Automation of Magnetic Particle Inspection Process

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In automating the magnetic particle inspection process for rack and pinion type steering racks, the problems were the false indication generated on the ridgeline of rack teeth and the variety of defect modes. Focusing on the strength of magnetization and flow of magnetic particles, we have developed a magnetic particle application technology suitable for image recognition. In addition, by using deep learning for image recognition, we were able to overcome these challenges. By combining magnetic particle application technology and image recognition technology, a recognition accuracy of 0% non-detection and less than 5% over-detection is achieved.

Key Words: *magnetic particle testing, automation, deep learning, image recognition*

1. Introduction

Due to its declining birthrate and aging population, Japan's working-age population peaked in 1995 and has been declining ever since[1], and so, in the coming years, labor shortages in the manufacturing industry are expected to become more severe.

In order to address this issue, we have been striving to improve productivity through automation, reducing the number of on-site workers, and by shifting them to higher value-added tasks.

Among these tasks, the inspection process is particularly difficult because it includes tasks using human senses, and the automation of this process has not progressed as much as expected.

In particular, the magnetic particle inspection process is used to ensure that there are no defects such as burn cracks in the rack and pinion, which are component parts of the rack and pinion steering system, and the constant velocity joint outer race, which is a component part of the drive shaft. Visual inspection is conducted on all of these parts. This inspection requires skilled workers, and it is difficult to train them. Also, because the work requires workers to concentrate for long periods of time, there have been strong demands for automation.

In addition, because the defects to be detected are minute and occur extremely infrequently, the inspection quality is highly dependent on the operator. Therefore, if the decision criteria can be quantified by automation, stable quality assurance can be achieved that is not dependent on the skills of individuals.

This paper describes the development of an automation technology for magnetic particle inspection and the results of the development.

2. Automation Issues

2. 1 What Is the Magnetic Particle Inspection Test?

The magnetic particle inspection test is an inspection process that uses magnetic particle testing to detect microscopic aperture defects on the surface of a product[2].

When a ferromagnetic material such as iron is placed in a magnetic field, magnetic flux penetrates into the material. During this process, if there are defects on the material surface in a direction that blocks the magnetic flux, some of the flux leaks out from that area to the surface. This is called the flux leakage.

In this process, when magnetic particles, which are iron powder coated with paint, are applied to the surface of the material, the magnetic particles are adsorbed by the flux leakage and form a pattern. This pattern makes it possible to visualize the location of microscopic aperture defects that cannot be observed with the naked eye. This is the principle of the magnetic particle testing (**Fig. 1**).

In the actual inspection process, multiple alternating magnetization is used to detect defects occurring in any direction, and a magnetic particle solution made of magnetic particles dispersed in water is showered on the inspection object so that magnetic particles adhere to the entire object. Then, defects are visually checked by the workers.

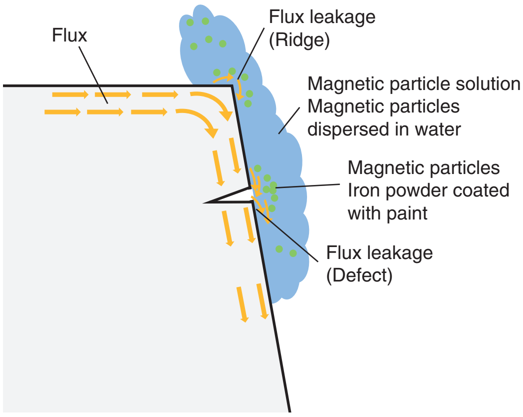

Fig. 1 Principle of magnetic particle testing

2. 2 Challenges of Conventional Technology

We examined prior technologies to determine a method for automating the magnetic particle inspection test. As a result of a literature survey and interviews with equipment manufacturers, there is prior technology for automation of magnetic particle inspection for defects that occur on flat or curved surfaces of simple shapes such as steel, and for automotive parts with limited defect locations and modes. However, the product to be automatically inspected in this test has complex irregularities, and the defect locations and modes are not limited, making it difficult to apply the inspection method as it is. The following issues are considered to be the reasons for the lack of progress in the development of automation technologies for magnetic particle inspection tests for objects with complex shapes.

Issue 1: Difficulty in extracting defects due to false patterns

Normally, when visual inspection is automated, the object is captured by a camera, image processing such as filtering and binarization are applied to the acquired image to extract defects, and a decision is made based on features such as the area and length[3]. During this process, in order to avoid incorrect decisions, it is important to acquire an image that removes noise other than defects so that defects can be extracted by image processing.

However, in the magnetic particle testing, magnetic particles can adhere and produce patterns even though no defects are present (**Fig. 2**). This is due to weak flux leakage occurring at places such as the ridges of the inspection object, and these patterns are classified as false patterns called a cross-section abrupt change indication[4].

When the inspection object has a complex shape, these false patterns are often generated, making it difficult to extract defects by image processing.

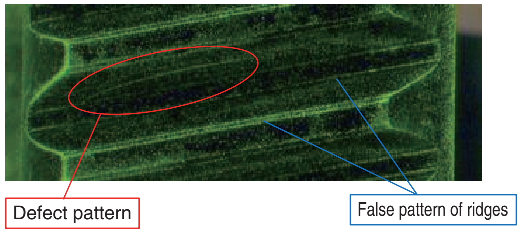

Fig. 2 False indication on rack teeth ridgeline

Issue 2: Defects occur in various modes

Defects to be detected by the magnetic particle testing include burn cracks, which occur when abnormal stresses occur on the surface of the material during heat treatment. As the shape of the target product becomes more complex, the stress state on its surface also becomes more complex, and the location, direction, and size of burn cracks may become more varied (**Fig. 3**).

It is not easy to design features and decision rules for image processing that can capture this variety of defects and distinguish them from false patterns.

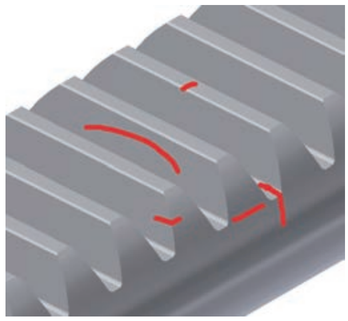

Fig. 3 Types of cracks in rack teeth

Therefore, development must be conducted to resolve these issues.

2. 3 Objectives

The objective of this development is to automate the process of magnetic particle inspection test of racks in rack and pinion steering systems.

We defined the false-negative rate and the false-positive rate as indices of decision accuracy (**Fig. 4**), and the development goal was to develop an automation technology where the false-negative rate is 0% and the false-positive rate is less than 5%.

✓ False-negative: Overlooking defective products
→ Leads to the release of defective products to the market
✓ False-positive: Misclassification of normal products as defective
→ Leads to a lower pass-through rate

$$\text{False-negative rate} = \frac{\text{Number of false-negative workpieces}}{\text{Number of inspected workpieces}}$$

$$\text{False-positive rate} = \frac{\text{Number of false-positive workpieces}}{\text{Number of inspected workpieces}}$$

Fig. 4 Definition of parameters

3. Development Technologies

To address the issues described in the previous section, this project aimed to achieve its objectives using a two-pronged approach by developing technology for applying magnetic particles and by developing image decision technology.

3. 1 Magnetic Particle Application Technology

The decision algorithm is important for image decisions, but it is also important to obtain images where recognition is easy.

In regular visual inspection, a combination of imaging methods and lighting is used to make the features of defects more prominent. In the magnetic particle testing, the process of adhering magnetic particles to the object is called applying magnetic particles, and since this method greatly affects the features of defects, this development focused on the method of applying magnetic particles.

With the current method of applying magnetic particles, the adhesion of magnetic particle to defects is uniform, but there are shades of adhesion in the false patterns that occur on the ridges of tooth tips and tooth bases (**Fig. 5**). This non-uniformity of magnetic particle adhesion makes the feature extraction difficult for the decision algorithm.

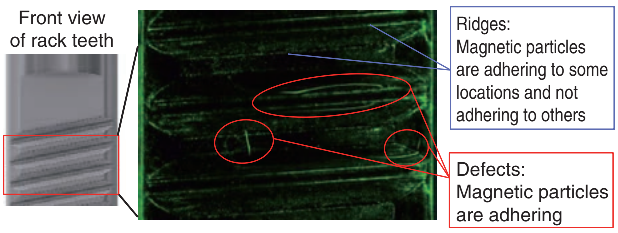

Fig. 5 Current magnetic particle application (rack teeth)

The cause of these types of non-uniform false patterns is thought to be the effect of the strength of the magnetization and the strength of the flow of the magnetic particle solution when applying the magnetic particles.

During the application of magnetic particles, there are two forces acting on the magnetic particles: the force F_1 that adsorbs the particles at the magnetic poles and the force F_2 (**Fig. 6**)[4] generated by the flow of the magnetic particle solution. In the defect area, the flux leakage is large and always $F_{1\ \mathrm{defect}} \gg F_2$, and so the magnetic particles adhere evenly to the surface. On the other hand, it is known that the flux leakage at ridges, where cross-section abrupt change indications occur, is smaller than the flux leakage at a defect, and if the strength of the flow is non-uniform, it is possible that locations could exist where $F_{1\ \mathrm{ridge}} > F_2$ and where $F_2 > F_{1\ \mathrm{ridge}}$. This is thought to produce a non-uniform false pattern.

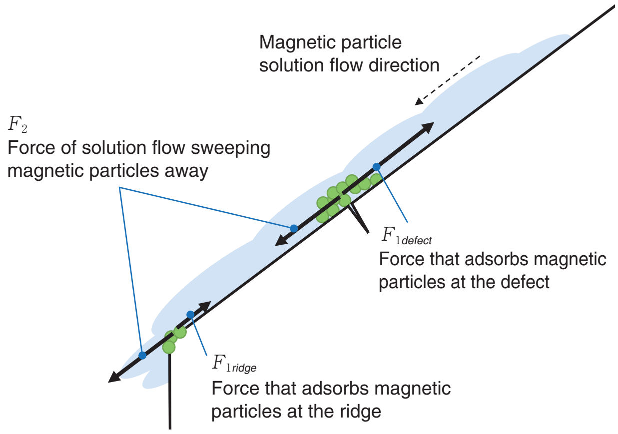

Fig. 6 Force acting on magnetic particles

To resolve this issue, we created a uniform flow of magnetic particle solution against the inspection surface and adjusted the balance between F_1 and F_2 by the magnetization strength and flow strength, and developed two methods of applying magnetic particles.

①Pattern 1: Applying magnetic particles without generating false patterns

By setting $F_{1\ \mathrm{defect}} > F_2 > F_{1\ \mathrm{ridge}}$, the false patterns at the ridges are always swept away by the flow of the magnetic particle solution, and the false patterns at the ridges do not occur (**Fig. 7**). This image has the property that defects can be easily extracted by the decision algorithm.

②Pattern 2: Applying magnetic particles to stably generate false patterns

By setting $F_{1\ \mathrm{defect}} > F_{1\ \mathrm{ridge}} > F_2$, false patterns are not swept away and uniform false patterns are generated (**Fig. 7**). This image has the property that both crack and ridge features can be obtained by the decision algorithm.

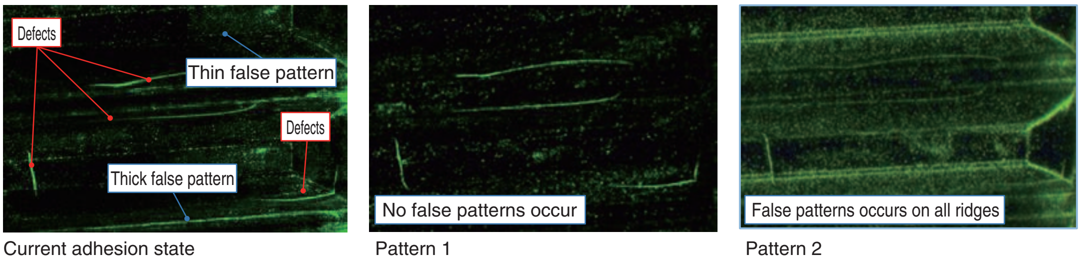

Fig. 7 Comparison of magnetic particle application methods

3. 2 Image Decision Technology

Existing rule-based processing could not handle the extraction of defects from images containing false patterns and the detection of a variety of defects. To deal with these issues, we decided to use an image classification method based on deep learning as the decision method.

Deep learning is characterized by the fact that features are automatically extracted and decisions are made by learning the data. This is expected to enable it to distinguish between a variety of defects and false patterns. In this development, supervised learning using convolutional neural networks (CNNs) was adopted as the learning method to provide the training for deep learning. Compared to rule-based decision making, CNNs are known to be robust to shifts in image position and changes in shape, color, and brightness, and can recognize a variety of objects with a single model by training appropriate data beforehand. In the production lines that are subject to automated inspection, the products that flow have different diameters, modules, and gear cutting directions and angles. Also, these properties of CNN are a great advantage because the way that magnetic particles adhere varies from one product to another.

As a model for deep learning, we created a model based on EfficientNet[5)], which is known to have high image recognition accuracy among CNN architectures.

In supervised learning, both the quality and quantity of the data used as a teacher have an important impact on the decision results. However, in actual mass production, the occurrence of cracking defects is extremely rare, and it is not possible to obtain sufficient data for model creation. Therefore, by deliberately manipulating the heat treatment conditions, defective samples with various modes of cracking were created for data acquisition, and images were acquired. In order to improve the robustness of the decision-making for various concentrations of magnetic particle solution, which vary daily, we also acquired images with different concentration levels.

Data enhancement was also performed by image processing in order to improve the decision accuracy. For the data enhancement, we prepared images with deformations and rotations, assuming differences in the shapes of products based on their model numbers. For defects that occur infrequently, simulated crack images are created by GAN*, and finally the obtained images are divided by a grid, and about 200 000 defect images are used for training. These processes are expected to improve the decision accuracy rate even for model numbers that are not used for learning.

* GAN: A type of machine learning model that can learn the features of the data for generating previously non-existent data based on those features.

4. Results

4. 1 Batch Test Results

Two types of images obtained by the developed magnetic particle application method patterns 1 and 2 were acquired for training and decision-making, respectively. The conditions for the images used for training were as follows (**Table 1**).

Table 1 Details of image data

Item	Conditions
Model No.	6 types
Quantity	580 total
Concentration	Level 6
Number of images (after division)	NG (Fail): 200 000 OK (Pass): 150 000

The conditions under which we conducted the study were as follows (**Table 2**).

Table 2 Details of deep learning

Item	Conditions
Framework	Tensor Flow
Model	EfficientNet-based model
Optimization algorithm	Adam
Learning rate	1E-4
Batch size	24
Number of epochs	10

The accuracy rate for decisions made under the above conditions is shown in **Fig. 8**. The high-dimensional features that are output from the model were dimensionally compressed using the t-SNE method**, and the visualization of the classification status is shown in **Fig. 9**. The decision accuracy rate is the average of the results of the three-part cross-validation.

** t-SNE method: Algorithm for compressing dimensions in order to represent the analysis of high-dimensional data in two or three dimensions

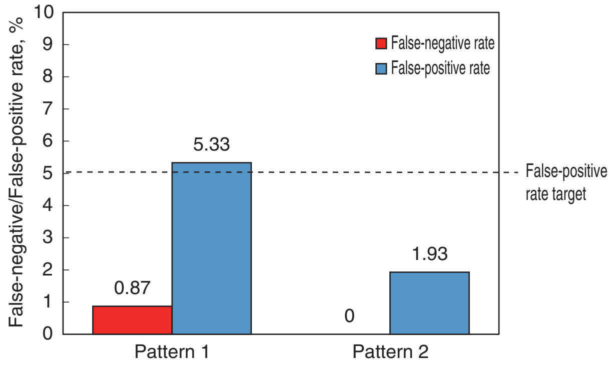

Fig. 8 Accuracy of the image recognition

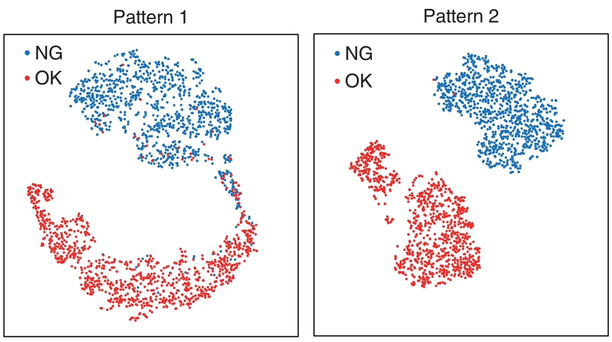

Fig. 9 Visualization of classification

The decision results showed that pattern 2, where the false pattern of the ridges was evenly applied, achieved the goal of no false-negatives and a low false-positive rate. It can be confirmed that, under these conditions, the defective section (NG) and the normal section (OK) are more separated. It is thought that the learning model captured the respective features of both defects and false patterns for enabling stable decision-making.

On the other hand, image pattern 1, which does not generate a false pattern, resulted in false-negatives. This is thought to be due to the force that sweeps away the false pattern becoming stronger, causing the magnetic particles of some defects to be swept away, making it difficult to discern the features of the defects. Also, there was a tendency to misclassify a small amount of false patterns as defects, resulting in a large number of false-positives.

4. 2 Decision Accuracy Rate in Mass Production

Based on the results of the batch tests, a method of applying magnetic particles that stably adhere to the false patterns was used for the automatic inspection machine installed in the production line. This inspection machine (**Fig. 10**) was installed in the production line and flowed in parallel with the conventional manual inspection machine.

Fig. 10 Automatic inspection machine

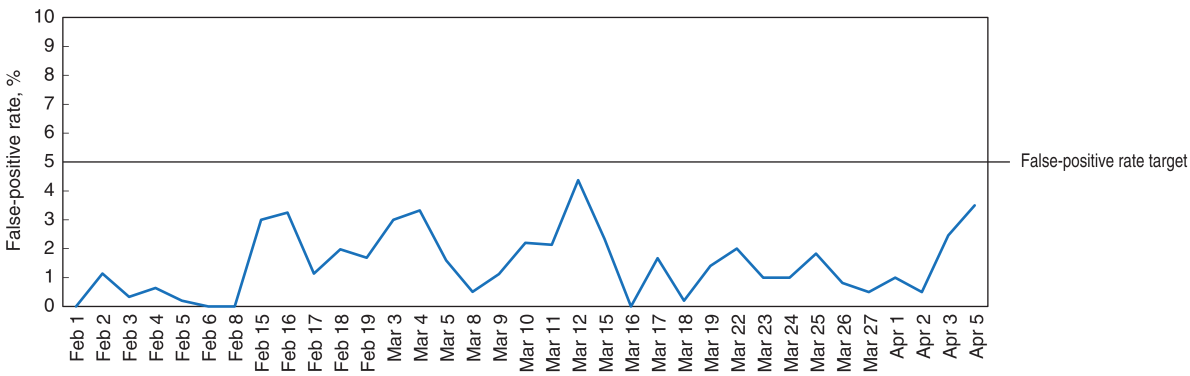

Fig. 11 Over-detection rate in mass production

Parallel flow was conducted from February to April 2021 with approximately 50 000 products, and the results of automatic and human decisions during this period were recorded to calculate the false-positive rate (**Fig. 11**). Because there were no defects during the entire period, verification of false-negatives was conducted using the NG (Fail) samples prepared beforehand.

Immediately after installation, the number of false-positives increased due to the difference in the magnetic particle solution state from the batch test, but the defect data was acquired again and the model was relearned in order to adjust to the magnetic particle solution state, and it was confirmed that the false-positive rate remained less than 5%. During this process, verification was performed using NG samples to ensure that no false-negatives occurred.

In this period, many products with part numbers not used for training were flowing, but the decision accuracy did not decrease, confirming the generalization performance of the decision model.

5. Conclusion

The automation technology that was developed for the magnetic particle inspection test process is capable of detecting multiple crack modes in products with complex shapes, and it has attained a decision accuracy having a 0% false-negative rate and less than 5% false-positive rate in mass production.

We were able to achieve our objective by combining decision-making by deep learning, which is capable of capturing complex features, with a method of applying magnetic particles that makes it easier to extract features.

Looking forward, we also intend to implement this technology to the magnetic particle inspection test process for pinion shafts and drive shafts to further reduce human labor and improve product quality in the factory.

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