Engine Wear State Recognition Based on Image Analysis and Genetic Algorithm

Zhen Zhang¹,², Cheng Zhao¹,², Zhaoyu Liu¹,²

¹Zhengzhou University of Aeronautics, Zhengzhou 450015, China
²Collaborative Innovation Center for Aviation Economy Development of Henan Province, Zhengzhou 450046, China

Abstract

The characteristic of oil filter debris on aero-engine can reflect the engine wear state, and through the analysis of debris on the oil filter can be obtained image characteristic data of debris. After the introduction and analysis of the advantages and disadvantages of aero-engine oil filter debris detection principle and common method, the engine wear state recognition technology based on the engine oil filter debris image is proposed. Firstly, characteristic quantities of oil filter debris image which can reflect wear state were extracted with the mathematical morphology method. Then, oil filter debris images that can reflect normal state were collected, and the normal training sample sets were constructed through image analysis and feature extraction. Finally, the normal domain of oil filter image was obtained through normal training samples using outlier detection, and to identify the severity of the wear state of aero-engine according to the normal domain. Besides, the self-adaptive parameter of novelty detection was obtained by genetic algorithm. Experiments show that this wear state recognition technology has high accuracy and can provide the theoretical foundation for the design of an automatic detection system of aero-engine wear state.

Key words: Aero-engine, Image Analysis, Genetic Algorithm, Wear State, Outlier Detection

1. INTRODUCTION

Engine oil filter number and size of the debris reflects the severity of engine wear, wear debris on the oil filter be acquired by an image of the image and how much reflects the degree of accumulation of debris. Therefore, to efficiently extract oil filter debris from the debris in the target image, and as calculated to reflect the degree of wear of quantitative indicators, is the key to effective recognition engine wear state. Research engine oil filter debris monitoring method, the establishment of quantitative, standardized and easy process for standard operating and monitoring, which can effectively fill the existing spectrum monitoring methods cannot effectively predict fatigue failure due to spindle bearings, etc. caused by the technical limitations of the risk of failure, improve engine oil system fault prediction success rate, which is important for the safe use of the engine to solve problems and complete combat training mission.

2. STUDY OF AERO-ENGINE OIL FILTER MONITORING

1970s, aero-engine oil filter monitoring studies have been carried out in foreign countries, mainly taken periodically check the oil filter, oil filter and the debris down on cleaning methods for quantitative analysis, but this method takes a long time, generally only as an auxiliary detection method. In recent years, foreign debris on the oil filter using X-ray fluorescence spectroscopy and scanning electron microscopy techniques such as spectroscopy study many reports, these systems are generally more complex and larger investment. The most commonly used iron spectral analysis method using the image of wear debris analysis tools, also have their limitations, mainly in: demanding sampling, observation of the iron spectrum depends on the person's level of experience, and non-iron spectral method ferromagnetic abrasive detected some difficulties (Nelson 2014; Podsiadlo and Stachowiak, 2013).

This design aero-engine oil filter wear image monitoring system, using mathematical morphology to extract the perimeter and area parameters on oil filter image abrasive wear debris, to fully reflect the degree of engine wear; aviation engine oil filter for debris image normal samples to obtain easy, and abnormal samples Get a difficult problem, the introduction of outlier detection based on genetic algorithm, through the normal sample study to obtain normal domain boundary normal wear and oil filter image through this border to achieve the oil filter image wear identifying the state and the practical application of analysis to verify the validity of this method.
3. FEATURE EXTRACTION OF OIL FILTER DEBIRS IMAGE

Oil filter debris from the captured images Figure 1 can be found: the image of wear debris (low gray image area) of the number of engine wear reflects the severity of the condition, if the image is segmented from the debris area, the region is calculated area and perimeter, it can quantitatively reflect the severity of engine wear. Thus, selective extraction from the oil filter image abrasive wear debris perimeter and area as the image characteristics extraction step is specific: to extract images debris goal first using the maximum entropy threshold segmentation method, and then, in Second debris on the target value of the image extraction perimeter and area values. Binary image of Figure 1 divided image shown in Figure 2.

(a) Normal wear                   (b) Abnormal wear

Figure 1. The oil filter debris image

3.1. Area Calculation

With the advancement in networking and multimedia technologies enables the distribution and sharing of multimedia content widely. In the meantime, piracy becomes increasingly rampant as the customers can easily duplicate and redistribute the received multimedia content to a large audience. Insuring the copyrighted multimedia content is appropriately used has become increasingly critical (Jadranka, 2013).

In the binary image Figure 2, wear debris showed gray value area 0, area calculations converted to statistics the number of gray values of 0. Distribution area is located wear debris image I, the image of wear debris S grayscale value of 0 and the number of pixels, that is

\[ S = N_f = \sum_{i=0}^{m} \sum_{j=0}^{n} f(i, j), (i, j) \in I \] (1)

Wherein, \( N_f \) represents the number of pixels of a region of the gray value of 0; \( f(i, j) \) is the gray value binary image pixel correlation function, when the pixel gray scale is 0, the function is 1; when the pixel gray 255, whose function value is zero. Therefore, the statistics of the debris area gray value of 0 is the number of pixels, is the area of debris.

3.2. Perimeter Calculation

A collection of the border represented as \( \beta(A) \), it can use mathematical morphology corrosion by first by
B to A, then A minus by corrosion results, which is

\[ \beta(A) = A - (A \Theta B) \] (2)

Wherein, B is a suitable structural elements (such as a square, triangular, etc.); A\( \Theta B \) is the result of corrosion B to A.

When the boundary \( \beta(A) \) with a set of data points \( \Omega = \{ V_i = (x, y), i = 0, 1, \cdots, N - 1 \} \) represents the time, and even into a closed polyline point is the length of wear debris perimeter \( P \), which is

\[ P = \sum_{i=0}^{N-1} | V_{i+1} - V_i | \] (3)

Experiments show that the use of this method to extract the area \( S \), perimeter \( P \) values accurately reflect the true value of the image, effectively showing the wear debris characteristics of the image, therefore, \( (S, P) \) becomes the sample is representative of the image of wear debris data for detecting wear.

4. GENETIC ALGORITHM IN OUTLIERDETECTION

Genetic algorithm is an adaptive probabilistic simulation of global genetic and evolutionary processes in the natural environment and the formation of the search algorithm. It was first proposed by Holland professor at the University of Michigan, the origin of natural and artificial adaptive research in the 1960s and 1970s De Jong natural environment and the formation of the search algorithm. It was first proposed by Holland professor at the University of Michigan, the origin of natural and artificial adaptive research in the 1960s and 1970s De Jong

In a series of studies based on the 80’s by Goldberg summarized, form the basic framework for genetic algorithms. Hereinafter will analyze and discuss how to use genetic algorithm engine oil filter debris image outlier detection(Haggett and Chu, 2015).

4.1. Determined Decision Variables and Constraints

Identify the decision variables and constraints that determine the individual’s phenotype solution space \( X \) and issues. Obviously, the decision variables of the system is \( x \) and \( y \), the solution space is the range of \( |x, y| \), namely the range of \( \lambda_1 \) and \( \lambda_2 \) (Guo X. and Yang X.Y. et al, 2014).

4.2. Optimization Model And Coding

Mathematical system model \( f(\lambda, x, y) \), the objective function of \( F(x, y) \). Coded representation of the solution space is the midpoint in this selection of binary symbols way to represent. Now the decision variables system is \( x \) and \( y \), \( x \) and \( y \) corresponding to the amount of change set of \( \lambda_3 \) and \( \lambda_2 \) is

\[
\begin{cases}
(\Delta \lambda_3)_{\text{max}} = c_1 \\
(\Delta \lambda_2)_{\text{max}} = c_2
\end{cases}
\] (4)

\( c_1, c_2 \) is a constant. \( x, y \) can be determined by the formula (4) is

\[
\begin{cases}
x \in [\lambda_{b1} - c_1, \lambda_{b1} + c_1] \\
y \in [\lambda_{b2} - c_1, \lambda_{b2} + c_1]
\end{cases}
\] (5)

\( \lambda_{b1,2}(j=1, 2) \) is Outlier values. The Discrete domain of \( x, y \) is

\[
\begin{cases}
x \in [\lambda_{b1} - c_1 + c_4, \lambda_{b1} - c_1 + 2c_4, \cdots, \lambda_{b1} - c_1 + n_1c_4] \\
y \in [\lambda_{b2} - c_1 + c_4, \lambda_{b2} - c_2 + 2c_4, \cdots, \lambda_{b2} - c_1 + n_2c_4]
\end{cases}
\] (6)

\( c_4 \) is System requirements for measurement accuracy/2, \( n_{1,2} = \text{int}(c_1 / c_4) + 1 \).

4.3. Decoding

Decoding required binary coding sequence \( n_1 + n_2 \) bit cut into three segments, lengths of \( n_1 \) and \( n_2 \), each corresponding to a decimal number, referred to as \( X_e \) and \( Y_e \), based on the individual in front of the
encoding method and the method of discrete domain we can see that the code of \( X_a \) and \( Y_a \) decoding formula is

\[
\begin{align*}
X_i &= \lambda_{a1} - c_i + 2c_1(X_a / 2^n), i = 1, 2, \cdots, n_1 \\
Y_i &= \lambda_{a2} - c_2 + 2c_2(Y_a / 2^n), i = 1, 2, \cdots, n_2 
\end{align*}
\]

(7)

4.4. Chromosome And Fitness

Each point is called chromosome after coding, the length of each chromosome is \( n = (n_1 + n_2) \), segment length respectively were \( n_1 \) and \( n_2 \). Selecting a number of chromosomes from the solution space component called population. In the genetic algorithm, the initial population \( P(t)(t = 0) \) is composed of \( m \) chromosomes computer in the solution space composed of randomly selected. Value of \( m \) should be much smaller than the number of points in the solution space. In this system, the fitness of a chromosome is a function of its corresponding system objective function value \( F_i \) of \( F(x,y) \). The probability of being selected is

\[
P_{pi} = \sum \frac{F_i}{\sum F_i}, i = 1, 2, \cdots, m \quad (8)
\]

4.5. Outlier Detection Principle

The outlier detection method based on the boundary, its essence is to find the minimum sphere containing all positive class samples, outside the spheres are outliers area. For the sample set \( \Xi = \{x_1, x_2, \cdots, x_N \} \), wherein the samples are positive class (Larry and Malik, 2013; Zhuang and Hu, 2016).

When the radius which surrounded whole sample completely by the minimum sphere is \( R \), the center of the sphere is \( a \), the optimizing equation is:

\[
\min L(R) = R^2 \quad (9)
\]

\[
s.t. R^2 - (x_i - a)(x_i - a)^T \geq 0 \quad (10)
\]

By equation (9) and (10) Lagrange function can be defined:

\[
L(R, a, \lambda) = R^2 - \sum_{i=1}^{N} \lambda_i \left[R^2 - (x_i \cdot x_i - 2a \cdot x_i + a \cdot a)\right] \quad (11)
\]

In Equation (11), \( \lambda = \{\lambda_i\}, \ i = 1, 2, \cdots, N \); \( \lambda_i \) is Lagrange coefficient, \( \lambda_i \geq 0 \).

By Equation (11) to solve can get the optimization equation:

\[
\max L = \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j x_i \cdot x_j - \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j x_i \cdot x_j \quad (12)
\]

Constraints are \( \sum_{i=1}^{N} \alpha_i = 1 \) and \( \alpha_i \geq 0 \). According to the most optimal condition of KKT, most of the elements in \( \lambda \) are 0, only a small part \( \alpha_i > 0 \). This corresponds to the boundaries of the sample point determination, namely support vector. From the known \( \lambda \) can calculate the center of the sphere \( a = \sum_{i=1}^{N} \alpha_i x_i \). Optionally a support vector can be calculated and it is from the center of the sphere radius \( R \) (Tax and Duin, 2014; Camci and Chinnam, 2015).

Let pending state data point \( z \), determine whether it is wild point is based on:

\[
\begin{align*}
\left\{ f(z1) > R^2 \right. \\
\left. f(z2) \leq R^2 \right\} \quad (13)
\end{align*}
\]

Wherein, \( z1 \) are outliers, \( z2 \) are not outliers, \( R \) is radius. The optimization equation for outlier detection is
\[ f(z) = K(z, z) - 2 \sum_{i=1}^{N} \alpha_i K(z \cdot x_i) - \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j K(x_i \cdot x_j) \quad (14) \]

5. WEAR STATE RECOGNITION AND EXPERIMENT

5.1. Recognition Method

① Image acquisition debris, enter the normal sample of cases from the image; ② Normal wear debris image using mathematical morphology to extract the perimeter and area feature quantities; ③ Normal samples with debris area and perimeter feature amount for training, construction comprising minimum hypersphere all normal samples, and find the location of ball center and the radius; ④ Wear debris collected a new image processing step above them, according to step③ smallest hypersphere the center of the sphere position to strike function, the results obtained with the smallest hypersphere of radius R in comparison, if less than the radius, namely a new image in the debris of the smallest hypersphere, is considered to be normal wear and tear of the engine, on the contrary, it was considered abnormal engine wear, the need for further examination of the engine. The debris image detection process shows in Figure 3 (Roylance , 2014; Sahoo and Arora, 2014).

![Debris image detection process](image.png)

5.2. Experiment results

In order to verify the effectiveness of oil-based debris filtered image diagnosis method of image analysis and genetic algorithm, a number of normal and abnormal wear of the engine to collect images from randomly selected 70 images of normal and abnormal images 30, a total of 100 sample images, composed of experimental samples. From 70 normal image, randomly selected 35 images as training samples outlier detection; the remaining 35 normal and 30 abnormal images as a test sample. Area S and perimeter P of the image feature extraction, and the data normalized to the interval [0,1] to obtain normalized area S and perimeter P, use outlier detection methods seek decision surfaces.

By experiment of outlier detection optimizing equation (14) can prove the Gaussian kernel function better than other nuclear functions. Optimization equation slack variables exist to allow some point in the super ball in vitro, the number of sample points is determined by in vitro hypersphere penalty factor C, in other words C can determine the degree of punishment the edge of the sample. Sample recognition rate different penalty factor C and different Gaussian kernel function parameters under σ obtained by comparing the results shown in Table 1.

<table>
<thead>
<tr>
<th>Penalty factor C</th>
<th>Parameters σ</th>
<th>Number of support vectors</th>
<th>Recognition rate of normal sample, %</th>
<th>Recognition rate of abnormal sample, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.08</td>
<td>0.2</td>
<td>20</td>
<td>68.2</td>
<td>100.0</td>
</tr>
<tr>
<td></td>
<td>0.7</td>
<td>16</td>
<td>79.1</td>
<td>100.0</td>
</tr>
<tr>
<td></td>
<td>1.0</td>
<td>13</td>
<td>82.7</td>
<td>100.0</td>
</tr>
<tr>
<td></td>
<td>5.0</td>
<td>15</td>
<td>84.5</td>
<td>100.0</td>
</tr>
<tr>
<td>0.10</td>
<td>0.2</td>
<td>17</td>
<td>68.4</td>
<td>100.0</td>
</tr>
<tr>
<td></td>
<td>0.7</td>
<td>13</td>
<td>71.8</td>
<td>100.0</td>
</tr>
<tr>
<td></td>
<td>1.0</td>
<td>11</td>
<td>84.5</td>
<td>100.0</td>
</tr>
<tr>
<td></td>
<td>5.0</td>
<td>12</td>
<td>84.5</td>
<td>100.0</td>
</tr>
<tr>
<td>.050</td>
<td>0.2</td>
<td>15</td>
<td>71.8</td>
<td>100.0</td>
</tr>
<tr>
<td></td>
<td>0.7</td>
<td>6</td>
<td>95.4</td>
<td>100.0</td>
</tr>
<tr>
<td></td>
<td>1.0</td>
<td>4</td>
<td>98.5</td>
<td>96.6</td>
</tr>
</tbody>
</table>
Table 1 shows that: in the case of the same penalty factor $C$, the recognition rate of the test sample with normal parameters $\sigma$ increases gradually increased, while the recognition rate of abnormal test samples with the parameter $\sigma$ increases gradually decreased; some the range, increasing the penalty factor $C$, the test sample recognition rate increases when beyond a certain range, the effect of $C$ will be obvious. Only when the $C$ and $\sigma$ when taken to an appropriate value, normal and abnormal samples to samples can reach high recognition rate, at this time, the corresponding number of support vectors usually less. Seen to some extent, these parameters have a great impact on classification accuracy of the model. In practical application, we choose the appropriate penalty factor $C$ and Gaussian kernel parameter $\sigma$ is particularly important.

With the above sample, the maximum number of iterations is located in GA80, the population size is 20, the individual string lengths of 10, crossover and mutation rates were 0.8 and 0.05, the optimal classifier model parameters: penalty factor $C = 0.48$ Gaussian kernel parameter $\sigma = 0.72$. In this parameter, by the 35 training samples is calculated: the radius $R = 0.5129$. Testing with the test sample, the ratio of the distance to the training samples with the radius of the central region of the positive type, and the ratio of the distance from the test sample to the radius of the n-type region scattergram showing the center, as shown in Figure 4. As can be seen, the normal test sample relative distance between the center of the n-type region to substantially less than 1 or close to 1, abnormal test sample relative distance to the center of the n-type region is greater than 1.1 as a classification threshold to obtain recognition results: normal test sample recognition rate of 95.7%, abnormal test sample identification rate of 100%, compared to Table 1, the recognition rate, this parameter under normal and abnormal wear identification rate reached over effect, describes the genetic algorithm and the effectiveness of this method automatically obtain optimal classifier method parameters on engine wear condition can be effectively identified.

6. CONCLUSIONS

Based on image analysis and outlier detection engine oil filter wear state recognition are carried out. Construction of the first image acquisition device acquires the oil filter image, then use mathematical morphology to achieve the effective extraction of the wear debris image characteristics, has been described oil filter image features perimeter and area values, the last based on genetic algorithm outlier detection methods, by normal case sets learning image samples to give normal domain boundaries, and the use of genetic algorithm to obtain the optimal parameters, thereby establishing a model outlier detection and diagnosis. This method requires only a class of samples for training, to effectively solve the oil filter to obtain a sample of normal wear debris image easily, abnormal samples get difficult. This method is very effective as an off-line testing, no abrasive ingredients can be detected automatically determines classification threshold, reducing the dependence of expertise.
Acknowledgements

This work was supported by the Scientific and Technological Research Project of Henan Province (No.132102210219), and the Aviation Science Fund Project(No.2014ZD55010).

REFERENCES