

Study of Inspection Technology for Gear Surface using Self-organizing Map

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ABSTRACT

Research was carried out on inspection technology for gear surface imperfection inspection that has the same degree of accuracy as that of a human inspector. Regarding the surface of the tooth which is the object of inspection, over-detection resulting from the extraction of uneven brightness other than that due to imperfections was an issue. For this reason, the features of imperfections that permit imperfections to be discriminated from non-imperfections were set based on visual observation. In addition, a self-organizing map which is a kind of neural network was employed as a method whereby these features are used to identify imperfections in the same way as a human inspector. By using this map to teach the inspection system the features of multiple imperfections and also uneven brightness and dirt on the surface of the gear, it was possible to recognize imperfections to the same degree of accuracy as that of a human inspector. Technology constructed using this imperfection recognition method enabled the work of visual inspection to be reduced to about 10% of that previously necessary.

1. Introduction

Automotive transmissions are composed of a large number of gears, and the quality level of these gears is known to have an effect on driving comfort⁽¹⁾. Tiny raised areas on the interlocking surfaces of gears caused by scratches and the like generate noise, which can cause discomfort to vehicle occupants. Therefore, gear tooth surfaces are visually inspected. However, visual inspection places a significant burden on the inspectors, and individual differences in the accuracy with which imperfections are detected may cause variations in quality, making automation of the inspection process desirable. This paper discusses the development of a method of detecting imperfections on gear tooth surfaces and of the inspection system in which it is employed.

2. Outline of Research

2.1. Goal

The goal of this research project was to develop a technology for the detection of imperfections on gear surfaces possessing an equivalent level of accuracy to visual inspection. Imperfections occurring on gear tooth surfaces can be classified into dents, chips and scratches, as shown in Fig. 1. If a method in which potential imperfections are identified by conventional image analysis is employed to inspect for these imperfections, accuracy can be reduced by instances of over-detection, in which uneven brightness, dirt, etc. is recognized as imperfections. Over-detection occurs for the following reasons:

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- Difficulty in ensuring uniform illumination: As Fig. 1 shows, the gear surfaces are curved, and therefore there are differences in the intensity of illumination at different points.
- Recognition of a variety of different imperfection types: Because the system must be able to detect a variety of different imperfection types, criteria for recognition are complex, and establishing system settings is therefore difficult.

By contrast, over-detection rarely occurs in visual inspection, because the inspector recognizes imperfections based on a concept of what constitutes an imperfection and his or her memory of past experiences in detecting them. The following research goals were therefore established to enable the development of a method possessing equivalent accuracy to visual inspection:

- (1) Development of a technique of defining the features of imperfections (Image analysis).
- (2) Development of an ability to recognize imperfections using features of sections of captured images
- (3) Development of a learning ability to increase the accuracy of recognition

2.2. Development of Imperfection Detection Technology

This development project employed the following three element technologies to create an imperfection detection technology with equivalent accuracy to visual inspection:

- (1) Imperfection recognition technology

The ways in which inspectors discriminate between imperfections and dirt, etc. during visual inspection were analyzed to enable the new system to recognize imperfections with an equivalent level of accuracy to visual inspection. Multiple features defining the appearance of an imperfection were established on the basis of this analysis.

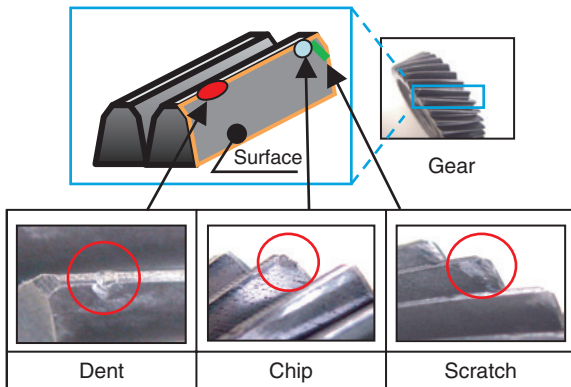


Fig. 1 Imperfection samples

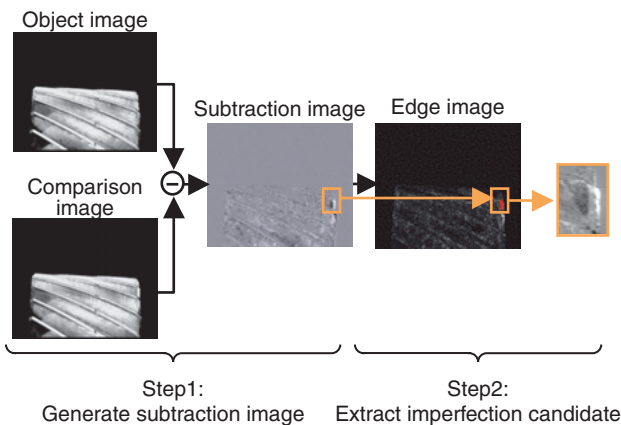


Fig. 2 Image processing to extract imperfection candidate

- (2) Practical application of imperfection recognition technology
A data classification method employing a self-organizing map (a type of neural net) has been employed to recognize imperfections. This enabled the formulation of a table grouping together similar data concerning previously detected imperfections, and over-detection elements such as uneven brightness on the surface. When an area which might be an imperfection ("imperfection candidate" below) is extracted by image analysis, the table is used to determine whether the candidate is most similar to an imperfection or an over-detection element, i.e. it enables recognition of imperfections by judgment on the level of similarity of a candidate to an imperfection.
- (3) Increased accuracy in recognition of imperfections
A learning function adds details of the imperfections, and over-detection elements encountered in inspections to date to the table, enabling the accuracy of imperfection recognition to be increased when required.

2.3. Extraction of Imperfection Candidates by Image Analysis

This section will discuss the technique used for extracting imperfection candidates, which formed the backbone of this development project. In this technique, an image of the gear tooth surface under inspection (object image) is compared with an image of another gear tooth surface (comparison image), and any area of difference is extracted as an imperfection candidate. The gear tooth surfaces are compared using a subtraction image generated according to the following formula (Fig. 2: Step 1):

$$\text{Subtraction image} = \text{Object image} - \text{Comparison image}$$

The area of difference between the original two images, in which the potential imperfection is located, becomes an area differing in brightness on the subtraction image. An edge image in which this area of differing brightness is emphasized is generated and compared with the original subtraction image, enabling the area to be extracted from the image (Fig. 2: Step 2). This becomes the imperfection candidate. Over-detection elements such as dirt and areas of uneven brightness are included among imperfection candidates; the priority in this method is to ensure that no imperfection is overlooked.

The following discussion will focus on the method of recognizing imperfections by means of classifying the features of imperfection candidates.

3. Development of Imperfection Recognition Technology

3.1. Methods Used in Visual Inspection

Multiple parameters relating to features of the external appearance of imperfection candidates have been input to the system, and these are used to recognize imperfections. The features that inspectors focus on to recognize imperfections in visual inspections were used as a reference in selecting these features. Figure 3 shows imperfections and over-detection elements (surface dirt, etc.) isolated from subtraction images. Our research suggested that human inspectors use the shape of an imperfection and the pattern of distribution of brightness around the imperfection to discriminate imperfections from dirt, areas of uneven brightness, etc. Therefore, the development team focused on the following features to ensure the achievement of an equivalent level of ability in recognizing imperfections as that of visual inspection:

- (1) Geometric features of imperfections
- (2) Features of distribution of brightness around imperfections

3.2. Determining Features of Imperfections

1: Geometric features of imperfections

In visual inspection, the geometric features that define the external appearance of an imperfection are size (area), direction (angle) and shape (circularity). These features were therefore employed as parameters in the inspection system (Fig. 4).

- (1) SA : Area
- (2) θA : Angle
- (3) CA : Circularity ($CA = SA/C$, where C is the area of a circumscribed circle of the imperfection)

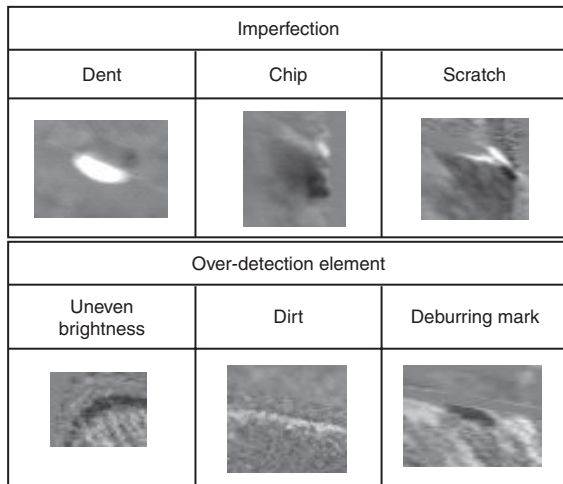


Fig. 3 Images of imperfections and over-detection elements

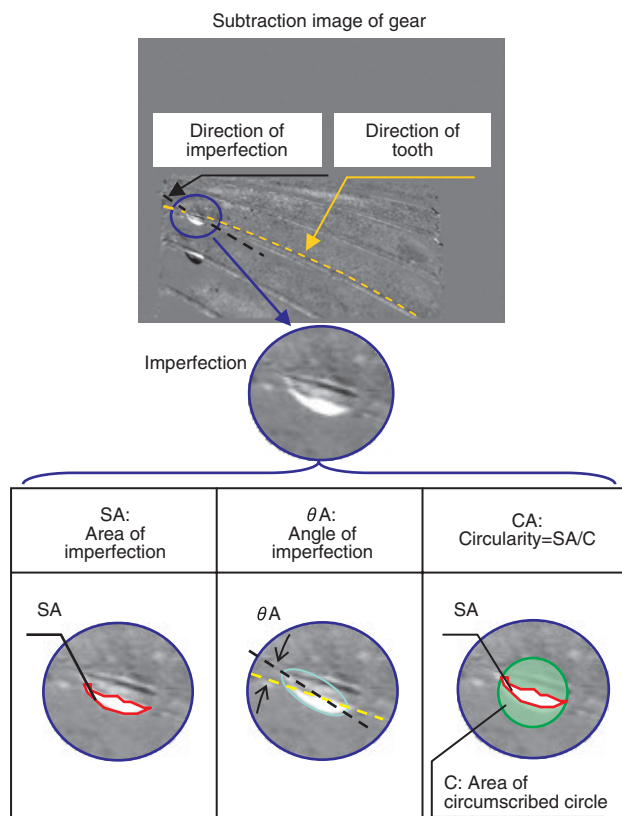


Fig. 4 Geometrical features of imperfection

2: Features of distribution of brightness around imperfections

Features of the pattern of distribution of brightness around imperfections were similarly employed as parameters. These were the messiness of the image (entropy), the symmetry of the distribution of brightness (anisotropy) and the change in brightness (average brightness of the edge image).

- (4) $entB$: Messiness (entropy)
- (5) $ansB$: Symmetry (anisotropy)
- (6) $edgB$: Change in brightness (average brightness of edge image)

By this means, the external appearance of imperfections was defined by a feature vector which imparted directionality to the six individual features. The feature vector, x , can be expressed mathematically as:

$$x = (SA, \theta A, CA, entB, ansB, edgB).$$

3.3. Feature Vector Example

Figure 5 shows feature vectors for an imperfection (a dent) and an over-detection element (uneven brightness) as an example of the extraction of feature vectors from imperfection candidates. When these are compared, significant differences are observed in CA (circularity), $entB$ (messiness) and $edgB$ (change in brightness). These features enable an imperfection to be discriminated from an over-detection element. This indicates the successful development of a technique for defining the features of imperfections, to enable imperfection candidates to be accurately judged as imperfections.

4. Practical Application of the Technique

Having developed a technique for defining the features of imperfections, it would be possible to recognize imperfections by comparing the feature vectors of imperfection candidates with existing data on imperfections and over-detection elements. A recognition table was constructed by means of the two-dimensional map shown as (a) in Fig. 6 to enable this. Images of dents, etc. and the feature vectors discussed above were imported to each node of this table (shown as (b) in Fig. 6). Judgments on whether these were imperfections or over-detection elements were also entered. This enabled the achievement of an equivalent level of accuracy in judgment of an imperfection candidate as an imperfection or an over-detection element to that achieved in visual inspection.

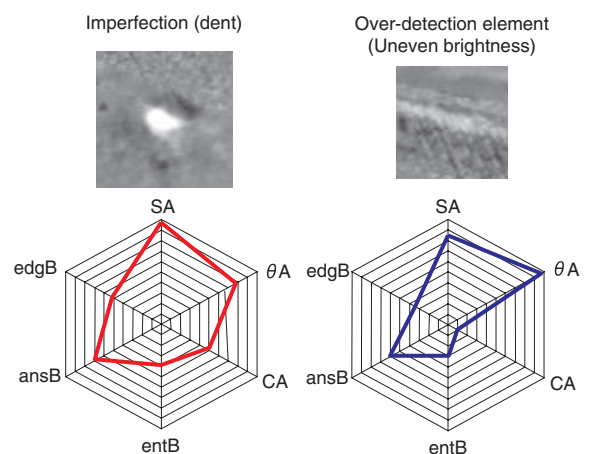


Fig. 5 Feature vector

4.1. Creation of Recognition Table

A self-organizing map⁽²⁾, a type of neural net, was employed in creating the recognition table. A self-organizing map is one method of classifying multi-dimensional data. It is an algorithm that gathers and groups similar items in multiple pieces of data. On the basis of the features delineating the external appearance of imperfections defined in section 3, this enables pieces of data (dents, dirt, etc.) with a high level of similarity to be grouped together on the two-dimensional map, as shown in Fig. 7. Imperfections are judged during inspection by determining which group the imperfection candidate resembles.

However, there are elements among the data which confuse the ability to recognize imperfections, for example dirt that resembles chips. Therefore, if a self-organizing map alone is used, there is a possibility that data that is close to the boundaries of groups will be inaccurately classified into a group. In addition, at this stage the data showing similarities was only grouped, and no judgments on imperfections had been added to the recognition table. Therefore, visual recognitions on whether the imperfection candidate was an imperfection or an over-detection element were entered for all the

data composing each group to correct inaccurate groupings. Therefore, the judgment in each group matched visual inspection values. This resulted in the creation of a recognition table equaling the accuracy of visual inspection.

As shown in Fig. 7, the recognition table was created by means of the following steps:

- (1) Calculation of similarity levels between different data
- (2) Grouping of similar data utilizing self-organizing map
- (3) Input of visual recognition

4.1.1. Calculation of similarity levels between different data

The level of similarity between data on the recognition table can be determined by the distance between their feature vectors. The smaller the distance between the feature vectors, the closer the component values of the vectors, and the higher the level of similarity. As shown below, the distance d_{ij} between the feature vector of an imperfection candidate, X (shown here as (1)) and the feature vector of a node coordinate i and j , X_{ij} , shown as (2), can be calculated using the equation shown as (3).

$$X = (SA, \theta A, CA, entB, ansB, edgB) \quad (1)$$

$$X_{ij} = (SA_{ij}, \theta A_{ij}, CA_{ij}, entB_{ij}, ansB_{ij}, edgB_{ij}) \quad (2)$$

$$d_{ij} = \sqrt{(SA - SA_{ij})^2 + \dots + (edgB - edgB_{ij})^2} \quad (3)$$

4.1.2. Grouping of similar data utilizing the self-organizing map

Data with a high level of similarity are grouped together on the two-dimensional map by the self-organizing map by means of the following steps.

Step 1: Selection of the node expressing the similarity relationship of the data

The closest node (best match node below) at that point in time is selected to express the relationship of similarity between data on the two-dimensional map. The best match node is the node possessing the feature vector most similar to a particular piece of data (Fig. 8: Step 1).

Step 2: Grouping the data

The feature vectors of the best match node and surrounding nodes are revised to ensure similarity with the various pieces of data. The amount of revision at this time is greater the closer the node is to the best match node, and smaller the further away the node is. As

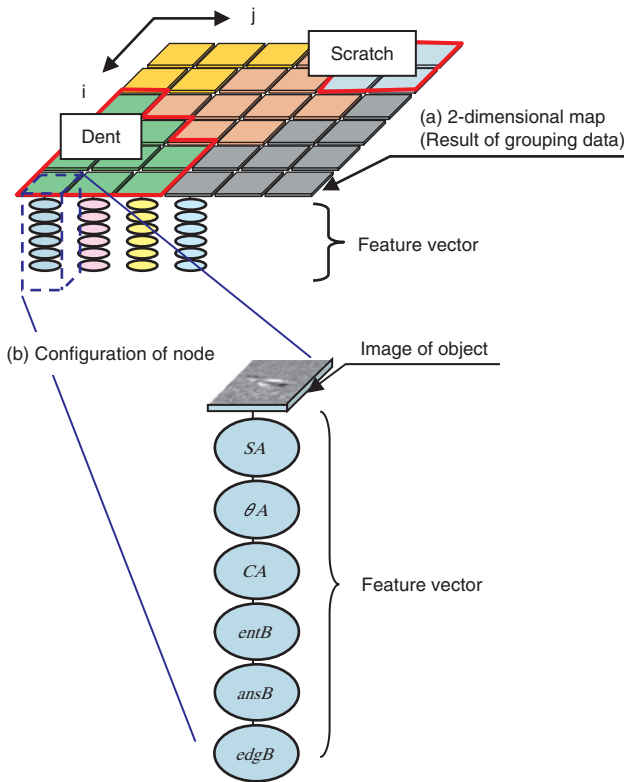


Fig. 6 Construction of recognition table

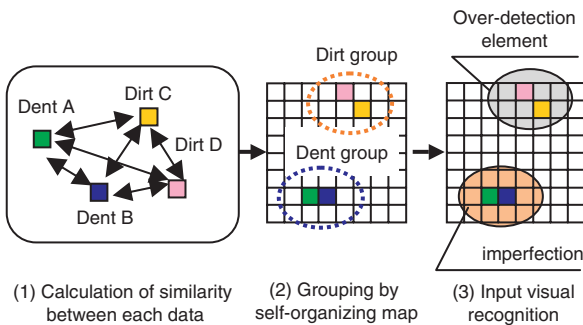


Fig. 7 Sequence of making recognition table

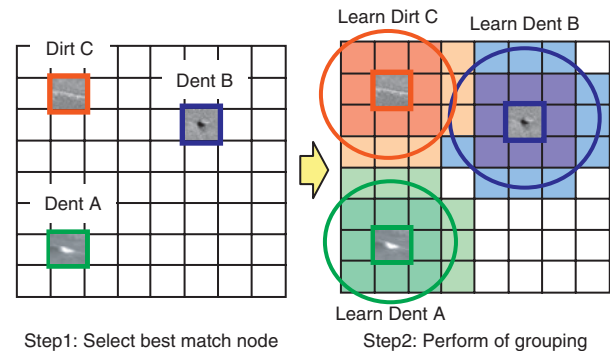


Fig. 8 Grouping data by self-organizing map

classification proceeds, the range of nodes which are revised becomes increasingly smaller. By this means, node areas are created possessing feature vectors similar to the various pieces of data (Fig. 8: Step 2).

The repetition of steps 1 and 2 ensures that the best match nodes for data with a high level of similarity are clustered closely together. By this means, as Fig. 9 shows, the level of similarity between the different data groups is expressed by the relationship between the positions of the node areas possessing feature vectors most similar to them.

- (1) When there is a high level of similarity between data
The node areas of dent A and dent B which has a high level of similarity to it are generated close together, and therefore form a single group.
- (2) When there is a low level of similarity between data
The node areas of dents A and B and the node area of dirt C, which has a low level of similarity to them, are generated in positions far apart, and dirt C therefore forms a separate group.

The shape of the node area for each piece of data and the boundaries with other node areas are automatically determined by the positional relationships of the best match nodes.

4.1.3. Input of visual recognition

To ensure that each of the groups on the recognition table match with standards for recognition in visual inspection, previous visual recognition of imperfections and over-detection elements are input for each node area forming a group. Because input is conducted for node areas, it is not necessary to input for each node, and the procedure can therefore be carried out in a short period of time.

4.1.4. Recognition table features

Figure 10 shows the recognition table formulated using the method discussed thus far. This table groups 100 pieces of data by means of 1600 (40 X 40) nodes. It is clear that the initial aim has been achieved, and that the table is composed of groups of data for dirt, dents, etc. possessing similar features.

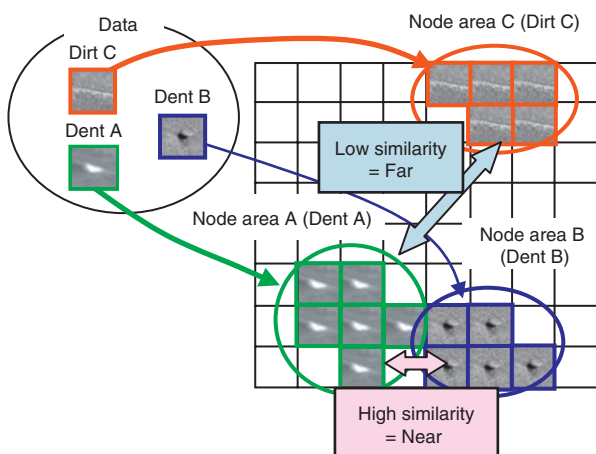


Fig. 9 Result of data grouping

The recognition table offers the following advantages.

- (1) Human judgment
The self-organizing map enables multiple pieces of multi-dimensional data to be grouped on the basis of relationships of mutual similarity with no requirement for prior knowledge. This enables the possibility of a form of recognition close to human intuition⁽³⁾.
 - (2) Stable imperfection recognition
Expressing data as node areas makes it possible to fill in the gaps between each group. This enables stable recognition of a diverse range of imperfection candidates, even with comparatively low numbers of data.
 - (3) Visual representation of relationships of data similarity
It is difficult for humans to intuitively grasp relationships of similarity between multi-dimensional data. This method enables these relationships to be represented visually on a two-dimensional map, thereby making them easy to grasp.
- The next section will explain the method of recognizing imperfections employing the recognition table shown in Fig. 10.

4.2. Recognition of Imperfections Using the Recognition Table

Imperfections are recognized using the recognition table by comparing imperfection candidates and nodes with similar feature vectors. To ensure accuracy, the imperfection candidates are compared with multiple, similar feature vectors. To enable this, match node areas are established from multiple pieces of recognition data possessing similar features to the imperfection candidate, and judgment on whether the candidate is an imperfection or not is made on the basis of these areas.

4.2.1. Calculation of match node areas

The following two elements define match node areas.

- (1) Size (Number of nodes)
The size of the match node area varies with the imperfection candidate. If the match node area is excessively large, there is

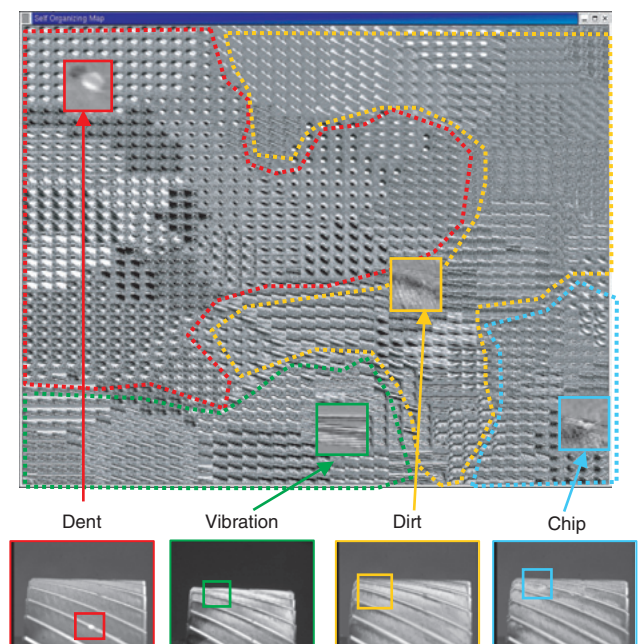


Fig. 10 Groups of data on recognition table

the possibility of an error in recognition. Therefore, an upper limit has been set for the size of the match node area. If the number of nodes in the match node area exceeds the upper limit, only the nodes with the highest level of similarity are allowed. The upper limit for the number of nodes in each area on this recognition table is 100.

- (2) Distance between the feature vector of imperfection candidate and feature vector of nodes

The match node areas are the areas in which the distance between the feature vectors of the imperfection candidate and the nodes falls below the value set as a threshold. The distribution of the number of nodes, which is the distance d between feature vectors, is calculated for the feature vector of the imperfection candidate, X , and the feature vectors of all nodes, x , as shown in Fig. 11. Threshold value (a) is set as 50% of the minimum distance (c) (best match node) from the average distance between feature vectors (b). Node areas (d) with distances between feature vectors smaller than this are taken to be the match node area (e).

4.2.2. Imperfection recognition processing

A candidate is judged as an imperfection on the basis of the percentage of nodes recognized as imperfections (imperfection nodes), including those falling within the match node areas, as shown below.

- Imperfection node ratio: $F = \text{Number of imperfection nodes} / \text{Number of nodes in match node area}$
- Imperfection recognition threshold value: D

When $F \geq D$, the candidate is recognized as an imperfection; when $F < D$, the candidate is recognized as an over-detection element. D has been set at 0.5 in this table.

Figure 12 shows an example of the recognition of an imperfection, in this case a dent. The composition of the 80 nodes making up the match node area was as follows:

- Imperfection nodes: 79
- Non-imperfection nodes: 1

This generates an imperfection node ratio (F) of 0.99. F is therefore $\geq D$, fulfilling the condition for recognition as an imperfection.

4.3. Increasing the Accuracy of Imperfection Recognition

To increase the accuracy of the recognition of imperfections, the existing recognition table is able to learn the relationships of similarity between newly acquired data (new data below) and

existing data, and generate a new table reflecting these relationships. As Fig. 13 shows, this processing is conducted off-line, unlike imperfection recognition processing.

To explain this processing in greater detail, feature vectors for imperfection candidates obtained during inspection (new data) are added to the existing recognition table, and the self-organizing map regroups the data. By this means, similarity between the new data and the existing data is determined and the data is realigned.

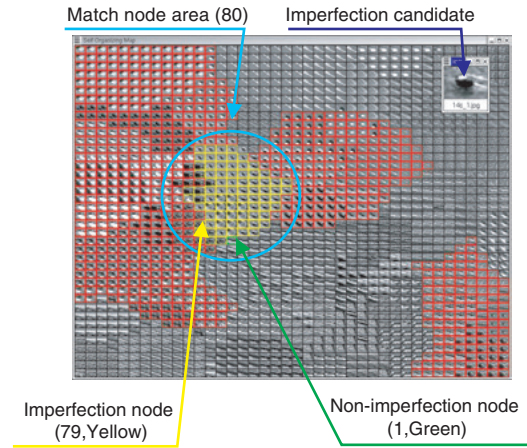


Fig. 12 Result of imperfection recognition

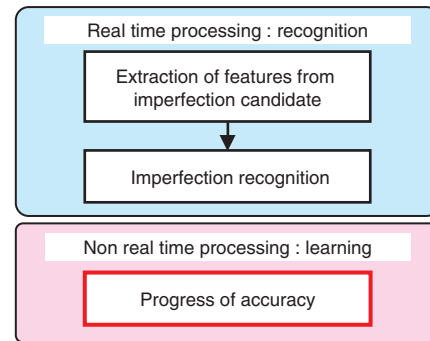


Fig. 13 Sequence of inspection for imperfection candidate

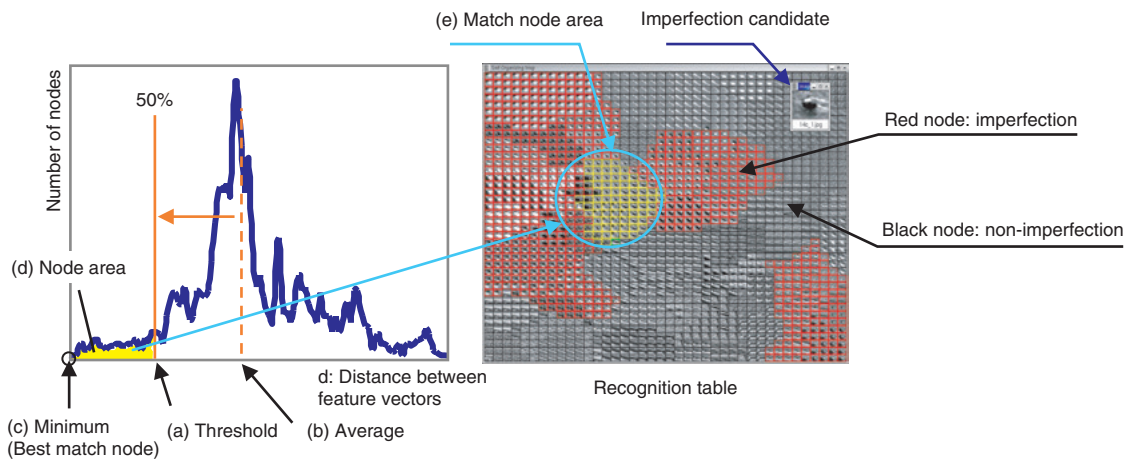


Fig. 11 Distribution of distance between feature vectors

Figure 14 shows an example of the revision of a recognition table with the addition of ten types of new data. After the revision, node areas for new data have been added to the table.

5. Inspection System

An inspection system was constructed to put the imperfection recognition method discussed thus far into practical operation. As shown in Fig. 15, the major components of this inspection system were (a) a rotation table to position the gear tooth surface being inspected, (b) a wide dynamic range CMOS camera to image the gear⁽⁴⁾, and (c) an LED illuminator. The system also employed a PC.

6. Test Results

This section will discuss the results of tests conducted to verify the accuracy of the inspection system. Table 1 shows a comparison of inspection accuracy for one gear when the new recognition processing system is used (b) and when it is not used (a). In both cases, accuracy in recognizing imperfections was equivalent to that of visual inspection. However, there is a 40:1 difference in the rate of over-detection between cases b and a. This result indicates that there will be a difference in inspection accuracy of 180:1 per gear between case (d) on the table, when the new system is applied, and case (c), when it is not applied, assuming 40 teeth on a gear. Using the new processing system will therefore ensure correct judgment in 90% of cases (d). The remaining 10% of cases in which it is difficult to recognize an imperfection should be reinspected visually.

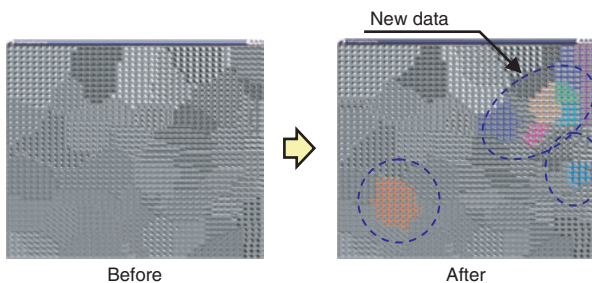


Fig. 14 Add new data to recognition table

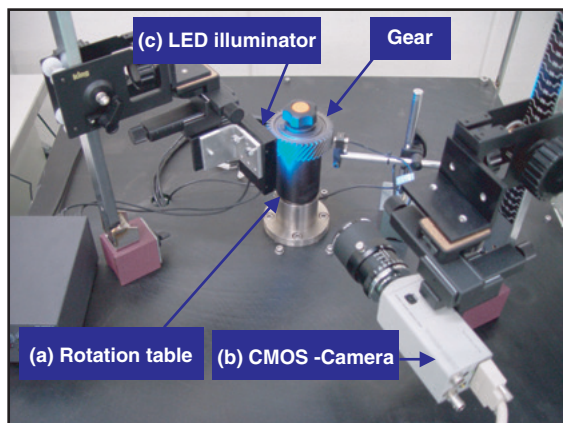


Fig. 15 Gear inspection setup

Table 1 Inspection accuracy

Recognition	Rate of over-detection: α	Inspection accuracy for one gear: A $A=100-(1-\alpha/100)^N$
No use	12.4% (a)	0.5% (c)
Use	0.3% (b)	90% (d)

N : Number of teeth on one gear
 $N = 40$

The results discussed above demonstrate that the inspection technology developed in this project equals visual inspection in terms of ability to recognize imperfections. The use of the system will reduce the burden on human inspectors.

7. Conclusion

A variety of new technologies have been developed for the inspection of gear tooth surfaces.

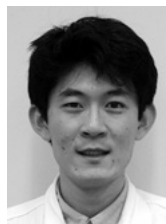
- (1) A technology has been developed to define the features of imperfections on gear tooth surfaces and enable them to be recognized. This technology can identify imperfections with an accuracy equivalent to visual inspection.
- (2) The development of a recognition table which “learns” the features of existing imperfections and over-detection elements has reduced the ratio of gears requiring visual inspection to approximately 10% of the former level.
- (3) Revision of the recognition table on the basis of feature vectors of imperfections and over-detection elements found during inspection has increased the accuracy of imperfection recognition.

The application of these technologies has enabled the production of an inspection system which both reduces the burden of visual inspections on human inspectors and enables an increase in gear quality.

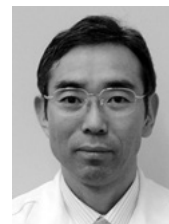
References

- (1) Komori, M., Kubo, A., Takahashi, T., Tanaka, T., Ichihara, Komiyama, M.: Failures of Involute Gears Due to Contact of Side Edge and Creep of Tooth (1st Report, Chipping of Side Edge of Tooth and Progress to Tooth Breakage), Transactions of Japan Society of Mechanical Engineers(C), Vol. 69, No. 685, p. 273-280 (2003)
- (2) Kohonen, T.: Self-Organizing Maps, Springer-Verlag (1995)
- (3) Kamomoto, N., Wang, B., Omatu, S.: Quality Test of Interphones Using Two kinds of Neural Networks, Transactions of Institute of Electrical Engineers of Japan, Vol. 122-C, No. 10 (2002)
- (4) Seki, H., Nakajima, A., Ohtsuka, K., Arai, H.: Observation of Welding Phenomena by Wide Dynamic Range Camera, Journal of the Japan Welding Society, Vol. 70, No. 7, p. 8-11 (2001) (in Japanese)

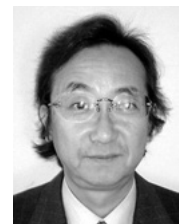
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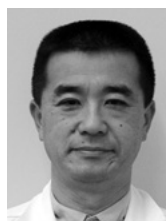
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