Defect Classification on Automobile Tire Inner Surfaces with Functional Classifiers*

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In this paper, we present a method that functionally combines a convolutional neural network (CNN) and a support vector machine (SVM) to classify defects occurring on the inner surface of an automobile tire. Because such defects are usually small, the image requires high resolution to show the shape change of the defect in the image. Dividing one image into multiple images of smaller regions increases the number of images, which limits the applicable machine learning methods. For this reason, CNN is applied to the divided images of the whole tire, while SVM is applied to the divided images within the range delimited by CNN. Experimental results demonstrate that the defect detection rate of the proposed method is 100%, with an area rate of over-detection of 0.040% in the inspection range of a non-defective tire, demonstrating that the method is effective for reducing over-detection errors while maintaining defect detection accuracy.

1. Introduction

During an appearance inspection of an automobile tire (hereafter, simply “tire”), the appearance of the external side (or “outer surface”) and the internal side (or “inner surface”) of the tire are comprehensively examined by an inspector using visual observation and the tactile sensations of the hand. Defects on a tire’s inner surface occur during the curing process, wherein the shape of the tire is imparted by loading unvulcanized tires consisting of unvulcanized rubber and composite materials into a curing machine, which raises the temperature and adds pressure. Inside the curing machine, the tire shape is imparted by inflating a bladder for vulcanizing the tire and pressing it to the mold outside. The bladder surface has various unevenly shaped patterns that are transferred to the inner surface of the tire (Fig. 1). The rubber bladder undergoes irregular expansion and contraction upon pressing. Therefore, the patterns transferred to the tire’s inner surface (“background patterns”) differ among tires.

When inspectors detect potential defects on the background patterns using tactile sensation and visual observation, they judge the presence or absence of a defect by collating these sensations and observations with defects specified in the inspection standard. However, because the accuracy of human inspectors is influenced by the inspector’s level of skill and experience, maintaining a high degree of accuracy is a challenging task.

We propose an approach that uses a device for imaging the entire range of a tire’s inner surface, together with a computer-based method for detecting defects with a high degree of accuracy. The approach can be implemented in combination with inspections conducted by human inspectors. Displaying the data obtained from imaging the tire’s inner surface over a region classified as defective by the computer enables the inspector to observe the tire’s inner surface using a visual check only, without touching the tire. The approach should result in a reduction in the defect detection workload of inspectors and an improvement in inspection accuracy, as the inspector examines only those regions classified by the computer as defects.

As described herein, the target detection rate is 100% for the implementation of automated inspections. If the number of over-detection regions (the
number of regions incorrectly identified as defective) of a non-defective tire is only one area per tire, then the target area rate of over-detection is set as 0.075% or less, which will not be much of a load on the inspector. This result is obtained by converting the figure of the region of over-detection into a percentage of the surface area of the tire’s inner surface.

2. Related Studies

Studies related to outer surface and inner surface tire appearance inspections have been described in earlier reports.

Regarding the outer surface, Takahashi and others developed a three-dimensional (3D) shape-measuring device using a light-section method[1] intended for sidewalls (the surfaces perpendicular to the tire contact surface) of truck and bus tires[2] and a defect detection method performed by removing designs (characters, numeric characters, logo, etc.) using image processing for irregular surface defects (limited to those generated on the assembled parts of composite materials)[3].

Funahashi and others reported an external surface feature extraction method using a light-section approach and image processing to judge the presence or absence of a convex type elliptical thin and wide surface defect having a thickness of approx. 0.4mm and an area of approx. 100mm$^2$ generated on the tread surface (tire contact surface)[4].

A representative defect affecting the appearance of the tire might consist of an expansion of the rubber surface due to air remaining in the tire. Because such a defect often forms a gently rounded shape, slight changes in the amount of reflected light necessary for defect classification can be identified using an imaging method for measuring the amount of reflected light irradiated at a fixed angle. In this way, obtaining the characteristics necessary for defect detection can be expected for defects associated with shape changes using the light-section method. However, while many cases of its application[2,4] to the outer surface of tires have been reported in the literature, there have been only a few reported cases of its application to a tire’s inner surface, due to the fact that the light-section method requires space for installing imaging devices such as cameras and lasers.

In related studies, image processing has been used for defect classification. Several of the approaches[3] share a common methodology. Data defining the designs and background patterns of non-defective tires are created in advance. The data defined with non-defective tires are then removed from the imaged data of a tire with a defect, which allows the identification of defective parts. However, it has been difficult to improve the versatility of the approach as it requires the division of processing into the respective types of non-defective tires and limits the classification of objects to specific defect types.

To deal with inner surface inspections, we examine the light-section method for imaging, and a method that combines a convolutional neural network (CNN)[5] and a support vector machine (SVM)[6] to classify defects and non-defective areas. We verify the effectiveness of the approach for defect classification for various background patterns.

3. Definition of Classification Objects

We divide the classification objects into three categories: defective parts (DP), quasi-good parts (QGP), and good parts (GP). As described below, in the final classification, DPs are classified as defects, whereas both GPs and QGPs are classified as non-defective. The definition of DP is based on the judgement of a specialist. The specialist, who is a qualified tire appearance inspector, checks the tire surface and determines the locations of the defects. An area judged to be free of defects by the inspector but having an uneven shape different from the background patterns on the tire’s inner surface is defined as QGP. An area that is neither DP nor QGP is defined as GP. The definitions and examples of the three classification objects are shown in Figs. 2, 4, and 5. Delimited DP areas are shown in Fig. 3.

4. Outline of the Suggested Method

The defect occurrence rate for tire inner surfaces tends to be quite low 1% or lower and the ratio of the number of training images for each classification class tends to be asymmetrical. In addition, because DP and QGP have similar characteristics, images with similar characteristics exist among the training images of each classification class, which engenders a loss in the symmetry of characteristics. Therefore, a highly accurate classification of objects as GP + QGP or as DP using only one classifier is difficult. An ensemble technique[7] has been proposed for resolving the difficulty presented by such an unbalanced dataset. Wu and others suggested a classifier with a
cascade structure that considers the balance of the number of training images for asymmetric data[8]. We developed this method as a multistep classifier using CNN[9,10]. After close examination, we discovered that the method of combining two classifiers[9] and the ratio of the number of training images to the classification class[10] simultaneously produced both an improvement in defect detection accuracy and a reduction in over-detection. However, because it was impossible to detect all defects, further improvement in defect detection accuracy was necessary[11]. In this study, we propose a method for functionally combining CNN and SVM based on a multistep classifier. Although CNN is effective for extracting invariant characteristics, it is unable to acquire a globally optimal solution in all cases. On the other hand, SVM, with a fixed kernel function, is unable to extract complicated invariant characteristics but can guarantee a globally optimal solution by maximizing the margin using the soft margin method[12]. However, unlike CNN, which can perform mini-batch learning, SVM requires a very large amount of memory for training. Therefore, applying it to a large-scale dataset with multiple dimensions is difficult. Because many of the object defects in this study are quite fine, the surface shape images are necessarily of high resolution and shape changes are included in the images. If a single image is divided into multiple images of smaller regions, the increase in images can make the use of SVM alone infeasible. Thus, in our approach, CNN is applied to the divided images of the entire tire, while SVM is applied to the divided images within the region delimited by CNN. This structure enables CNN to process an enormous volume of images, while SVM classifies the images with defects and those of characteristics similar to the defects.

The experimental procedure is described in Figs. 6 through 9. The surface shape with the tire curve removed is converted to an image. First, the surface shape images of the tire inner surface are produced (Fig. 6). Next, as a training step, a single-step classifier and a two-step classifier are created (Fig. 7). The single-step classifier classifies objects as GP + QGP or as DP. The two-step classifier is a combined classifier by which the first classifier classifies objects as GP or QGP + DP, and the second classifier classifies objects as QGP or DP. Finally, as a testing step, the divided images classified as DP by each classifier are extracted for the divided image where the entire area of the tire’s inner surface is segmented by a sliding window (Fig. 8). The extracted divided images are reconstructed into one piece of the tire to verify the accuracy of the classification (Fig. 9).

5. Creating Surface Shape Images on the Tire Inner Surface

5.1 Imaging Method

The light-section method is used to measure 3D shapes on the tire’s inner surface. The measurement principle is presented in Fig. 10. The cross-section shape is obtained by imaging the area where a slit
laser light is irradiated on the measured object with a camera tilted at a predetermined angle. The shape data are obtained by moving the measured object continuously. Where the tire inner surface is the object, sectional shapes are measured by dividing the imaging area of the tire’s inner surface into three parts: upper inner sidewall, inner tread, and lower inner sidewall. Depth images of the tire’s entire inner surface are obtained by rotating the tire more than one turn. Because there is little space inside the tire, the imaging device is installed outside the tire, and the irradiation light direction and the reflection light direction are changed by mirrors as depicted in Fig. 11. The three divided imaging areas are set as mutually overlapping across the tire width, as presented in Fig. 12. This overlapping prevents any unintentional omission of imaging on any area.

5.2 Image Creation Method

The minimum image height and width of the object defect to be classified were set at 0.5mm; the maximum dimensions were set at 15mm. The minimum spatial resolution in the depth range was set at 0.1mm; the maximum spatial resolution was set at 1mm. The camera resolution and tire rotation speed were set such that the image resolution of the tire width and tire circumference would be approx. 0.1mm to include the shape change of the defect in the image. The resolution in the depth range is determined by the camera resolution and camera and slit light angles: it was set at approx. 0.02mm. When one tire is imaged, a depth image of approx. 20,000 × 1,500 pixels in the tire circumference (corresponding to the image height) and the tire width (corresponding to the image width) is obtained for each three-division imaging area of the tire’s inner surface.

The tire cross section includes a curved component, as shown in Fig. 11. It is desirable to remove the curved component from the image to be input in the classifier beforehand, as a defect is a fine shape on the tire’s inner surface. For this study, curved component images are created by processing a filter, such as a median or average, on the depth images, so that the curved component images are removed from the depth images[11]. After removing the curved component images, the gradation value is adjusted. The gradation values are ± 50 (equivalent to ± 1mm in the depth range) and are converted to a grayscale image to obtain surface shape images. Fig. 13 shows the process flow that is followed when creating the surface shape images of the tire’s inner surface.

6. Outline of the Experiments

6.1 Classification Objects used in the Experiments

A total of 531 tires collected at various tire factories were used as classification objects. A qualified tire appearance inspector judged the presence or absence of defects while we simultaneously confirmed the positions of the DP and QGP. The number of classification objects is shown in Tables 1 and 2. Images were selected randomly for training and testing after classifying them by tire size, background patterns, and defects.

6.2 Evaluation Index of Classification Accuracy

Detection accuracy based on 27 pieces of DP and over-detection accuracy based on 216 pieces of non-defective tires are calculated according to Eq. (1) and
Table 1 Number of classification objects (training)

| Tires | DP  | QGP | GP |
|-------|-----|-----|----|
| TIRES | 271 | 146 | 610|
|       | 23  | 0   | 0  |
| Entire area | 0 | 0 | 0 |

Table 2 Number of classification objects (testing)

| Tires | DP  | QGP | GP |
|-------|-----|-----|----|
| TIRES | 21  | 27  | 0  |
|        | 216 | 0   | 148|
| Entire area excluding QGP | 0 | 0 | 0 |

Equation (2), respectively. Equation (1) is the detection accuracy for defects and the index for quantifying defect detection capability. Equation (2) is the area rate of over-detection compared with the surface area of the inner surface of a non-defective tire and the index for quantifying the work amount of an inspector for confirmation on a display.

Recall and precision are often used as evaluation indexes of classification accuracy; however, they were not adopted for examination in these analyses. Regarding the DP on the tire’s inner surface, one DP is cut out as a plurality of images by a sliding window. Because the defect detection must detect at least one plurality of images as a defect, it is necessary to calculate the defect detection rate based not on the divided image but on the number of defects. Defect detection accuracy is defined in Eq. (1). However, for over-detection of the tire’s inner surface, the ratio of the surface area to be inspected must be quantified by the inspector. Therefore, it is necessary to calculate over-detection based on the divided image. The over-detection accuracy calculation is shown in Eq. (2).

\[
\text{Defect detection rate} = \frac{\text{DP detection count}}{\text{Total number of DP}} \times 100 \quad (1)
\]

\[
\text{Area rate of over-detection regions} = \frac{\text{Over-detection total area of QGP and GP}}{\text{Total area of QGP and GP}} \times 100 \quad (2)
\]

6.3 Classifier

CNN and SVM were used for the classifier. The network-in-network[13] structure (Fig. 14) widely applied to general image recognition was used for CNN. The input image size was 256 × 256 pixels. Stochastic gradient descent[14] was used as the optimization method. The linear kernel was used for the kernel function in SVM. Two conditions were used for SVM, one using an input image size of 256 × 256 pixels and a grayscale image input, and the other replacing the global average pooling layer of network-in-network by SVM (CNN + SVM) (Fig. 15).

6.4 Creating Testing Image and Training Image Conditions

This step in testing requires a function for detecting defects from the entire image of the tire and a function for detecting the positions of the defects. In the field of image recognition, Selective Search[15] and BING[16] are suggested as methods for the high-speed extraction of object candidate regions from high-resolution images. However, clear definition of the boundary surfaces of the QGP and DP examined in this study is difficult given the background patterns, making it challenging to apply the methods[15,16]. Therefore, segmenting the entire tire image using a sliding window was adopted as an effective method, although the calculation cost is high. The segmented image size and the slide pitch were considered as follows. Because the maximum size of the object defects used in the experiment was 15mm, the condition that “the size of a segmented image − the slide pitch > the maximum sizes of the object defect” must be met in order to include the entire object defect in the segmented image. While the size of a segmented image was set at approx. 25 × 25mm (256 × 256 pixels) because of use with no change in the number of layers of the network-in-network of the classifier, the slide pitch was set as 80 pixels so that two-thirds of each divided image was mutually overlapping. The number of divided images per tire is approx. 12,000. The segmented images are then divided into images including DP, images including QGP, and GP (Fig. 16). Among multiple DP images containing one DP, if at least one is identified as being in the DP class, then DP detection is performed. For GP and QGP images, over-detection is checked for each image. The GP and QGP images confirm the over-detection. (Fig. 17).

In training, the creation conditions of the training images were divided between the first classifier and the second classifier as follows: In the first classifier, the number of QGP and DP is smaller than that of
GP was added to adjust the number of training images for each classification class. The creation conditions of the training images of DP, QGP, and GP in the first classifier are shown in Tables 3, 4, and 5. In the second classifier, the condition of randomly selecting images so that the number of images for each of DP and QGP can be approx. 5,000 and the condition without sliding were set. The creation conditions of the training images of DP and QGP are presented in Tables 6 and 7.

### Table 3 Training image creation of the first classifier (DP)

| Creation condition | Number of DP | Slide pitch [px] | Number of slides | Number of images |
|--------------------|--------------|------------------|------------------|-----------------|
| DP1-1              | 146          | 5                | 8                | 41,905          |
| DP1-2              | 146          | 2                | 25               | 371,586         |

### Table 4 Training image creation of the first classifier (QGP)

| Creation condition | Number of QGP | Slide pitch [px] | Number of slides | Number of images |
|--------------------|---------------|------------------|------------------|-----------------|
| QGP1-1             | 610           | 5                | 8                | 174,964         |

### Table 5 Training image creation of the first classifier (GP)

| Creation condition | Number of GP | Slide pitch [px] | Number of slides | Number of images |
|--------------------|--------------|------------------|------------------|-----------------|
| GP1-1              | Entire area  | 80               | Unlimited        | 262,488         |
| GP1-2              | 3.8% of GP1-1, randomly selected | 80 | Unlimited        | 9,982           |
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| Table 6 | Training image creation of the second classifier (DP) |
|---------|-----------------------------------------------------|
| Creation condition | Number of DP | Slide pitch [px] | Number of slides | Number of images |
| DP2-1   | 16         | 5                | 8                | 4,488          |
| DP2-2   | 146        | 0                | 0                | 146           |

| Table 7 | Training image creation of the second classifier (QGP) |
|---------|-----------------------------------------------------|
| Creation condition | Number of QGP | Slide pitch [px] | Number of slides | Number of images |
| QGP2-1 | 18         | 5                | 8                | 5,202          |
| QGP2-2 | 610        | 0                | 0                | 610           |

7. Change of Classification Accuracy by Multistep Classifier

The classification accuracy of a single-step classifier and that of the first classifier of a two-step classifier are compared next. Experiments using CNN as a classifier were conducted as described in Sections 7.1 and 7.2; experiments using SVM as a classifier were conducted as described in Sections 7.3 and 7.4.

In using CNN for the classifier, the following were set as the fixed parameter values: The scheduling of the learning rate was set as $\eta \times 0.97^E$. The initial learning rate $\eta$ was selected from $\{5 \times 10^{-3}, 1.0 \times 10^{-2}, 2 \times 10^{-2}\}$. $E$, the number of epochs, was selected from $\{20, 30\}$. The mini-batch was selected from $\{16, 32, 64\}$. The parameter shown experimentally to have good defect detection accuracy was adopted for each classifier.

In using SVM for the classifier, the regularization coefficient $C$ was fixed at 1.0.

7.1 Creation of Each Classifier (CNN)

7.1.1 Single-Step Classifier (CNN)

Details of the single-step classifier are presented in Table 8. Regarding the creation conditions of each training image, GP is described as GP1-1, QGP as QGP1-1, and DP as DP1-2.

7.1.2 First Classifier in a Two-Step Classification approach

Details of the first classifier of a two-step classifier are presented in Table 9. Regarding the creation conditions of each training image, GP is described as GP1-2, QGP as QGP2-1, and DP as DP2-1.

7.2 Experimental Results

The defect detection accuracy of each classifier with respect to 27 pieces of DP is shown in Fig. 19(a). According to the figure, the first classifier of the two-step classifier has a 42.9% higher accuracy of defect detection than the single-step classifier, detecting all 27 defective pieces. In addition, the over-detection accuracy of each classifier with respect to 216 non-defective tires is shown in Fig. 19(b). According to the figure, the first classifier of the two-step classifier has 0.063% higher over-detection accuracy than the single-step classifier, which has an accuracy of 0.081%, slightly greater than the target value of 0.075%.

Consequently, multistep classifiers appear to be effective in maintaining high defect-detection accuracy. The second classifier is necessary for reducing over-detection.

7.3 Creation of Each Classifier (SVM)

7.3.1 Single-Step Classifier (SVM)

Details of the single-step classifier are presented in Table 10. Regarding the creation conditions of each training image, GP is described as GP1-2, QGP as QGP2-1, and DP as DP2-1.

7.3.2 First Classifier in a Two-Step Classification approach (SVM)

Details of the first classifier of the two-step classifier are presented in Table 11. Regarding the creation conditions of each training image, GP is described as GP1-2, QGP as QGP2-1, and DP as DP2-1.

7.4 Experimental Results

The defect detection accuracy of each classifier with respect to 27 pieces of DP is shown in Fig. 20(a).
Table 10 Training image details of a single-step classifier (SVM)

| Class       | Classification object (Creation condition) | Number of images |
|-------------|--------------------------------------------|------------------|
| GP+QGP      | GP(GP1-2) + QGP(QGP2-1)                    | 15,184           |
| DP          | DP(DP2-1)                                  | 4,488            |

Table 11 Training image details of the first classifier in a two-step classification approach (SVM)

| Class  | Classification object (Creation condition) | Number of images |
|--------|--------------------------------------------|------------------|
| GP     | GP(GP1-2)                                  | 9,982            |
| QGP+DP | QGP(QGP2-1) + DP(DP2-1)                    | 9,690            |

8. Change of Classification Accuracy for Each Method in the Second Classifier

This section compares the classification accuracy that results from using CNN, CNN + SVM, or SVM for the second classifier in a two-step classification approach.

The following values were set as the fixed CNN parameters: The scheduling of the learning rate was set as $\eta \times 0.97^E$; the initial learning rate $\eta$ was selected from $\{5 \times 10^{-3}, 1.0 \times 10^{-2}, 2 \times 10^{-2}\}$. $E$, the number of epochs, was selected from $\{20, 30\}$. The mini-batch was selected from $\{16, 32, 64\}$. The parameter shown experimentally to have good defect detection accuracy was adopted for each classifier.

As shown, the first classifier of the two-step classifier has a 7.4% higher accuracy of defect detection than the single-step classifier, detecting all 27 defective pieces. The over-detection accuracy of each classifier with respect to the 216 non-defective tires is presented in Fig. 20(b). As indicated, the first classifier of the two-step classifier has a 14.059% better over-detection accuracy rate than the single-step classifier, which has an accuracy of 32.808%.

Thus, multistep classifiers appear to maintain a high level of defect detection accuracy. The second classifier is necessary for reducing over-detection.

In the CNN + SVM case, the global average pooling layer of the trained network-in-network is replaced by SVM, which is to be trained in the structure.

For the SVM case, the images are input “as-is” to be trained in the structure, as in CNN. For SVM, the regularization coefficient $C$ was fixed at 1.0.

8.1 Creation of Each Classifier

8.1.1 Second Classifier in the Two-Step Classification Approach (CNN)

Details of the second classifier in the two-step classification approach (using CNN) are presented in Table 12. Regarding the creation conditions of each training image, QGP is described as QGP2-1 and DP as DP2-1.

8.1.2 Second Classifier in the Two-Step Classification Approach (CNN + SVM)

Details of the second classifier in the two-step classification (using CNN + SVM) are presented in Table 13. Regarding the creation conditions of each training image, QGP is described as QGP2-1 and DP as DP2-1.

8.1.3 Second Classifier of in the Two-Step Classification Approach (SVM)

Details of the second classifier in the two-step classification (using SVM) are presented in Table 14. Regarding the creation conditions of each training image, QGP is described as QGP2-2 and DP as DP2-2.

8.2 Experimental Results

The defect detection accuracy of each classifier with respect to the 27 pieces of DP classified as QGP+DP by the first classifier of the two-step classification approach described in Section 7.1.2 is presented in Fig. 21(a). The respective defect detection accuracies of CNN and CNN + SVM were confirmed as 92.6% and 96.3%. For SVM, the defect detection accuracy was confirmed as 100%.

Fig. 21(b) shows the over-detection accuracy of each classifier with respect to the images of over-detection classified as being in the QGP+DP class by the first classifier described in Section 7.1.2. The respective over-detection accuracies of CNN and CNN + SVM were 0.049% and 0.054%, whereas the over-detection accuracy was confirmed as 0.040% in the case of SVM.

It is reasonable to infer from the findings presented above that SVM is most suitable for classifying DP and QGP. Furthermore, CNN + SVM has fewer
Table 12 Training image details in the second classifier in a two-step classification approach (CNN)

| Class | Classification object (Creation condition) | Number of images |
|-------|-----------------------------------------------|------------------|
| QGP   | QGP(QGP2-1)                                   | 5,202            |
| DP    | DP(DP2-1)                                     | 4,488            |

Table 13 Training image details of the second classifier in a two-step classification approach (CNN+SVM)

| Class | Classification object (Creation condition) | Number of images |
|-------|-----------------------------------------------|------------------|
| QGP   | QGP(QGP2-1)                                   | 5,202            |
| DP    | DP(DP2-1)                                     | 4,488            |

Table 14 Training image details of the second classifier in a two-step classification approach (SVM)

| Class | Classification object (Creation condition) | Number of images |
|-------|-----------------------------------------------|------------------|
| QGP   | QGP(QGP2-2)                                   | 610              |
| DP    | DP(DP2-2)                                     | 146              |

(a) Defect detection accuracy  (b) Over-detection accuracy

Fig. 21 Classification performance of each method in the second classifier

changes in classification accuracy than CNN. Little improvement is achieved by replacing the global pooling layer of CNN with SVM, as the weight of CNN is not optimized when the number of samples of DP and QGP is limited.

9. Conclusion

Using the light-section method to take shape measurements and functionally combining CNN and SVM were shown to constitute an effective approach to classifying the defects on a tire’s inner surface. With the proposed method, surface shape images of the entire area of the tire’s inner surface were created, and accuracy meeting particular target values, such as a defect detection rate of 100% and an area over-detection rate of 0.040%, was obtained by applying CNN for the first classifier and SVM for the second classifier.

In light of the findings presented here, it can be reasonably inferred that the suggested method improves inspection accuracy. In future explorations, further improvements in classification accuracy will be sought by expanding the experimental scale and by analyzing the relations among training images.

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