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Wear Particle Classifier System Based on an Artificial Neural Network

Valdeci Donizete Gonçalves[1,*] - Luis Fernando de Almeida[2] - Mauro Hugo Mathias[1]
[1] UNESP – São Paulo State University, Brazil
[2] UNITAU – Taubaté University, Brazil

This paper describes a method to identify morphological attributes that classify wear particles in relation to the wear process from which they originate and permit the automatic identification without human expertise. The method is based on the use of Multi Layer Perceptron (MLP) for analysis of specific types of microscopic wear particles. The classification of the wear particles was performed according to their morphological attributes of size and aspect ratio, among others.

Keywords: artificial neural network, wear particles analysis, expert system

0 INTRODUCTION

Wear particles, contained in lubricating oil, carry with them important information related to the condition of the corresponding machinery. Microscopic analysis of the wear particles in lubricating oil provides a powerful tool for predicting potential machine failure. The development of advanced systems for wear particle analysis is an essential tool for proactive maintenance in industrial plants.

This paper describes the use of a Multi Layer Perceptron (MLP) for analysis of the most common types of microscopic wear particles, i.e., Rubbing (R), Cutting (C), Severe Sliding (SS) and Fatigue (F). The MLP was trained and tested using a database, constructed with records related to the wear modes that are examined in this work.

The wear particles classification was performed according to their morphological attributes of size and aspect ratio, among others. Oil monitoring, also known as wear particle analysis and physical analysis of lubricant properties, has been recognized as one of the most important approaches for condition monitoring and failure analysis [1].

Recent research efforts have been focused on the development of an automatic and efficient system to perform wear particle analysis, such as those using image processing, expert systems, knowledge-based systems and so on [2] and [3].

1 ARTIFICIAL NEURAL NETWORKS

Artificial Neural Networks (ANN) are known for their application in classification problems, including those related to the maintenance of machines [2] to [6]. They are composed of many simple elements, called neurons, operating in parallel and connected to each other by multipliers, called weights. Basically, an ANN is composed of the following:

– Processing units or neurons (xi, hj, yk) receiving input from neighbours or external sources and using this to compute an output signal which is propagated to other neurons.
– Weights determine the effect of one neuronal signal on another.
– The activation function (*f*), an element that determines the level of neuron activation, is based on the effective input Σ.

There are many types of ANN, and Multilayer Perceptron (MLP) stands out as one of the most widely used. Fig. 1 illustrates a standard MLP with one hidden layer. The learning of a MLP is supervised; each input signal received from the environment is associated with a specific desired target pattern.

Usually, the weights are synthesized gradually, and at each step of the learning process they are updated so that the error between the network output and corresponding desired target is reduced [7].

[*]Corr. Author's Address: UNESP - São Paulo State University, Av. Dr. Ariberto Pereira da Cunha, 333, Zip Code: 12516-410, Guaratinguetá, SP, Brazil, valdecidgoncalves@gmail.com

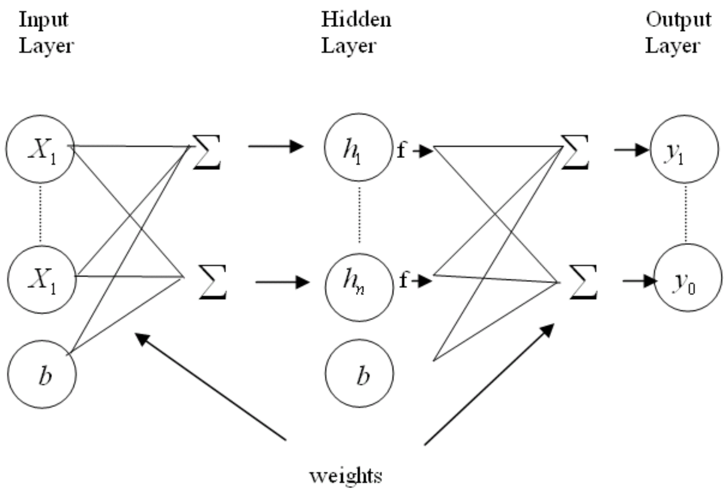

Fig. 1. *Standard MLP with one hidden layer*

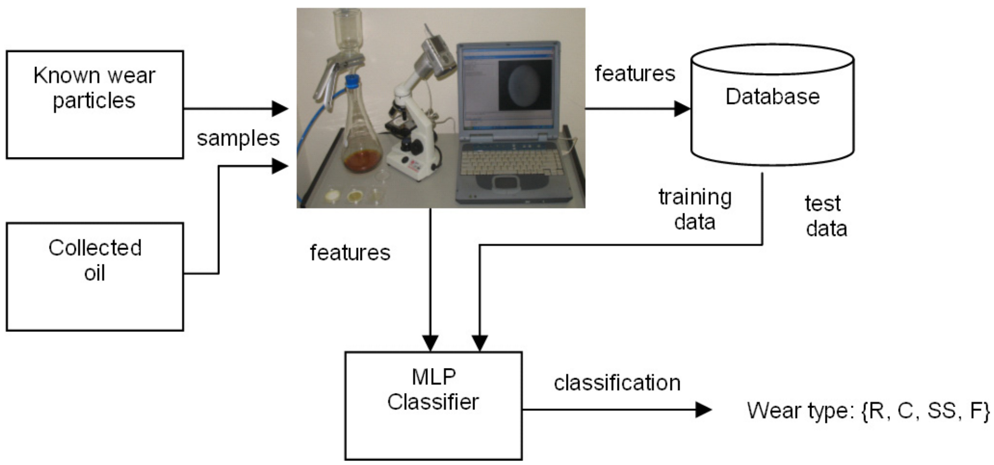

Fig. 2. *Classification system architecture*

2 PROCEDURE FOR DEVELOPMENT

The learning and classification procedures are described in Fig. 2. At the initial phase, pictures of four kinds of known wear particles are introduced into a system to extract their features, and they are then saved into a database. Rubbing wear, severe sliding, cutting wear and fatigue were the types of wear particles used in this study. Ten individual features of each type of wear particle were analyzed to structure the database, which is used for MLP training and testing. After that, the MLP can be applied to classify unknown data from its features.

2.1 Features Extraction

The wear particle modelling proposed in this work is based on morphological attributes, which include area, perimeter, width, height, circularity, elongation, Feret diameter, major diameter, minor diameter and aspect ratio [11]. The process applied to identify the particle types consists of matching features extracted from a given input particle with those of the wear particle type models.

The system can be integrated with an automatic particle analyzer previously developed by the authors [10]. The first version of the system was developed using different stylized particles created from the set of wear mechanisms analyzed in this work.

Ten stylized particles of each kind of wear mechanism were prepared, forming a sample of forty binarized particles images related to the wear mechanisms under study. The Fig. 3 illustrates stylised particles type for cutting wear.

Table 1 shows the features of ten stylized particles, related to cutting wear mechanisms. Such features were obtained using ImageJ software [12].

The data obtained for all wear particles are used to feed the neural network system, which will process the data and classify the particles according to the kind of wear mechanism.

2.2 MLP Classifier

In this paper, a MLP with one hidden layer is used for particle classification. In order to define the appropriate net architecture, a set of tests with varying numbers of neurons in the hidden layer from 3 to 15 were carried out. The database content was divided in two groups: training and test data. Both are represented by a *P*x*F* matrix, where *P* represents the total number of training particles and *F* is the number of features used.

Due to the importance of input data pretreatment [8], both datasets have been normalized by using a simple linear scaling of the data, according to Eq. 1. The $\min_i$ and $\max_i$ variables represent the range of "i" normalized features, while $d_{\min}$ and $d_{\max}$ are the lower and upper values for that feature, respectively.

$$nd_{i,j} = \frac{\min_i + (\max_i - \min_i) \times (d_{i,j} - d_{\min})}{(d_{\max} - d_{\min})} \tag{1}$$

In order to provide faster learning, weight initialization, developed by Nguyen and Widrow [9], was used. According to Fausett [7], this analysis is based on a hyperbolic tangent activation function, which is closely related to the bipolar sigmoid activation function described in Eq. 2.

$$f = -1 + 2/(1 + \exp(-\Sigma)) \tag{2}$$

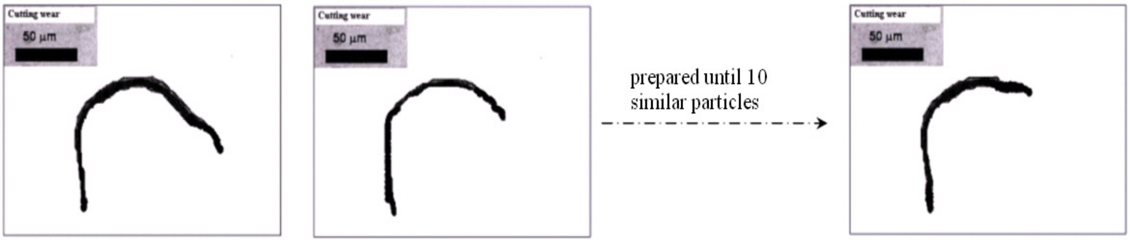

Fig. 3. *Stylised particles cutting wear*

Table 1. *Features extracts of cutting wear*

Cut-ting	Area	Peri-meter	Width	Height	Major diam.	Minor diam.	Circu-larity	Feret	Elongation	Aspect ratio
1	1436.57	385.25	108.28	83.43	60.56	30.20	0.12	113.57	2.98945	1.2978
2	1408.21	469.78	120.12	98.82	55.24	32.46	0.08	123.70	3.84980	1.2155
3	1333.99	431.45	108.28	100.59	55.08	30.84	0.09	120.36	3.54450	1.0764
4	766.43	347.65	91.12	84.02	46.57	20.95	0.08	105.93	2.63540	1.0845
5	1533.91	491.82	120.71	108.28	56.21	34.74	0.08	128.62	4.23610	1.1147
6	1093.10	376.65	90.53	100.00	56.43	24.66	0.10	122.71	2.55240	0.9053
7	981.41	401.65	117.75	50.89	56.79	22.00	0.08	118.24	2.26470	2.3138
8	965.65	406.38	97.63	99.41	51.01	24.10	0.07	118.49	2.79110	0.9820
9	1325.58	554.81	129.59	95.27	60.74	27.79	0.05	150.86	2.68670	1.3602
10	1206.54	531.65	118.34	100.00	48.24	31.85	0.05	124.52	4.88650	1.1834

2.3 Neural Network for Wear Particle Classification

The first version of the program "Neural Network for Wear Particle Classification", Neural_WPC, was used to perform the tests. This program was created to analyze appropriated ANN configurations to classify wear particle mechanisms. This tool was divided into two modules, training network and particle classifier. The training network executes the MLP training and presents a graphic of the set rate of the trained ANN, and also allows the analyzing of a specific architecture related to the training time. The classification module allows for a classification of set particles according to wear modes trained into the ANN. Such resources are illustrated by Fig. 4.

3 TESTS AND RESULTS

The tests were carried out to determine the best set of features of the MLP to be used by the classifier. For this reason, all possible combinations between these features were considered. The MLP used has 5 neurons in the input layer, 10 in the hidden layer, and 4 in the output layer. Table 2 shows the results of the best configuration.

From the best configuration, presented in Table 2, a test was conducted as a function of the performance, as measured by the number of epochs, i.e., learning time, varying from 100 to 2000. The final results are presented in Fig. 5, which shows the stability in training with 1000 epochs.

4 CONCLUSION

This article presents an important tool for the analysis of microscopic wear particles, found in the lubricating oil, by using Artificial Neural Networks. The results have demonstrated that the presented method, when executed through an ANN, may be successfully used for the characterization of wear particle profile attributes. However, it is also noted that the rate of accurate characterization can increase or decrease depending on the features chosen as inputs to the ANN. For the features used in these experiments, accurate classification was obtained at a maximum rate of 96%, with a standard deviation of 2%.

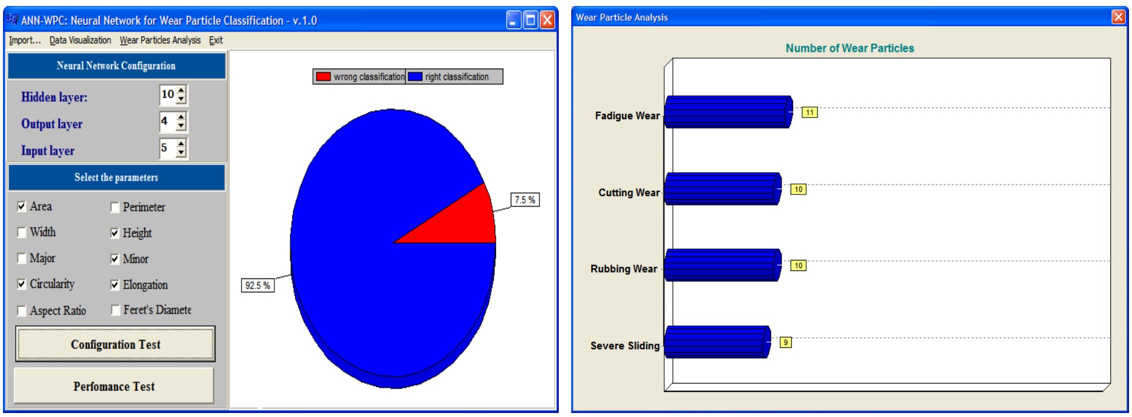

Fig. 4. *ANN_WPC windows*

Table 2. *Best configuration for combinations between extracted features*

Features - Input Layer					Right Classification [%]
Area	Height	Minor	Elongation	Aspect Ratio	96.0
Area	Height	Minor	Circularity	Elongation	95.2
Area	Minor	Circularity	Elongation	Aspect Ratio	95.2
Area	Height	Minor	Elongation	Aspect Ratio	95.2
Area	Height	Minor	Circularity	Aspect Ratio	94.1

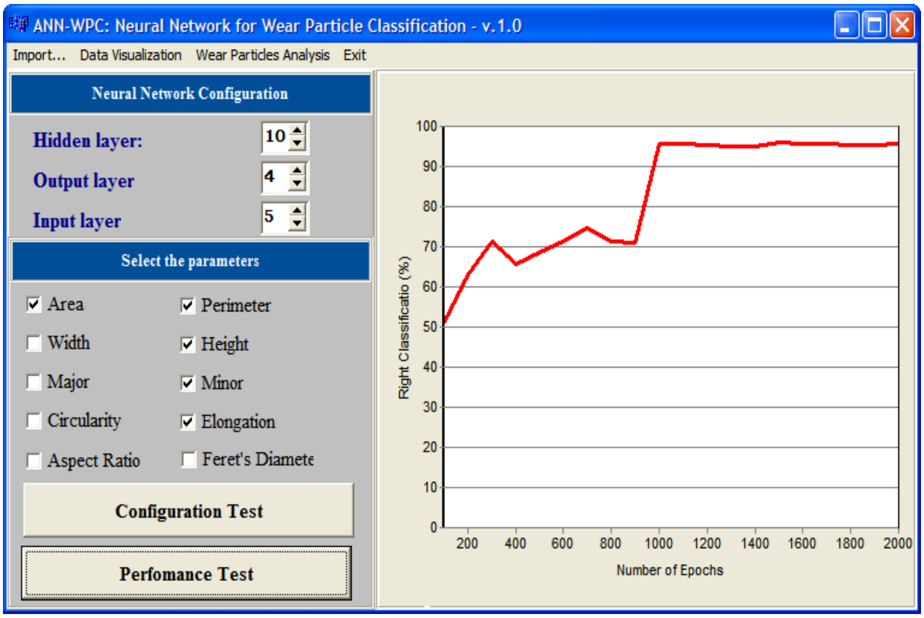

Fig. 5. *Performance of the best configuration*

Finally, the input data normalization and weight initialization used in this work allowed for a reasonable training time, about 1000 iterations. In future works, other analysis methods, like those for edge detail and texture and other wear particles types, will be analyzed.

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