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A Study on Recognition of Operating Condition for Hydraulic Driving Members

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ABSTRACT

The morphological analysis of wear debris can provide early a failure diagnosis in lubricated moving system. It can be effective to analyze operating conditions of oil-lubricated tribological system with shape characteristics of wear debris in a lubricant. But, in order to predict and recognize an operating condition of lubricated machine, it is needed to analyze and to identify shape characteristics of wear debris. Therefore, If the morphological characteristics of wear debris are recognized by computer image analysis using the neural network algorithm, it is possible to recognize operating condition of hydraulic driving members. In this study, wear debris in the lubricating oil are extracted by membrane filter (0.45µm), and the quantitative values of shape parameters of wear debris are calculated by the digital image processing. This shape parameters are studied and identified by the artificial neural network algorithm. The result of study could be applied to prediction and to recognition of the operating condition of hydraulic driving members in lubricated machine systems.

Key words : Wear debris, Image processing, Shape parameters, Computer image analysis, Neural network

1. Introduction

In order to maintain a smooth driving of machine elements and reduce a loss by a mechanical failure in lubricated moving system, it requires that the fault diagnosis and machine condition monitoring is developed for the lubricated machine elements.

This technology has been researched with activity in an advanced nation from early 1980s. But, it is need to apply the accurate signal processing method by an expert researcher[1~3]. For this, the machine condition monitoring technique by the wear debris analysis is presented recently. It is the diagnosis method by using morphological characteristics of wear debris in lubricated system. This machine condition without stop or disassembly of system can be observed by this method and it is effective to recognize an operating condition of the lubricated machine systems.[4]

But it is hard to represent that the morphological characteristics of wear debris have relation with the operating condition because of a complex interaction between each other. Therefore, it is need to use such the mathematical model as a neural network for automatic system.

In this study, wear debris were extracted through a lubricated friction and wear tester that simulated the hydraulic moving system, and the morphological characteristics of wear debris were calculated by image processing[5]. The shape parameters of wear debris represented with quantitative numerical values by

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image processing were learned by using the neural network for a nonlinear relationship between input and output data[6~7]. And the operating conditions of the lubricated machine systems were recognized by the learnt neural network.

2. Experiments

2.1 Lubricated friction experiment

The ball-on-disk type tester[8] was used for lubricated friction experiment. Ball specimens were used the 99.7% alumina ceramics(Al_2O_3) with 4.76mm in diameter, and disk specimens were the carburized Cr-Mo steel SCM440 and the leaded tin bronze castings LBC3 used for slipper-pad and piston ball of hydraulic piston motor as shown Fig. 1. The dimension of a disk was with 50mm in diameter and 10mm in width. The surface of a disk was polished into Ra 0.2㎛. And the lubricant used in this study was paraffin series base oil (8.2cSt@40℃).

The applied loads were 3 kg, 5 kg and 7 kg and the sliding distance was set up to 860mm. The sliding speed of contact point was set up to 3 class of 40mm/sec, 80mm/sec and 120mm/sec. An oil bath was set up under the contact point of a disk. Lubricant was supplied on the contact point through a silicon tube by rotary pump. Wear debris in oil were taken out through a membrane filter of 0.45 ㎛ (pore size), 47 mm (diameter).

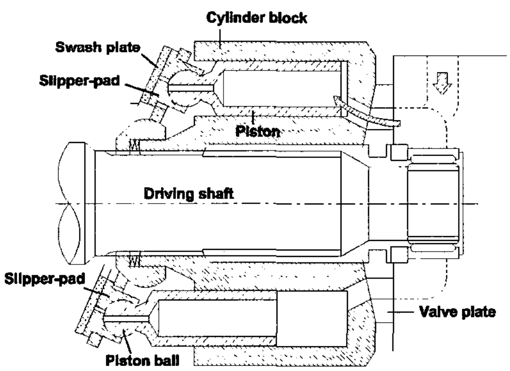


Fig. 1 Schematic diagram of hydraulic piston motor

2.2 Computer image processing

Fig. 2 shows the flow chart of the image processing algorithm in order to get the shape parameters of wear debris taken from the experiment. Reflected and transmitted images were captured by color CCD camera on the optical microscope with reflected and transmitted halogen lights, and were saved to HDD (hard disk drive) by the frame grabber within the computer. The resolution of image was 640×480 pixels, and the grayscale was 8 bit per pixel.

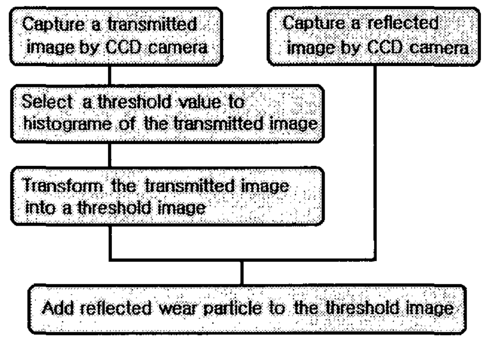


Fig. 2 Image processing algorithm

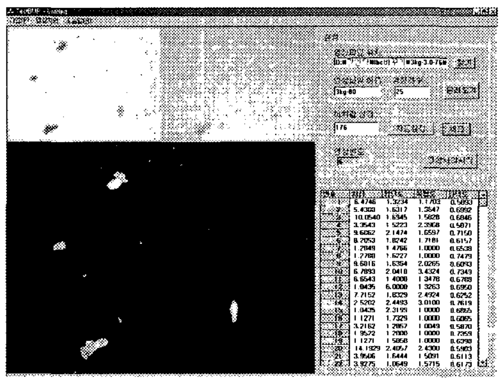


Fig. 3 Image processing program

And the optical microscope had objective and ocular lens of 10 times. The reflected and transmitted images were captured though a frame grabber within the computer. Transmitted images were transformed into the threshold image with threshold value selected from the histogram. The reflected images were added to threshold image and the boundary and morphology of each wear debris were extracted through the image processing.

Fig. 3 shows the software for computer image processing of wear debris. The four shape parameters such as aspect, roundness, reflectivity and 50%

volumetric diameter were calculated with this software.

2.3 Learning and Composition of Neural Network

Fig. 4 shows the multi-layer neural network model. The neural network consisted of input layer, hidden layer and output layer. The input data were 50% volumetric diameter, aspect, roundness and reflectivity

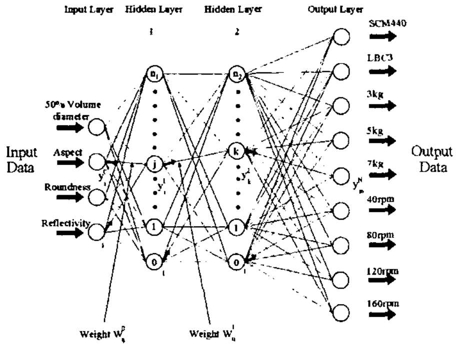


Fig. 4 Neural network model

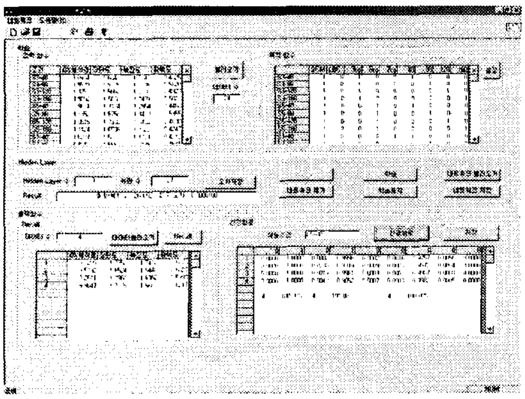


Fig. 5 Neural network program

Fig. 5 shows the neural network program made with visual C++. The neural network learned the 24that were shape parameters of wear debris. In the output layer, response about two material, three conditions of the applied load and four conditions of the sliding speed were outputted. The number of hidden layers was from 1 to 4 layers, and the number of units in the hidden layers was set up to 9, 18, 27 and 36. In this study, the neural network was constructed to be the optimum condition on the learning error and iteration number. learning pattern that consisted of the average value of 4 shape parameters of wear debris as input data and the several operating conditions of experiments as the target value. The learning error was less then 0.0001 and the iteration number was set up to more than 50,000.

Table 1 Error comparison

Hidden Layer \ Unit Number		9	18	27	36
1	Error	0.086549	0.104571	0.083729	0.10453
	Iteration number	50000	50000	50000	50000
2	Error	0.041998	0.0001	0.041729	0.020896
	Iteration number	50000	32800	50000	50000
3	Error	0.986264	0.325066	0.0001	0.041709
	Iteration number	50000	50000	23700	50000
4	Error	0.722059	1.023294	0.901899	0.14585
	Iteration number	50000	50000	50000	50000

Table 1 shows the learning error and the iteration number on the hidden layer and unit number. In the 18 unit of 2 hidden layer and the 27 unit of 3 hidden layer, the limited convergent value of learning error reached 0.0001. And the learning error converged most rapidly in the 27 unit of 3 hidden layer.

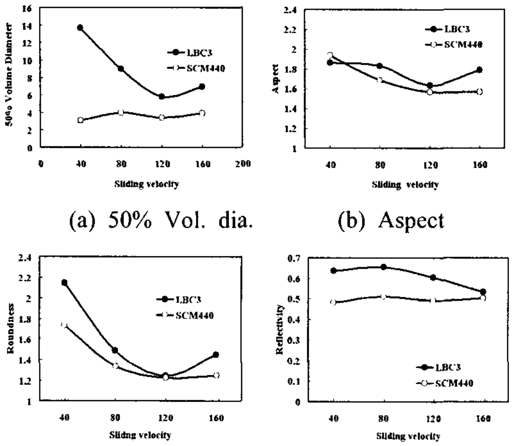
Therefore, the optimum neural network was selected in the 27 unit of 3 hidden layer.

3. Results and Discussions

3.1 Shape parameters of wear debris

Fig. 6 shows the average value of 4 shape parameters of all wear debris on the sliding speed for the applied load of 3kg. The shape parameter value of LBC3 is higher than carburized SCM440 in all speed conditions. This means that a particle morphology of

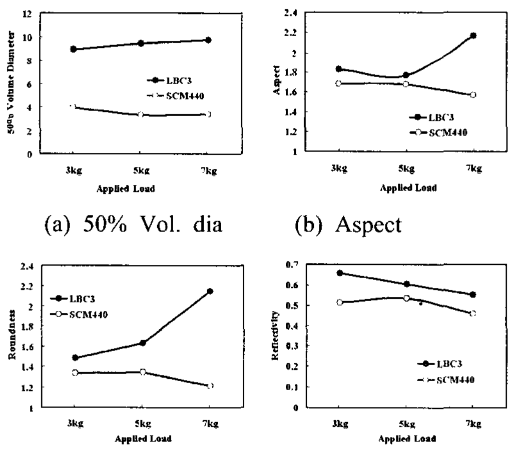
LBC3 is bigger, more complex and glossy than



(a) 50% Vol. dia. (b) Aspect

(c) Roundness (d)Reflectivity

Fig. 6 Average value of the shape parameters of wear debris on sliding speed, applied load : 29.4N



(a) 50% Vol. dia (b) Aspect

(c) Roundness (d) Reflectivity

Fig. 7 Average value of the shape parameters of wear debris on applied load, sliding speed : 80 mm/sec

SCM440. In the aspect and roundness, a morphology of wear debris is generally long and complex in the low sliding speed.

Fig. 7 shows the average value of 4 shape parameters of wear debris on the applied load in the sliding speed of 80 mm/sec. According to the increasing load, wear debris of LBC3 are more complex and longer than carburized SCM440. And reflectivity for two materials decreases according as the applied load increases. It is considered that two materials are oxidized quickly due to the increased temperature of the rubbed surface.

Therefore, as shown in Fig.6 and Fig.7, the morphological characteristics of the wear debris on operating condition can be classified by the average value of four shape parameters.

3.2 Formation of group for identification of wear debris

Because the morphological characteristics of each wear debris occurred in the hydraulic moving system are distributed widely and very various, it is very difficult to apply directly to morphology identification of the wear debris by the neural network. Therefore, in order to identify the morphological characteristics of wear debris, it is effect to use the property of small group of wear debris such as the average value of shape parameters for the suitable number of wear debris.

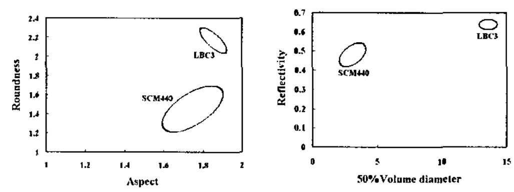


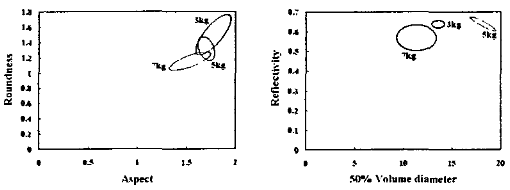
Fig. 8 The distribution of average value of the shape parameters in every 100 wear debris for materials, applied load : 3 kg, sliding speed 40 mm/sec.

Fig. 8 shows the distribution of average value of the shape parameters in every 100 wear debris for materials in the applied load of 3 kg and the sliding speed of 40 mm/sec. As shown in figure, the distribution of the shape parameters for the materials is separated very well, so the decision rate in neural network is expected to be high for materials of the hydraulic moving system.

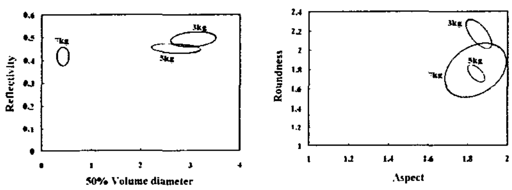
Fig. 9 shows the distribution of average value of the shape parameters in every 100 wear debris of (a) LBC3 and (b)SCM440 for the applied load in the sliding speed of 40 mm/sec. In (a) LBC3, the distribution of the 50% volumetric diameter and the reflectivity are separated well. But the aspect and the roundness are overlapped a little. In case of (b)SCM440, the 50%

volumetric diameter and the reflectivity are overlapped partly, and the aspect and the roundness are overlapped very much. From these results, the decision rate in the neural network is expected to be high for the applied load of LBC3, but the decision rate on SCM440 is considered to be low.

Fig. 10 shows the distribution of the average value in every 100 wear debris for the sliding speed in the applied load of 7 kg. The distribution of shape parameters of (b) SCM440 is overlapped much more than those of (a) LBC3. Therefore, the decision rate for the sliding speed is also expected to be low.

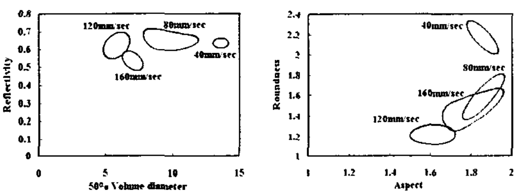


(a) LBC3

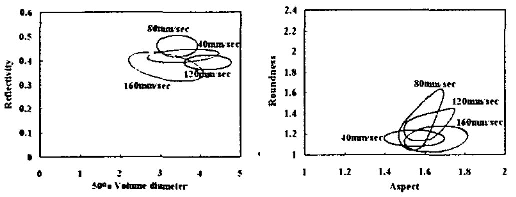


(b) SCM440

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.

3.3 Morphological identification of wear debris by the neural network.

In order to recognize the operating conditions with the morphology of wear debris occurred in the hydraulic driving members, the neural network of the 3 hidden layer with 27 unit was constructed, and learned the 24 pattern on the operating condition. And the average value in every 50 and 100 wear debris on each operating condition was used as the input data.

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

Table 2 and table 3 represent the results of identification by the neural network for the materials, the applied load and the sliding speed. The decision rate for the material is 100 % in all operating conditions because the distribution of the shape characteristics for the materials is separated obviously as shown in Fig. 8. The decision rate for the sliding speed and the applied load with groups of every 100 wear debris is higher than groups of every 50 wear debris. The decision rate in every 100 wear debris is over 90 %.

Although the distribution is overlapped, if the average values of shape parameters for group of wear debris are investigated overall, the shape characteristics on the operating condition can be identified obviously. The various operating conditions of the lubricated machine elements can be recognized by using the neural network with the optimum condition.

4. Conclusions

From the wear debris occurred in the lubricated machine system, the fore shape parameters, such as 50% volumetric diameter, aspect, roundness and reflectivity were calculated with the image processing, and the neural network learned these parameters and identified the operating conditions.

The shape parameters of LBC3 were higher than SCM440 and the morphological characteristics of wear debris of LBC3 were big, complex and glossy. When the neural network learned the 24 learning pattern in the different hidden layer and unit number, the learning error converged most rapidly in the 27 unit of 3 hidden layer. The distribution of average value of shape parameters in every 100 wear debris for materials was separated well, but the distribution was overlapped a little for the applied load and the sliding speed. The decision rate for the material was 100 % in all operating conditions and it was higher with groups of every 100 wear debris than groups of every 50 wear debris for the sliding speed and the applied load.

In this study, the neural network was able to recognize the operating conditions of the hydraulic machine elements.

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