Decision of Lubricated Friction Conditions for Materials of Automobile Transmission Gear Using Neural Network

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It is hard to inspect the state of lubrication of an automobile transmission visually. Thus, it is necessary to develop a new inspection method. Wear debris can be collected from the lubricants of an operating transmission of an automobile, and its morphology will be directly related to the friction condition of the interacting materials from which the wear debris originated in the lubricated transmission. In this study, wear debris in lubricating oil are extracted by membrane filter (0.45 μm), and the quantitative values of shape parameters of wear debris are calculated by digital image processing. These shape parameters are studied and identified by an artificial neural network algorithm. The results of the study may be applicable to the prediction and diagnosis of the operating condition of transmission gear.

Key Words : Transmission Gear, Wear Debris, Image Processing, Diagnosis

1. Introduction

The nitrocarburizing process for surface modification of transmission gear has a low cost and a small deformation because the treatment temperature is lower than in the carburizing process (Dawes and Tranter, 1982 ; Dawes, 1991). Wear resistance and fatigue strength of transmission gears are very important because of the presence of friction and wear between elements and the occurrence of fatigue fracture around surfaces resulting from the repeated load. In order to determine the suitability of this heat treatment, it is necessary to develop a method for diagnosing wear resistance.

One general method for doing this is to measure the vibration of a transmission gear in action and the torque between the input and output shafts. Following the test, the transmission is disassembled to observe directly damage to the gear such as a pitting and scoring (Ko, 1984). The drawback is that it takes such a long time to diagnose the failure of the transmission gear, and an expert engineer, or at least expert knowledge, is needed, since these qualitative data are so difficult to analyze exactly. What is required, therefore, is to develop a new method such as lubricant or wear debris analysis for assessing the condition of transmission gear (Sato et al., 1987 ; Ahn, 1992 ; Hunt, 1996).

In this study, to get the basic information for the diagnosis of transmission gear condition, a lubricated friction experiment was carried out with carburized SCM420 and nitrocarburized NT100 used as the material of transmission gears of automobile. Wear debris was extracted from the lubricants, and the shape parameters of this debris, which are related to the moving condition, were calculated by the image processing system (Uedelhoven and Franzl, 1991 ; Roylance et al., 1993). A neural network (Sugimura and Yamamoto, 1995 ; Park, 1995) was then constructed to identify and classify shape characteristics of the wear debris.

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2. Experimental Detail

2.1 Lubricated friction experiment

A ball-on-disk type wear test, as shown in Fig. 1, was carried out under different experimental conditions. A ball specimen contacted with a disk specimen. The ball was ceramic with a diameter of 4.76 mm, and the disk specimens were of the two materials used for the transmission gear, carburized SCM420 and nitrocarburized NT100. They were 50 mm in diameter, 10 mm in width and ground as Rmax 0.2 μm. The lubricants were SAE75W gear oil, and its characteristics are shown in Table 1. The applied loads were set up at 2.5 kg, 5 kg, 7.5 kg and 10 kg, and the sliding speeds were 47 mm/sec, 94 mm/sec, 141 mm/sec and 188 mm/sec, as shown in Table 2. Wear debris was extracted from the lubricant with a membrane filter of 0.45 μm (a 0.45 μm membrane filter) and the morphological characteristics of the wear debris were calculated by image processing.

Fig. 1 Photograph of ball on disk type wear tester

Table 1 Characteristics of gear oil

Characteristics		Shell T/M (SAE 75W/85)
Specific gravity 15/4℃		0.8769
Viscosity	40℃ cST	61.36
	100℃ cST	12.12
Sulfur content (%)		0.864
Phosphorous content (%)		0.0468

Table 2 Experiment conditions

	Experiment condition
Applied load (kg_f)	2.5, 5.0, 7.5, 10.0
Sliding speed (mm/sec)	47, 94, 141, 188
Sliding distance (m)	1018

2.2 Digital image processing

Digital image processing (Roylance et al., 1993) was used to recognize and classify the shape of wear particles generated in the transmission gear. In order to describe the characteristics of wear debris of various shapes and sizes, the four shape parameters of wear particles are defined as 50% volumetric diameter, aspect, roundness and reflectivity. 50% volumetric diameter is a representative size of wear debris. It is defined the diameter of particle to the half of total volume in ascending order. Aspect is defined as length/width of particle and gives a larger vale for long particle. Roundness is to measure the smoothness of a particle's border. This gives unity for a circular particle, and larger values for irregular particles.

Figure 2 shows a flow chart of the image processing algorithm that was used to obtain the shape parameters of wear debris taken in the experiment. Reflected and transmitted images were captured by a color CCD camera on an optical microscope with reflected and transmitted halogen lights, and these were saved to HDD (hard disk drive) by a frame grabber within the computer. The resolution of image was 640×480 pixels, and the grayscale was 8 bit per pixel. The optical microscope had an objective and ocular lens with a magnification of 10X. The reflected and transmitted images were captured though the frame grabber. The transmitted images were transformed into a threshold image with threshold value selected from the histogram. The reflected images were added to the threshold image, and then, the boundary and shape of wear debris were extracted through image processing and the four shape parameters were calculated. In this study, 20 transmitted and reflected images were captured and processed to get the shape data of wear debris.

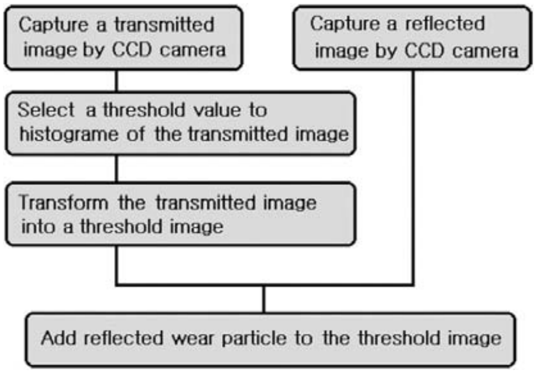


Fig. 2 Image processing algorithm

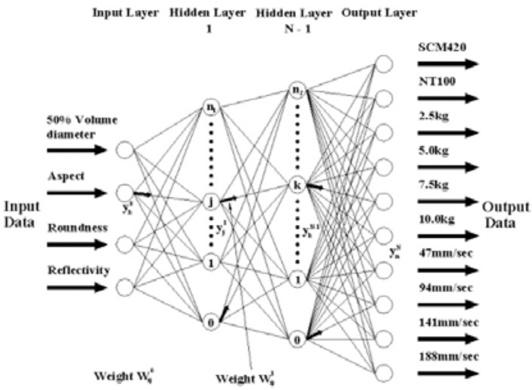


Fig. 3 Model of neural network

2.3 Construction of neural network

Figure 3 is a diagram of the multi-layer neural network model (Sugimura and Yamamoto, 1995). The network consists of input layer, hidden layer and output layer. The input data were 50% volumetric diameter, aspect, roundness and reflectivity, i.e. the shape parameters of the wear debris. In the output layer, responses were outputted for the two materials, four conditions of applied load, and four conditions of sliding speed.

Figure 4 shows the neural network program made with Visual C++. The neural network learned the 32 learning patterns that consisted of the average value of the 4 shape parameters of wear debris as input data and the several operating conditions of the experiments as target values. Learning error was less than 0.0001, and the learning iterative number was set up at more than 500,000.

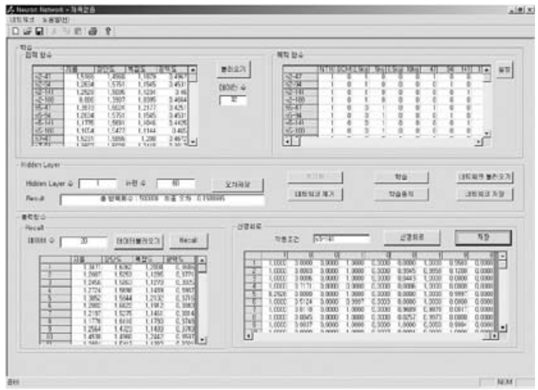


Fig. 4 Neural network program

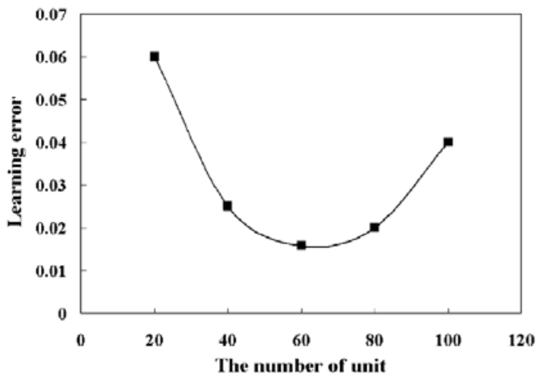


Fig. 5 Learning error on the number of unit (hidden layer : 1)

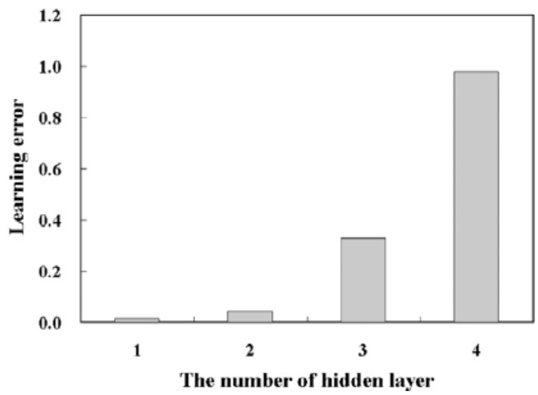


Fig. 6 Learning error on the number of hidden layers (units : 60)

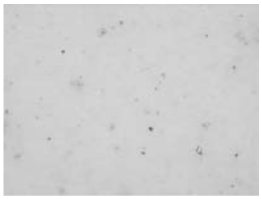
Figure 5 shows the variation of the learning error as a function of the number of units in one hidden layer. In this graph, the learning error has a minimum value when the number of units is

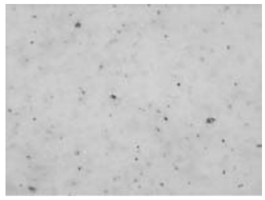
60, and as shown in Fig. 6, the learning error is smallest when the number of hidden layers is one. Therefore, the neural network was optimized with 60 units of one hidden layer.

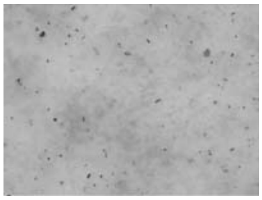
3. Results and Discussion

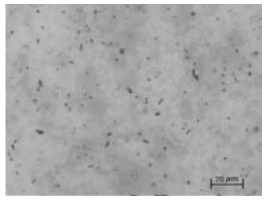
3.1 Shape characteristics of wear debris

Figure 7 shows the average value of 4 shape parameters on applied loads at sliding speed of 188 mm/sec. It shows that with an increase of applied loads, 50% volumetric diameter, aspect and roundness of all materials increase. This means that wear debris becomes larger and more complex in shape as the load increases. The decrease in reflectivity is considered to be due to a reaction of oxidation with the increase in average tempera-


(a) 2.5 kg

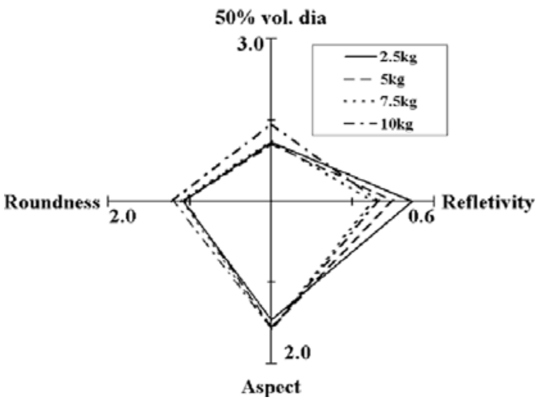

(b) 5.0 kg


(c) 7.5 kg

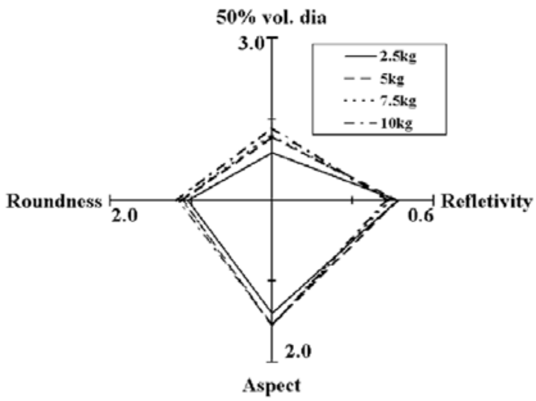


(d) 10.0 kg

Fig. 8 Photographs of wear debris on applied load for carburized SCM420 (sliding speed : 188 mm/sec)

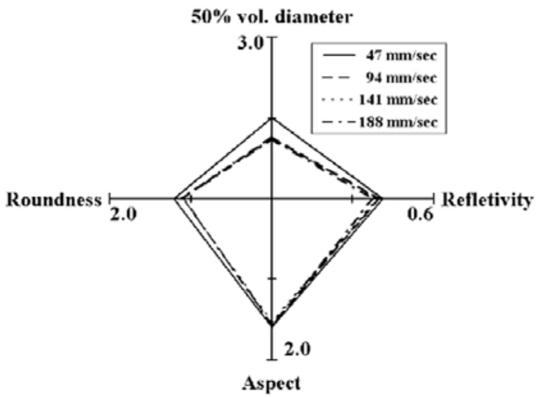


(a) Carburized SCM420

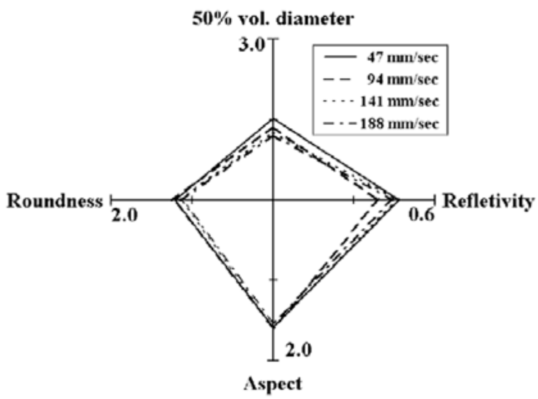


(b) Nitrocarburized NT100

Fig. 7 Average value of shape parameters of wear debris on applied load (sliding speed : 188 mm/sec)



(a) Carburized SCM420



(b) Nitrocarburized NT100

Fig. 9 Average value of shape parameters on sliding speed for each materials (applied load : 7.5 kg) ture of the rubbed surface. Photographs of wear debris on applied load for carburized SCM420 are shown in Fig. 8. From these photographs, it can be know that the shape characteristics of the wear debris are different on operating condition. Fig. 9 shows the average value of the 4 shape parameters on sliding speed when the applied load is 7.5 kg. With a decrease in sliding speed, wear debris particles are comparatively large and glossy, as all 4 shape parameters have high values.

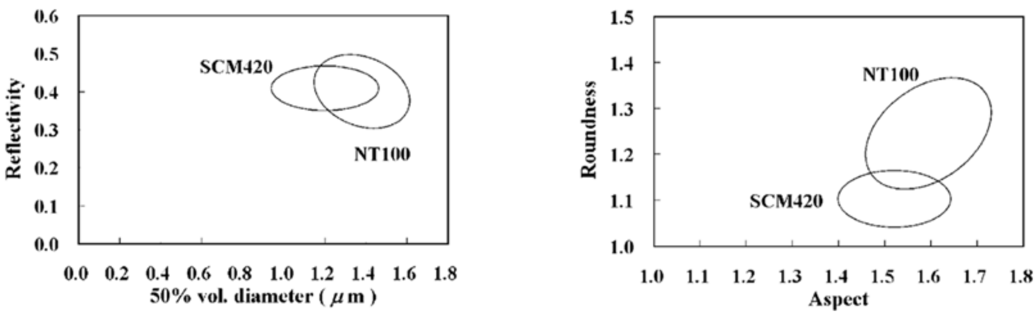
In sum, Figs. 7 and 9 indicate that the morphological characteristics of the wear debris on operating condition such as shown in Fig. 8 can be classified by the average value of the 4 shape parameters. These parameters were used for the study data of the neural network.

3.2 Groups of wear debris

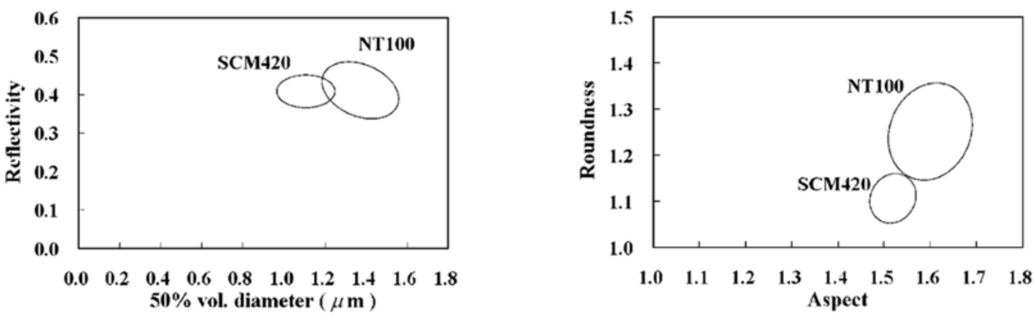
Because the shape characteristics of each particle of wear debris occurring in the moving system are widely distributed and varied, it is difficult to apply the neural network directly to identifying the characteristics of the wear debris. Therefore, in order to identify the shape characteristics, it is useful to use the properties of a suitable number of particles and find an average value for the shape parameters for that small group. In this study, average values of the shape parameters were calculated in every 50 and every 100 wear debris group. Because, small groups could not be made with over that by reason that wear debris in image were small in number.

Figure 10 shows the distribution of average values of the shape parameters in (a) every 50 and (b) every 100 wear debris group at an applied load of 7.5 kg and a sliding speed of 97 mm/sec. The figure shows that the distributions of the shape parameters in (b) every 100 wear debris group are separated much better than in (a) every 50, so the decision rate in the neural network is expected to be high for materials when the distribution of the parameters in every 100 wear debris group is used.

Figure 11 shows the distribution of average value of the shape parameters in every 100 wear debris group of (a) carburized SCM420 and

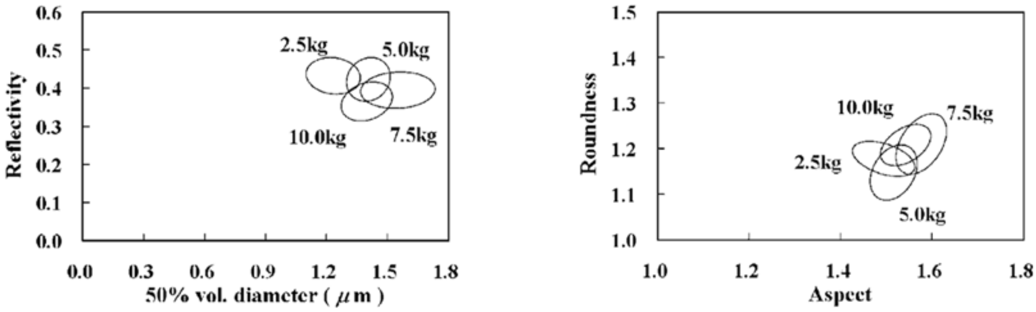


(a) Every 50 wear debris group

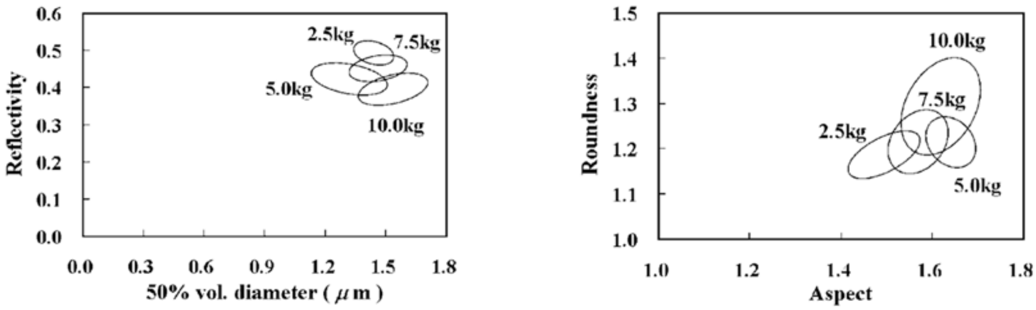


(b) Every 100 wear debris group

Fig. 10 Average value of shape parameters in every 50 and 100 wear debris groups for two materials (applied load : 7.5 kg, sliding speed : 94 mm/sec)

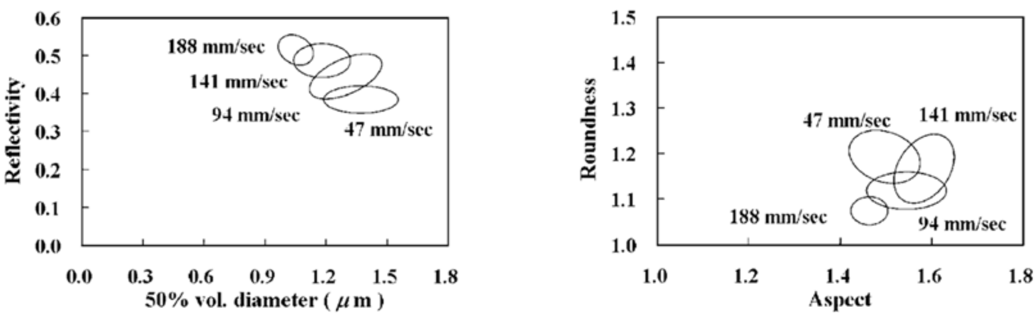


(a) Carburized SCM420

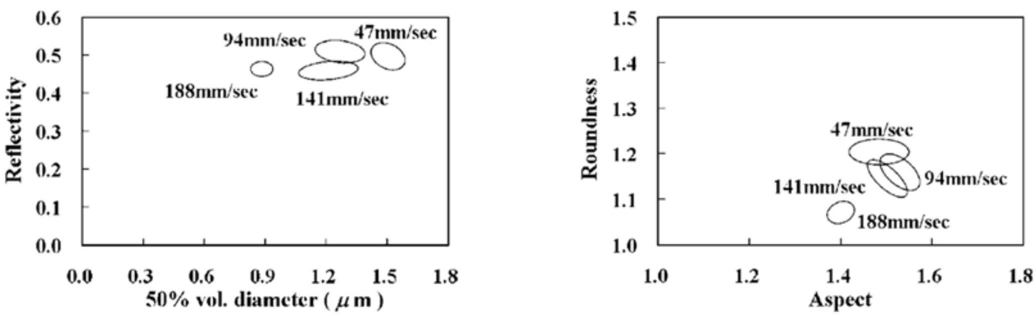


(b) Nitrocarburized NT100

Fig. 11 Average value of shape parameters in every 100 wear debris group for different applied loads (sliding speed : 47 mm/sec)



(a) Carburized SCM420



(b) Nitrocarburized NT100

Fig. 12 Average value of shape parameters in every 100 wear debris group for different sliding speeds (applied load : 2.5 kg)

(b) nitrocarburized NT100 for the different applied loads at a sliding speed of 47 mm/sec. In (a) carburized SCM420, the distribution of 50% volumetric diameter and the reflectivity overlap a little, while aspect and roundness almost overlap. In the case of (b) nitrocarburized NT100, the shape parameters partly overlap. Based on these results, the decision rate in the neural network is expected to be somewhat low for the applied load.

Figure 12 shows the distribution of the average value in every 100 wear debris group for different sliding speeds at an applied load of 2.5 kg. The distribution of shape parameters in (a) carburized SCM420 overlaps more than in (b) nitrocarburized NT100. Therefore, the decision rate on sliding speed is also expected to be lower in carburized SCM420 than in nitrocarburized NT100.

3.3 Identification of shape characteristics of wear debris

Figures 13 and 14 show the decision rate of neural network for the friction conditions. The decision rate for the material is over 80% in every 100 particle group, because the distribution of the shape characteristics for the materials is comparatively more separated, as shown in Fig. 11. In identifying the friction condition of the transmission gear, it is therefore more effective to use the average values of shape parameters in every 100 wear particle than in every 50 particle grouping order to distinguish the shape characteristics of wear debris using computer image processing.

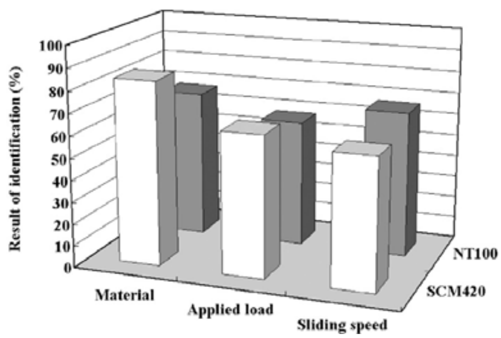


Fig. 13 Average decision rate for frictional condition in every 50 particle group

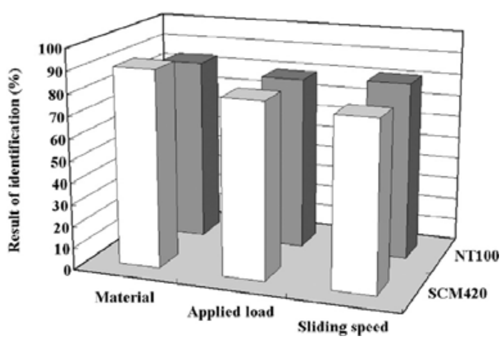


Fig. 14 Average decision rate for frictional condition in every 100 particle group

In these results, although the distributions overlap, if the average values of shape parameters for wear debris groups are investigated overall, the shape characteristics for the different operating conditions can be clearly identified. Moreover, the various operating conditions can be recognized by using the neural network with the optimum condition.

4. Conclusions

To identify the friction condition for a transmission gear using a neural network, a ball-on-disk type wear test was carried out for carburized SCM420 and nitrocarburized NT100 under different experimental conditions. The four shape parameters (50% volumetric diameter, aspect, roundness and reflectivity) of wear debris were calculated using image processing, and these were used as input values to identify the moving condition of the transmission gear using a neural network. The present study indicates that to distinguish the shape characteristics of wear debris, it is more effective to use the average values of the 4 shape parameters in every 100 wear debris group than in every 50 as the input values for the neural network. Further, the most suitable neural network has one hidden layer and 60 units in a hidden layer, and for the identification of the morphological characteristics of wear debris, it is most effective to set up the average values of the 4 shape parameters of all wear debris into the learning condition. By means of the neural network used in this study, it is possible to predict and to decide lubricated friction conditions of materials for the transmission gear of an automobile.

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