Anomaly Detection by Deep Learning Named "Sense Learning"

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In a visual inspection setting, quantitative and qualitative judgment is needed. To automate this particular judgment process, an algorithm that resembles human recognition ability is required. Sense Learning is our algorithm that mimics the human recognition ability using the images of non-defective products. With an autoencoder, a deep-learning-based network, the inspection AI progressively learns to reconstruct the images of non-defective products, thereby acknowledging the ideal characteristics of products. When the image of a defective product is input, the inspection AI fails to reconstruct the defective part because it has never learned the form. Based on the difference between the input image and the reconstructed image, Sense Learning detects the defective part and measures the degree of its severity.

Keywords: Sense Learning, deep learning, anomaly detection

1. Introduction

Recently, a third artificial intelligence (AI) boom brought about by the emergence of deep learning technology[(1)] has been applied not only to improving the functionality of products and services (e.g. automated driving technologies, big data analysis technologies) but also to automating technologies to increase efficiency at production sites. At Sumitomo Electric Industries, Ltd., one of the most important themes is to improve functionality of products and services in respective business fields and increase manufacturing efficiency by introducing AI technologies. We are continually developing more reliable AI (deep learning) technologies that can be applied to our products.

This paper discusses anomaly detection at production sites using AI technologies. Deep learning is an AI technology that has attracted much public attention. One precondition for its most general applications is to collect a large amount of data for each category subject to identification. However, in production sites, the variations of the environment are relatively more controllable than in real-world situations; as a result, the amount of data required for training AI could be reduced because there are only a limited number of factors to be considered.

It should be noted, however, that the defect rate of some products is extremely low. This poses a significant difficulty in collecting data used for training purposes, making the recognition of various defective patterns challenging.

To overcome this challenge, we came up with a completely different approach. We focused on training AI with many different images of defect-free products, instead of defective ones, so that AI senses a difference when an image of a defective product is input.

First, AI is allowed to learn only data from defect-free products to develop a model of good products. Then, data of defective products are evaluated against the model of good products so that AI can detect differences in the evaluation. This deep learning technology was designed to "sense" irregularities in data, and thus named "Sense Learning." The next section explains the basic configuration of Sense Learning.

2. Sense Learning

Sense Learning has three basic configurations. The first configuration is to learn the model of good products using deep learning. Data on the characteristics of good products are compressed, and a method to accurately reconstruct the images of good products is learned by using an autoencoder network.[(2)] When the image of a good product is input into the learned network, an image that is almost identical to the input image is output as a reconstructed image (see Fig. 1). In this paper, data on the characteristics of images that can be accurately compressed and reconstructed by the learned network are referred to as the good product model. When the image of a defective product is input into the learned network, the compression and reconstruction of defect characteristics fails, as shown in Fig. 2. The defect factors disappear from the reconstructed image.

The second configuration is to extract the differences between the input image and reconstructed image. The differences between the input image and reconstructed image are extracted by using a combination of filters based

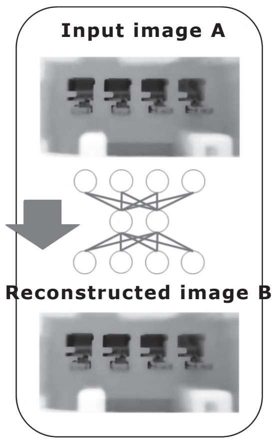


Fig. 1. Example of good product images input into the learned network

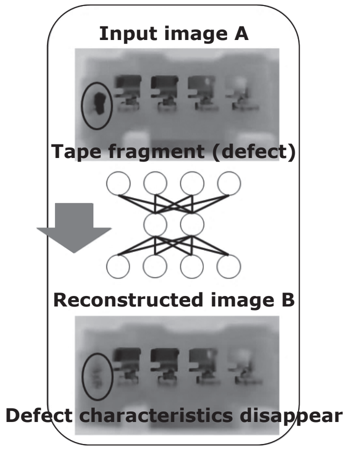


Fig. 2. Example of defective product images input into the learned network

on image processing technologies, depending on the image capture conditions and inspection targets. Difference extraction processing is performed to quantify the information of irregularity positions in the image and the extent of the irregularities. In this study, filters are used to remove slight noise (e.g. color unevenness not affecting the product specifications) from the images and to remove slight changes from the input image (occurring in the reconstruction process). For example, some actual products have color unevenness that is difficult to identify with the naked eye but that do not pose any problem in terms of product specifications. In this case, the values of pixels adjacent to each other are slightly different on the input image. When the input image is converted to a reconstructed image, the slight difference in the pixel values tend to be slightly blurred. However, filters are used to avoid associating such slight changes as irregularities. A single- or multi-layer filter is used depending on the inspection objects. Thus, filters should be tuned based on the opinions of individuals familiar with the production site.

The third configuration is a defect judgment unit. The extracted difference information is input into the judgment unit. There are two types of judgment unit configurations corresponding to two defect patterns in a factory plant: known defects and unknown defects. In the case of unknown defects, machine learning*[1] defines the boundary of good and defective products based on the good products data. Data outside the boundary are judged as defects. In the case of known defects, on the other hand, defect threshold has already been defined at individual plants. Thus, the defect boundary that is automatically set by machine learning cannot be used. For this reason, the boundary developed by the combination of deep learning and image processing is adjusted to meet the threshold boundary set by each factory plant. In Sense Learning, these two types of defect judgement units are combined to judge defects.

Figure 3 shows an example of the Sense Learning-based defect judgment system configuration for detecting unknown anomalies. The configuration consists of the deep learning unit, difference image binarization using multi-filters, and defect judgment using a one-class support vector machine.*[2]

3. Defect Judgement Experiment

3-1 Experiment setting

A camera was set up on a production line in a plant, and 5,000 connectors were captured for each of two types: Connector ① (Photo 1) and Connector ② (Photo 2). Of these images, 1,000 each were used as training images for the deep learning unit to learn good products. Since no defects occurred at the production plant, 100 types of defective connectors were fabricated for Connectors ① and ②, respectively, in line with the standard defined defect limit (marginally defective products) and were captured in the same environment. Under these conditions, the captured images were used to conduct a defect judgment experiment

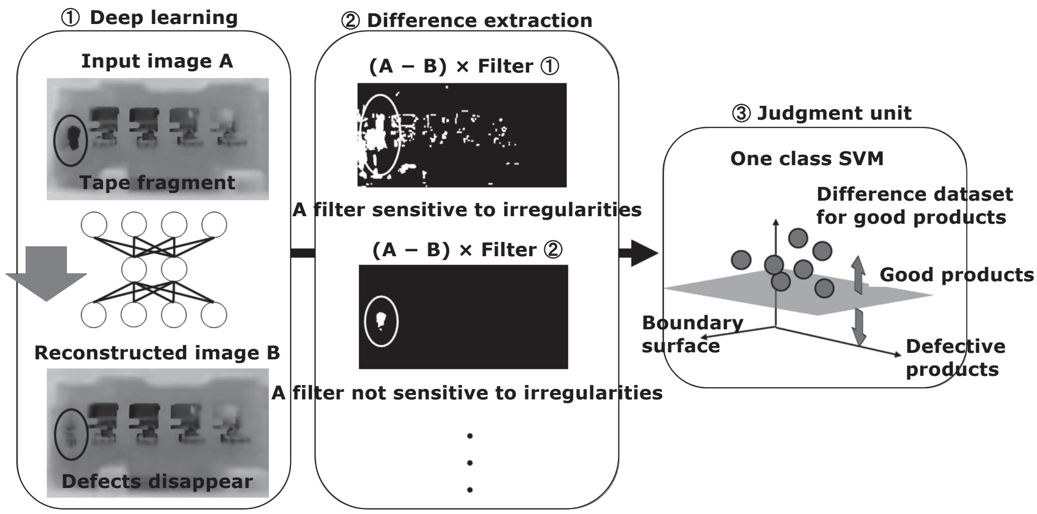


Fig. 3. Example of defect judgment system configuration based on Sense Learning

Photo 1. Connector ①

Photo 2. Connector ②

(defect definition: numerical values used at the plant, test result target values: a defect detection rate of 100% and a false positive rate [a rate at which good products are misjudged as defects] of 1%).

3-2 Experiment result

The defect judgment results of Connectors ① and ② were summarized in confusion matrices*3 (Tables 1 and 2). Examples of marginally defective products that were successfully detected are shown in Fig. 4.

The defect detection rate for Connector ① was 100%, and the false positive rate was 0.08%. The defect detection rate for Connector ② was 100%, and the false positive rate was 0.04%. The target values (a defect detection rate of 100% and false positive rate of 1%) were successfully achieved.

Table 1. Confusion matrix of defect judgment for Connector ①

Connector ①		Actual product	
		Good product	Marginally defective products
Judgment	Good	4996	0
	Defective	4	100
Result		False positive rate: 0.08%	Defect detection rate: 100%

Table 2. Confusion matrix of defect judgment for Connector ②

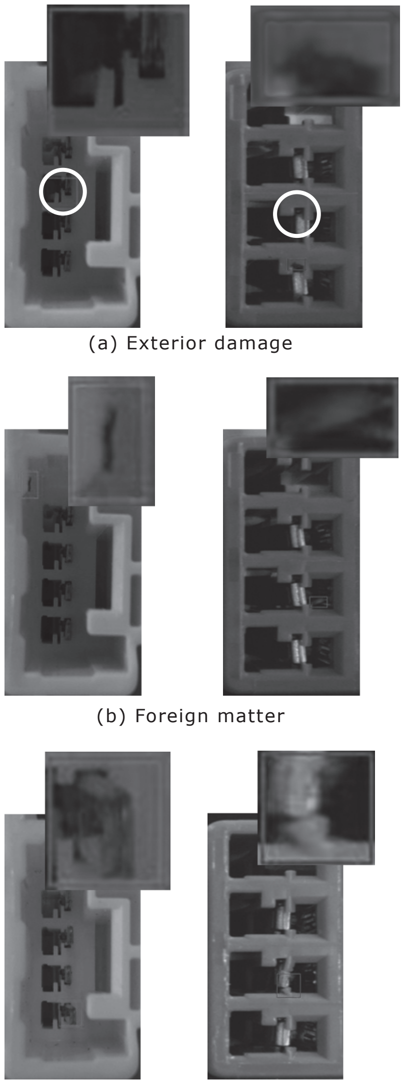
Connector ②		Actual product	
		Good product	Marginally defective products
Judgment	Good	4998	0
	Defective	2	100
Result		False positive rate: 0.04%	Defect detection rate: 100%

3-3 Discussion

As shown in Fig. 4, Sense Learning successfully detected defects regardless of their types. This demonstrated that defects could be detected only by learning the good product patterns and that detectable defect sizes were adequate for practical applications.

Issues remain to be considered. We conducted an experiment using 100 marginally defective products, but we believe that this number was inadequate for evaluating AI performance. In general, it is considered difficult to directly analyze the learned judgment process of deep learning. In most cases, performance is evaluated statistically using a large amount of evaluation data. However, to fabricate marginally defective products, advanced technology is required to attain the accuracy of fabricating products almost at the defect limit. To set a limit on unknown defects that have not been defined at a plant, it is required to hold in-depth discussions with the quality control staff at the production site.

Meanwhile, false positives are caused by detecting disturbances such as shadows as defects. Thus, unexpected disturbances (e.g. disturbances not included in the data of good products) and environmental changes (e.g. changes in the production environment after obtaining the data of good products) could result in a false positive rate that exceeds the test results. Thus, it is necessary to properly manage the environment at the production site to avoid such changes. An additional learning function is also necessary to cope with any changes.



(a) Exterior damage

(b) Foreign matter

(c) Defective terminal

Fig. 4. Example of marginally defective product that was successfully detected

4. Conclusion

We developed a new deep learning methodology named Sense Learning, in which only data of good products are used for learning, and differences from good products contained in defective products are sensed as irregularities. We used Sense Learning to detect defects using actual connectors and demonstrated that defects were successfully detected. As future issues, we will evaluate the number of marginally defective products required to guarantee the performance of Sense Learning and determine the limit, avoid misjudgments of noise caused by unexpected disturbances as a defect, and achieve automatic additional learning to cope with environmental changes after learning.

Technical Terms

∗1 Machine learning: A technology for analyzing a large volume of sample data (e.g. images and sensor values) and automatically extracting data classification patterns based on the data. This technology is similar to deep learning. The main difference is that in machine learning notable data are input by a user in a somewhat organized manner, while in deep learning AI automatically identifies notable data.

∗2 One-class support vector machines: A machine learning technology. A large volume of input data isregarded as belonging to the same data category, and the boundary that distinguishes the category is automatically learned.

∗3 Confusion matrix: A notation method for judgment results used in a task to recognize multiple categories. Actual categories and categories judged by AI are arranged in a matrix form. The confusion matrix has an advantage in comparing the numbers of correct judgments and misjudgments by AI and identifying the causes of misjudgments.

References

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