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A Study on Recognition of Friction Condition for Hydraulic Driving Members using Neural Network

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Abstract : It can be effective on failure diagnosis of oil-lubricated tribological system to analyze operating conditions with morphological characteristics of wear debris in a lubricated machine. And it can be recognized that results are processed threshold images of wear debris. But it is needed to analyze and identify a morphology of wear debris in order to predict and estimate a operating condition of the lubricated machine. If the morphological characteristics of wear debris are identified by the computer image analysis and the neural network, it is possible to recognize the friction condition. In this study, wear debris in the lubricating oil are extracted from membrane filter (0.45 μm) and the quantitative value for shape parameters of wear debris was calculated through the computer image processing. Four shape parameters were investigated and friction condition was recognized very well by the neural network.

Key words : Wear debris, shape parameters, computer image analysis, neural network

Introduction

The morphological analysis of wear debris can provide early a failure diagnosis in lubricated moving system.

It is need to maintain a smooth driving of machine elements and reduce a failure by a incapacious operating condition. For this, diagnosis technology for prediction of operating condition of the lubricated machine elements has been requested. This technology has been researched and developed from early 1980s in an advanced nation with activity. But, it have much problems that the accurate signal processing must be introduced and needs experts [1~3].

Morphological analysis of wear particles has been researched recently. Condition diagnosis technology to analyze wear debris occurred in tribological system can make up for defects of another diagnosis method, moreover, it also can obtain an information can not be obtained in the another measurement technique. It is a merit of this technique. This is to use shape parameters of wear particles fallen off in lubricated machine system. If it is possible to foresee and observe operating condition accurately, we can use it for a long time without a sudden stoppage and dismantlement of total machine system.

In this study, the wear debris were extracted through a lubricated friction tester be like the hydraulic moving system. The morphological characteristics of the wear debris are calculated by image processing. The shape parameters of wear debris are represented with numerical values [4].

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There are a nonlinear relationship between input data and output data through learning by neural network. If the neural network can be learned and decided the morphological characteristics of wear debris occurred from various friction condition, the neural network can also recognize the wear particles [5,6].

This study is undertaken to apply the computer image processing and the neural network to recognize fiction condition of hydraulic driving members.

Experiments

Lubricated friction experiment

The ball-on-disk type tester shown Fig. 1 is used for lubricated

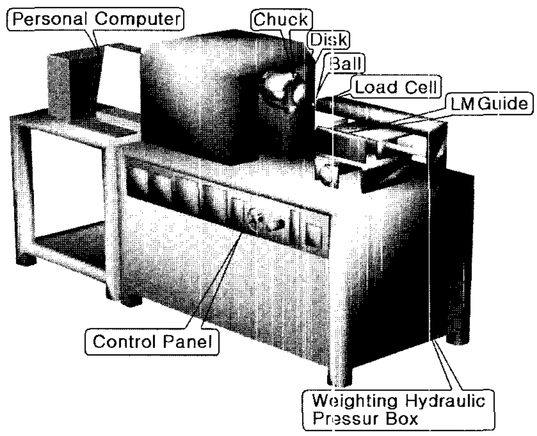

Fig. 1. Schematic diagram of ball on disk type wear tester.

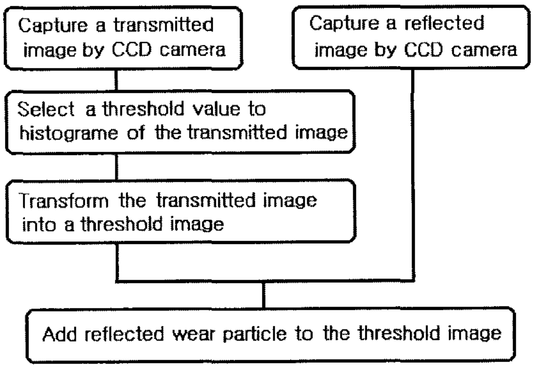

Fig. 2. Image processing algorithm.

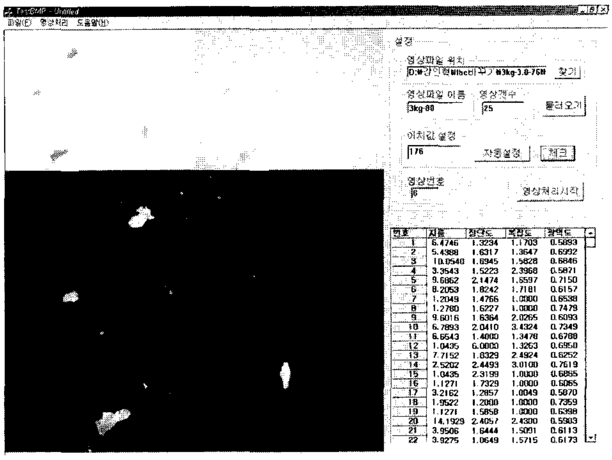

Fig. 3. Image processing program.

friction experiment. A ball material on the disk specimen is ceramics with 4.76 mm in diameter and disk specimen is used two kinds of material with different hardness, such as Cr-Mo steel SCM440 and Brass LBC3. Dimension of disk is 50 mm in diameter, 1 0mm in width and grinded as Rmax 0.2μm. The paraffin series base oil (8.2cSt@40°C) is used to the frictional surface.

The applied loads are 3 class of 29.4 N, 49 N and 68.6 N and sliding distance is set up to 860 mm. The sliding speed of disk is set up to 3 class of 40 mm/sec, 80 mm/sec and 120 mm/sec. The supply of lubricating oil maintained by dropping oil onto a rotating disk, and the used oil that drops from disk specimen by gravity is collected in a oil bath which is set up under the contact point of disk and oil is supplied on the contact point through a silicon tube by circulation pump. Wear debris in lubricating oil is taken out through a membrane filter of 0.45 μm (pore size), 47 mm (diameter).

Computer image processing

Fig. 2 show the image processing algorithm. The computer image acquisition equipment consists of an optical microscope equipped two kinds of halogen lamp with reflected and transmitted light and the color CCD camera is equipped on the microscope. The frame grabber is 640 × 480 pixels and the resolution per pixel is 8 bit (256 gray level) in each R (red), G (green) and B (blue). The reflected and transmitted image are grabbed through the frame grabber in the computer. After the threshold value is selected from the histogram of transmitted image, it is transformed into the threshold image. The transformed reflected image is added to the threshold image, and so, the boundary and the morphology of wear debris are extracted through the image processing definitely.

Fig. 3 show the software for computer image processing of wear debris. The four shape parameters such as, aspect, roundness, reflectivity and 50% volumetric diameter was calculated with this software.

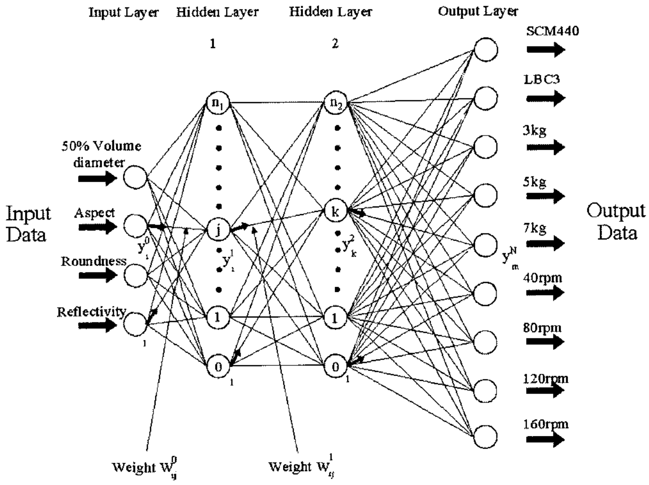

Fig. 4. Neural network model.

Learning and composition of neural network

The wear debris morphology generated from the friction process is various and complex. Although experts can observe and foresee the operating condition of the system intuitively, human intuitional power can detect a mutual relationship of the factors through a lot of information taken from the lasting observation of lubricated machine system. The multi-layer artificial neural network based on the error back-propagation through a learning can make it recognize.

Therefor, we expects that the friction condition of hydraulic driving members can recognize by the artificial neural network.

Fig. 4 show the multi-layer neural network model. The structural elements of neural network consists of input layer, hidden layer, output layer. And the input values of input layer has 50% volumetric diameter, aspect, roundness and reflectivity. The output data of output layer has nine class of two material, three load, four sliding speed. The hidden layers has four layer, and the unit numbers is set up to 9, 18, 27 and 36.

The neural network is made up of the most suitable condition minimizing the learning errors and the learning iterative number.

Fig. 5 show the neural network program made with visual C++. It is learned with total average values of four shape parameters. The four parameters are input data, and the operating conditions of experiment are object value. the

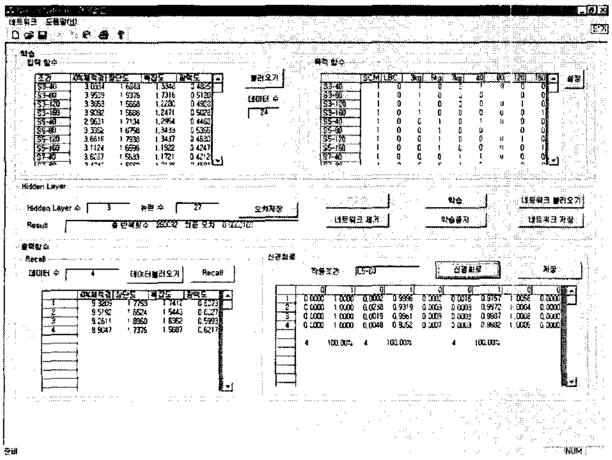

Fig. 5. Neural network program.

numbers of learning pattern are 24. Learning error was less then 0.0001 and learning iterative number are set up to more than 50,000. Table 1 show learning error and iterative number with hidden layer and unit number.

The convergent value of learning error is 0.0001 in the unit number 18 of 2 hidden layer, and unit number 27 of 3 hidden layer, As well as, the learning error are converged most rapidly in the 27 unit of 3 hidden layer.

Therefore, hidden layer with optimum neural network structure in this study is consisted of 27 unit of 3 hidden layer. Learning convergent condition is set up to learning error 0.00001 and iterative number is set up to more than 50,000.

Table 1. Error comparison

Hidden Laye	Unit Number	9	18	27	36
1	Error	0.086549	0.104571	0.083729	0.10453
	Iterative number	50000	50000	50000	50000
2	Error	0.041998	0.0001	0.041729	0.020896
	Iterative number	50000	32300	50000	50000
3	Error	0.986264	0.325066	0.0001	0.041709
	Iterative number	50000	50000	23700	50000
4	Error	0.722059	1.023294	0.901899	0.14585
	Iterative number	50000	50000	50000	50000

The recognition of operating condition is undertaken through this neural network learned and decided with four shape parameters of wear debris.

Results and Discussions

Shape parameters of wear debris

Fig. 6 show the total average value of the four shape parameters of wear debris on the sliding speed for the applied load 29.4 N. The shape parameters value of LBC3 are more high than SCM440. This means that particle morphology of LBC3 is more large and complex than it of SCM440, and has much metal gloss than SCM440. In case of the aspect and roundness, it is independent of material and the morphology of

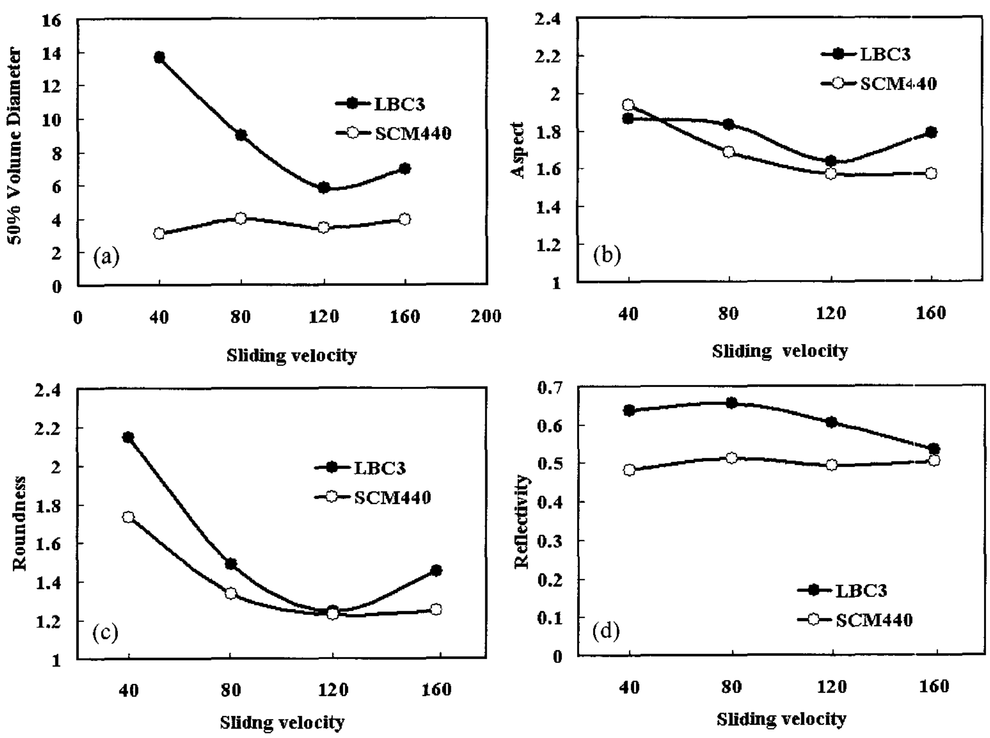

Fig. 6. Average value of the shape parameters of wear debris for sliding speed, applied load: 29.4 N (a) 50% Vol. dia. (b) Aspect (c) Roundness (d) Reflectivity.

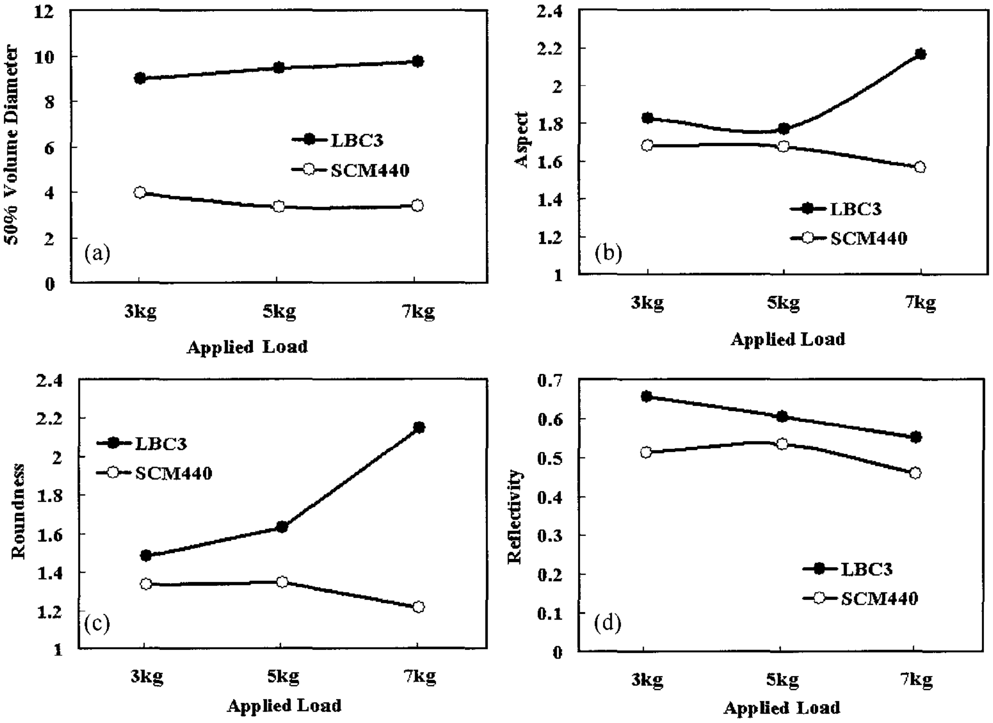

Fig. 7. Average value of the shape parameters of wear debris for applied load, sliding speed: 80 mm/sec. (a) 50% Vol. dia (b) Aspect (c) Roundness (d) Reflectivity.

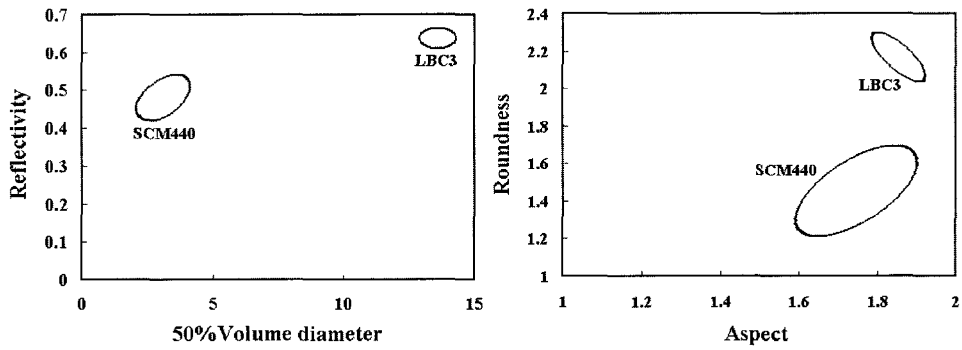

Fig. 8. Average distribution of the shape parameters in every 100 wear debris for materials, applied load: 29.4 N, sliding speed: 40 mm/sec.

wear particles are generally complex for low sliding speed.

Fig. 7 show the total value of four shape parameters of wear debris for sliding speed 80 mm/sec. In case of the aspect and the roundness of LBC3, the morphology of wear debris is more complex and longer than it of SCM440. And the aspect and the roundness of SCM440 means that the morphology of wear particles are round. As well as, in case of the reflectivity, as the applied load is increased, its value for two materials is decreased. This mean that two materials are oxidized quickly due to the increased temperature of the rubbed surface.

Therefore, Fig.6 and Fig.7 show that the wear debris on operating condition can be identified by the total value of four shape parameters sufficiently.

Formation of group for identification of wear debris

As Morphology of the wear particles occurred in the hydraulic moving system is very various. It is very difficult to apply for shape parameters to morphology identification of the wear debris. Therefor the average value of small group of wear debris, for example, a group with regular numbers of wear particles is used to shape parameters in order to identify the morphology of particles.

Fig. 8 show the distribution of average value in every 100 wear debris and every materials for the contact load 2 9 .4N and sliding speed 40 mm/s. This means that distribution of the shape parameters was separated effectively, so the rate of decision with neural network is expected to be high for materials of the hydraulic moving system.

Fig. 9 show the distribution of average value in every 100 wear debris of (a) LBC3 and (b)SCM440. In case of (a) LBC3, The 50% volumetric diameter and the reflectivity are separated easily. But the aspect and the roundness are overlapped partly.

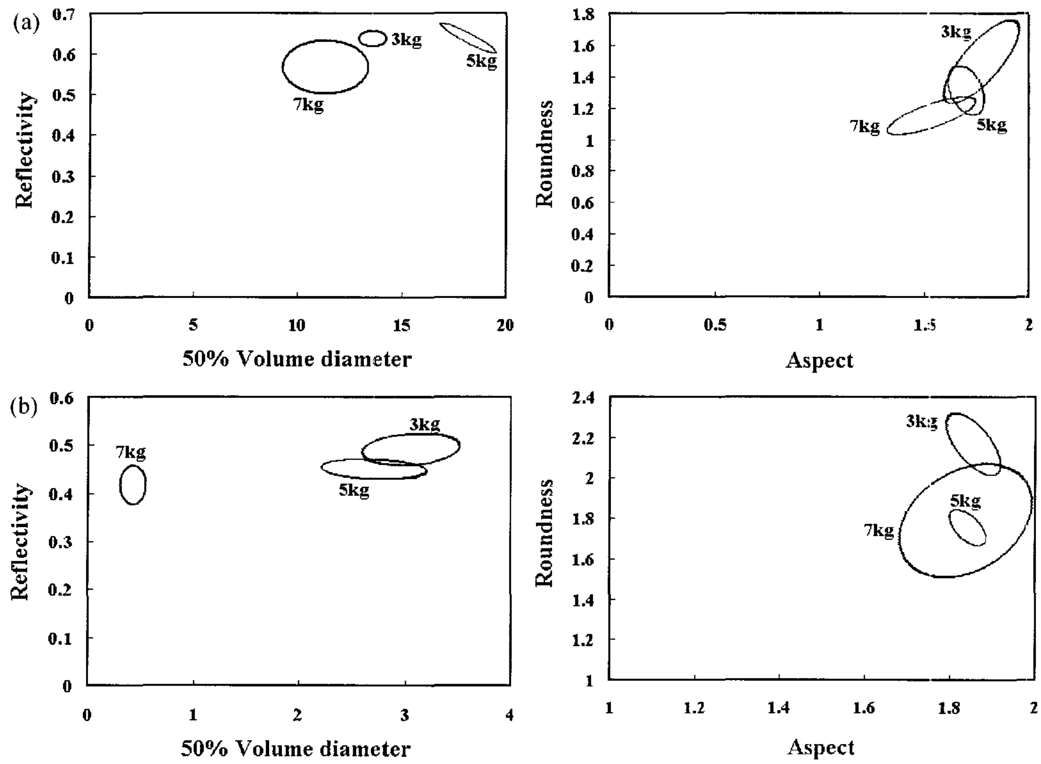

Fig. 9. Shape parameters in every 100 wear debris for applied load, sliding speed: 40 mm/sec. (a) LBC3 (b) SCM440.

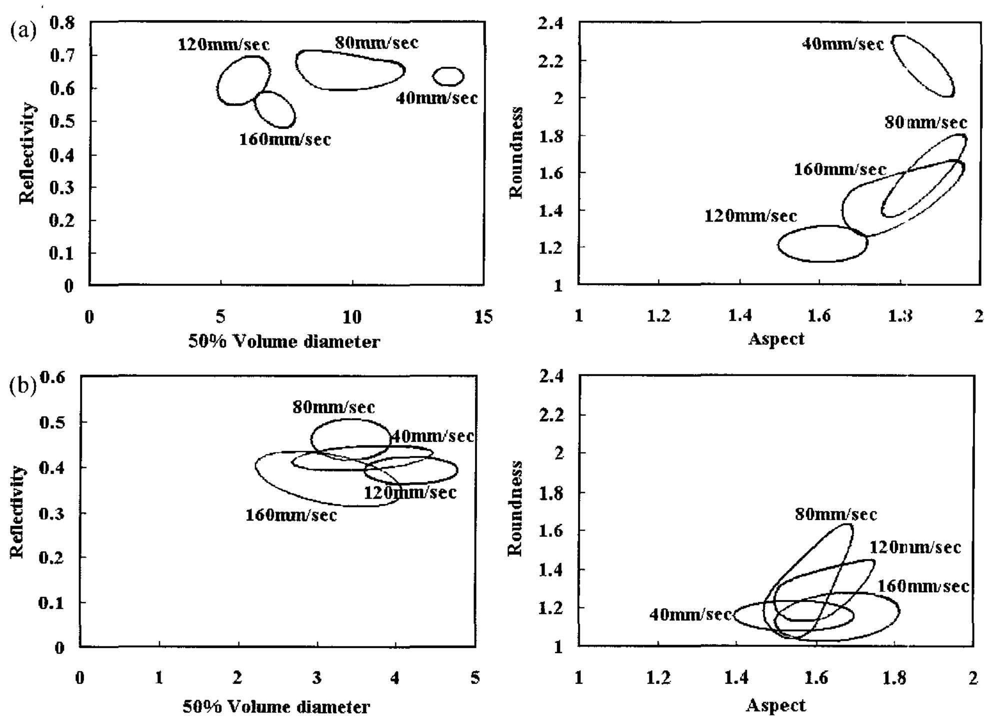

Fig. 10. Shape parameters in every 100 wear debris for sliding speed, (a) LBC3 (b) SCM440.

In case of (b)SCM440, The 50% volumetric diameter and the reflectivity are overlapped partly, and the aspect and the roundness overlapped a quite bit.

Therefore, from these results, the high rate of decision in the neural network is expected for the applied load of LBC3. But, in case of SCM440, The low rate of decision is expected for the applied load.

Fig 10 show the distribution of the average value in every 100 wear debris on the sliding speed for the applied load 68.6N and SCM440. The distribution is overlapped in many

Table 2. Results of identification for group of every 50 wear debris (%)

	Material	Applied load	Sliding speed
LBC3	100	100	87.5
SCM 440	100	95.83	87.5

Table 3. Results of identification for group of every 100 wear debris (%)

	Material	Applied load	Sliding speed
LBC3	100	100	100
SCM 440	100	95.83	91.67

area. this means the low rate of decision is expected about the sliding speed.

Morphological identification of wear debris by the neural network.

In order to identify the morphology of wear debris occurred in the hydraulic driving members, the neural network has the 3 hidden layer with 27 unit number, and learn 24 pattern on the operating condition.

The neural network has input data of the average value in every 50 and 100 wear debris on each operating condition. From this process, the neural network can recognize the operating condition of hydraulic moving system.

Table 2 and table 3 represent the decision rates of identification results by the neural network for the materials, the applied load and the sliding speed. The decision rate for the material is 100% in the all operating condition. This reason is that the characteristics of the shape parameters for the materials are separated obviously as shown in Fig. 8. And the decision rate of shape parameters in every 100 wear debris is higher than the decision rate in every 50 wear debris for the sliding speed and the applied load. The decision rate in every 100 wear debris is over 90%.

Although the distribution is overlapped a quite bit, if the average values of the four shape parameters are learned overall, the characteristic of wear debris on operating condition can be identified obviously. Therefore, if the learning error is reduced, we can expect that the neural network will very well recognize wear debris taken from the various operating condition in the oil-lubricated tribological system.

Conclusions

The wear debris taken from various operating condition in the oil-lubricated tribological system are analyzed and identify to determine shape parameters with image analysis and neural network. The four shape parameters, such as 50% volumetric, diameter, aspect, roundness and reflectivity are calculated with the computer image processing program and this parameters is learned and identified by multi-layer artificial neural network.

The experimental and analysis results showed following conclusions.

1. In the result of learning and identi- fying 24 learning pattern with a different hidden layer number and the learning error is the most rapidly converged on error critical value 0.0001 in the 3 hidden layer of 27 unit number.
2. The average value of shape para- meters is higher in the LBC3 than the SCM440. It means that the morphology of wear debris for the LBC3 is more large and complex.
3. The distribution of average value of shape parameters for materials is well separated but the parameters for sliding speed are overlapped a quite bit.
4. Identification for applied load and sliding speed get a higher decision rate in every 100 wear debris and the decision rate in every 100 wear debris is over 90% on the operating condition.

Acknowledgments

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