making mistakes at the same time is much lower than that of each individual. To further reduce the false detection rate, we propose a multi-model ensemble framework, whose block diagram is shown in Fig. 6. We train two different networks, Inception and MobileNet, on same training sets via transfer learning method. During testing, Inception and MobileNet make classification simultaneously.

Each image will obtain similarity scores to six classes. One image will be determined as "normal" only if the weighted sum of two models' results is larger than specific thresholds. More models, theoretically as many as you want, can be added in our multi-model ensemble framework to increase accuracy.

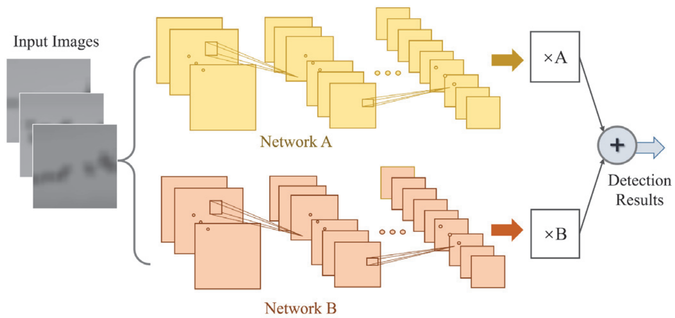


Fig. 6. Architecture of multi-model ensemble.

The ensemble framework completes the integrity of our work. On the other hand, it is not our major focus to locate the best weight of two models. There is plenty of extensive future work can be done for finding a better ensemble framework.

E. Visualization

In the experimental process, considering the real requirements on production line, we framed the questionable areas in images, helping further inspection.

In detecting process, we divide the original image into sub-images in size of 32*32 pixels. And input the sub-images into the trained CNNs to detect defects. If a sub-image contain potential defect, we frame it out. After all the sub-images are tested, the external contour of the whole frame will be attached to the original image. The results will be shown in Section 4.

IV. Experimental Results

A. Implementation Details

All of our algorithm is implemented in Python. We use the open source computer vision library OpenCV and WGAN code in our proposed data augmentation algorithms. We also use Tensorflow as our deep learning framework, with which we build and train our models and make prediction using our models.

B. Experiments of Weld Defect Detection

The training data set of weld defects consists of 7606 RGB labeled X-ray images, 2038 for "normal", 1907 for "burn through", 2097 for "crack" and 1564 for "porosity", respectively. "Burn through" and "crack" types of defects are generated by WGAN-based augmentation method and "porosity" type is generated by image-processing-based algorithm. "Normal" images are directly captured from the origin images of welds.

The training set is divided into two subsets: about 80% for training(1621 for "normal", 1563 for "burn through", 1699 for "crack" and 1259 for "porosity") and the rest for testing (417 for "normal", 344 for "burn through", 398 for "crack" and 305 for "porosity").

In this paper, the weight value of ensemble is not the focal point since ensemble method is diverse. We test several sets

TABLE I
Results of Weld Defect Experiments

		True Class			
		normal	burn through	crack	porosity
Predicted Class	normal	417	19	1	1
	defective	0	326	397	304
Accuracy		100.00%	94.77%	99.75%	99.67%

of weight values and the testing results are presented in Table 1 when Inception takes 0.6 while MobileNet takes 0.4.

As shown by the results, the accuracy of the proposed method for these three types of weld defects is satisfactory and quite acceptable for manufacturers.

C. Test on Realistic Defective Images

To further verify the effectiveness of our proposed methods of data augmentation, transfer learning, and multi-model ensemble, test on realistic defective images of welds is indispensable. Therefore, we collected some samples of X-ray images of welds with defects from manufacturers and use them for testing. In total, we have 56 defective images of welds containing the mentioned three types of defects. We employed our proposed method to detect the three types of weld defects mentioned in this paper. Delightfully, all the weld defects of the three types are detected. Some of the test results are shown in Fig. 7.

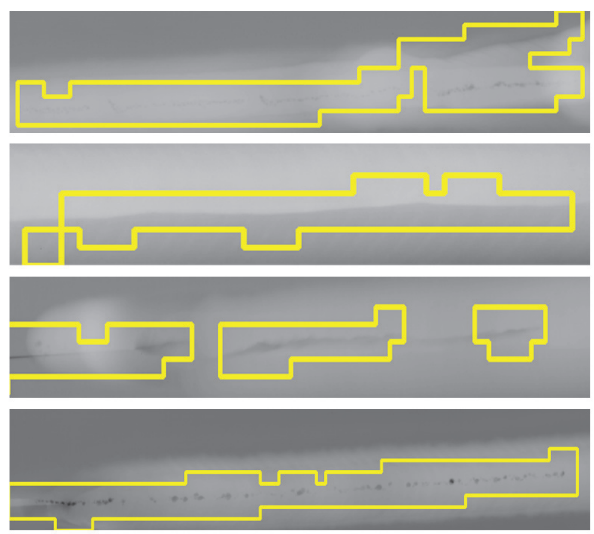


Fig. 7. Results of Realistic Defective Images

V. Conclusion and Future Work

This paper shows an exploration of image-based defect detection method in X-ray images of weld defects. The imbalanced classification images are augmented using prior human knowledge and generative adversarial networks. The transfer learning is applied in CNNs to reduce training time. A multi-model ensemble approach is used to reduce false detection rate. The inception results are visualized for further operation. The proposed approach is supported by some positive experimental results which indicates the potential of the possible application in industry. Different from the traditional image-based approach for defect detection, the proposed learning-based approach can detect defects in complex and diverse background.

But up to now, our method can only detect several certain types of weld defects which have been learned by the model. It can release some manual labor but can not totally replace the manual inception. So, in the future, we need more realistic images of all kinds of weld defects to train our model and make it more universal and accurate. Some kinds of weld defects that appear in entirety can not be detected effectively where the data sets or the algorithms may need some adjustment. And the ensemble framework of our method is very simple which can be improved to meet the different requires of manufacturers.

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