Application on Damage Types Recognition of Civil Aeroengine Based on SVM Optimized by DMPSO

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Abstract. In order to recognize the damage types of aeroengine automatically and Reliably, enhance the support capability of aeroengine maintenance, the feature extraction method based on color moments and gray level co-occurrence matrix (GLCM) is proposed to construct the feature database of the aeroengine damage images. The support vector machine (SVM) is utilized as intelligent classifier for damages recognition. Meanwhile, a double-mutations particles swarm optimization (DMPSO) algorithm is designed to optimize the kernel parameter and penalty factor for guaranteeing the recognition performance of SVM. Finally, the feature databases are constructed by different feature methods according to actual four damage types of a certain aeroengine, and then the proposed SVM optimized by DMPSO is used to compare with back propagation (BP) network, extreme learning machine (ELM) network, and k-nearest neighborhood (k-NN). The recognition results have proven the proposed feature extraction method is more suitable for aeroengine damage recognition. Meanwhile, the comparison results have demonstrated the optimized SVM always has better and stable recognition output.

1. Introduction
The safety of civil aviation aircraft is directly related to the life and property of passengers. As a highly integrated and precise complex industrial product, aeroengine can provide sufficient power for flight and is the key system to ensure flight safety. According to the statistics from the global civil aviation industry, the proportion of flight accidents caused by aeroengines is about 50%, while the maintenance cost of aeroengines accounts for 40% of the total cost [1]. Therefore, it is of great significance to carry out efficient and accurate research on maintenance decision-making of civil aerogine, which is help to reduce maintenance cost and time.

The civil aeroengine has been always working in the harsh environment of high temperature, high pressure and high load, so that the key components such as discs, blades, turbines and fuel nozzles are vulnerable to some kinds of impact loads, resulting in cracks, corrosion, tears, burns, falling blocks and other damages. Usually, the damages not only cause aeroengine performance degradation, but also easily lead to aeroengine failure, even threat to flight safety. With the help of non-destructive testing (NDT), the structural damage inside the aeroengine can be detected and image information can be captured accurately. Determining the aeroengine damage types is the key link of aeroengine image
analysis technology, which can guide further judging the damage mechanism, determining the damaged parts and evaluating the damage severity.

However, the damage types recognition based on digital image processing technology still relies on expert experiences. And the aeroengine structure is complex, the damage types are diverse, the traditional methods relying on expert experiences are more incompetent for the accurate recognition. With the rapid development of modern intelligent recognition technology, artificial neural network, deep learning, statistical pattern recognition and other methods are widely used in pattern recognition [2-4], which makes the damage types detection and recognition get rid of the excessive dependence on expert experiences, these methods can improve the recognition accuracy, and provide reliable technical support for aeroengine maintenance.

As shown in previous researches, the artificial neural network has the disadvantages of poor convergence and generalization, moreover, the settings of network parameters and topological structure are uncertainty [5]. Deep learning requires a large number of samples, and the efficiency of the algorithm is relatively low, which reduces the real-time requirements [6]. Statistical pattern recognition is sensitive to the probability distribution of samples [7]. As a classical machine learning algorithm, SVM (support vector machine) is built on VC (Vapnik-Chervonenkis) dimension and Structural Risk Minimum principle of statistical learning theory, which has complete theoretical basis and interpretability. SVM has been widely used in pattern recognition and regression estimation, especially with the introduction of kernel function, the application scope of SVM is expanded [8, 9]. Therefore, SVM will be used to recognize the aeroengine damage types in this paper.

Like other machine learning algorithms, parameter adjustment is the main factor affecting the performance of the algorithm. In this paper, an improved PSO (particles swarm optimization) is proposed. By enhancing the population diversity, balancing the exploitation and exploration, PSO can get better global optimization performance. The parameters optimized by PSO can improve the accuracy and stability of SVM when recognizing the aeroengine damage types.

2. Damage database based on color feature and texture feature

Figure 1 shows the recognition process for aeroengine damage types. After obtaining different damage images, it is essential that the digital image features would be constructed to build aeroengine damage database and further provide original samples for training SVM.

2.1. Feature extraction based on color moment and GLCM

The analysis and extraction of the image features, such as color, texture and shape, has become a widely used method in practical application. More research results have been achieved at home and abroad. Reference [10] proposed a color feature extraction method based on HSV (hue saturation value) space. In [11], the statistics of GLCM (gray level co-occurrence matrix) were used to describe

![Figure 1. The recognition process for aeroengine damage image types.](image-url)
the texture features of images. GLCM features and Tamura features were combined to form new digital features in [12].

Generally, the color feature of the image has strong robustness, which is the most intuitive and obvious to reflect the damaged parts of the aeroengine. The texture feature reflects the surface structure characteristics of an object and the surrounding environment information, which is the attribute of image graying. According to the characteristics of damage images, this paper proposes an image feature extraction method based on color moment and GLCM texture feature (CM-GLCM).

Let $R$, $G$ and $B$ represent the red, green and blue component matrix of the aeroengine damage image. According to the sensitivity of the human eyes to different color systems, the gray image can be obtained by weighted average of $R$, $G$ and $B$. The calculation expression is as follows:

$$f(i, j) = 0.30 \cdot R(i, j) + 0.59 \cdot G(i, j) + 0.11 \cdot B(i, j)$$  \hspace{1cm} (1)

where $f$ represents the gray matrix. The statistical characteristics of colors can be obtained by calculating the moments of gray image. Moreover, the color distribution information is mainly concentrated in the low-order moments, so the first three-order moments are used in this paper to indicate the color distribution of the image, and the calculation formulas are as follows:

$$\mu = \frac{1}{N} \sum_{i,j} p_{ij}$$  \hspace{1cm} (2)

$$\sigma = \left[ \frac{1}{N} \sum_{i,j} (p_{ij} - \mu)^2 \right]^{1/2}$$  \hspace{1cm} (3)

$$\zeta = \left[ \frac{1}{N} \sum_{i,j} (p_{ij} - \mu)^3 \right]^{1/3}$$  \hspace{1cm} (4)

where $N$ denotes the quantity of pixels in the matrix; $p_{ij}$ is the pixel of row $i$, column $j$; $\mu$ is first moment, also called the mean of matrix; $\sigma$ is second moment, also called the variance of matrix, which reflects the inhomogeneity of gray image; and $\zeta$ is third moment, also called the skewness of matrix, which defines the asymmetry of gray image.

On the other hand, GLCM describes the texture of image by studying the spatial correlation of gray level, which was proposed by R. Haralick et al in the early 1970s [13]. GLCM is statistics for the gray level of two pixels with a distance of $D$ and a direction of $\theta$, which reflects the comprehensive information about the direction, interval and amplitude changes of the gray image, and GLCM is the basis of analyzing the local pattern of the image. For the definition and calculation process of GLCM, please refer to [12, 13]. In order to describe image texture features intuitively, this paper uses angular second moment (ASM), contrast, correlation, entropy, inverse different moment (IDM) to characterize the texture features reflected by GLCM, and the specific calculation formula is as follows:

$$ASM = \sum_{i,j} p_{ij}^2$$  \hspace{1cm} (5)

$$CON = \sum_{i,j} (i-j)^2 p_{ij}$$  \hspace{1cm} (6)

$$COR = \frac{\sum_{i,j} (i-\mu_i)(j-\mu_j)p_{ij}}{\sigma_i\sigma_j}$$  \hspace{1cm} (7)
\( \text{ENT} = - \sum_{i,j} p_{ij} \log p_{ij} \) \hspace{1cm} (8) \\
\( \text{IDM} = \sum_{i,j} \frac{p_{ij}}{1 + (i-j)^2} \) \hspace{1cm} (9)

where
\( \mu_i = \sum_i \sum_j p_{ij} \) \hspace{1cm} (10) \\
\( \mu_j = \sum_j \sum_i p_{ij} \) \hspace{1cm} (11) \\
\( \sigma_i = \sum_i (i - \mu_i)^2 \sum_j p_{ij} \) \hspace{1cm} (12) \\
\( \sigma_j = \sum_j (j - \mu_j)^2 \sum_i p_{ij} \) \hspace{1cm} (13)

\( \text{ASM} \) reflects the uniformity of gray distribution and texture. When the elements in GLCM are centrally distributed, \( \text{ASM} \) has a relatively large value, which shows that gray image is a more uniform and regular texture mode. Contrast reflects the definition of gray image. Generally, the deeper the image groove, the larger the \( \text{CON} \), and the clearer the visual effect. Correlation measures the similarity of row elements or column elements in GLCM. When the elements are well-distributed, \( \text{COR} \) is larger, which reflects the local gray-scale correlation in the image. Entropy is a measure of random information carried by an image. When the elements in GLCM are scattered, \( \text{ENT} \) is larger, which indicates the heterogeneity level and complexity level of the image. The \( \text{IDM} \) reflects the roughness of the image texture, the \( \text{IDM} \) of the coarse texture is larger, on the contrary, it is smaller.

So far, 8 features of color moment and GLCM texture are extracted to describe the aeroengine damage image, Figure 2 shows the flow chart of image feature extraction. Then the aeroengine damage image database will be constructed to provide samples support for automatic recognition.

2.2. Construction of aeroengine damage image feature database
4 kinds of damage images of a certain civil aeroengine are collected, and one group of them is shown in Figure 3. Figure 3 (a) shows the burn-through damage of the fuel nozzle baffle. Figure 3 (b) shows the ablation damage of high pressure turbine blade (HPT blade). Figure 3 (c) shows the drop block and crack of high pressure compressor blade trailing edge (HPC blade TE). Figure 3 (d) shows the perforation of the combustion chamber.

According to the features extraction method discussed above, a test database of damage image features is constructed, and some feature data are shown in table 1. The basic characteristics of the
database are shown in Table 2, 339 samples are randomly selected as training samples and the rest of 86 samples are as test samples, they will be used to test the performance of the recognition algorithm proposed in this paper.

![Image](a) ![Image](b) ![Image](c) ![Image](d)

**Figure 3.** One group damage images of a certain aeroengine.

**Table 1.** Partial samples of damage image features database.

| Color features | GLCM features | Damage types |
|----------------|---------------|--------------|
| First moment   | Second moment | Third moment  | ASM | Contrast | Correlation | Entropy | IDM |
| 93.7363        | 11.6403       | 61.5801      | 0.0486 | 0.9658   | 0.9731       | 5.2483  | 0.8258 | burn-through |
| 96.4422        | 9.2361        | 67.4654      | 0.0068 | 8.4195   | 0.8006       | 7.5101  | 0.3426 | burn-through |
| 94.1228        | 10.6837       | 63.5223      | 0.0467 | 3.2251   | 0.9142       | 5.4002  | 0.8105 | burn-through |
| 93.7347        | 10.3823       | 52.2879      | 0.0607 | 0.7241   | 0.97063      | 4.8397  | 0.8692 | ablation    |
| 94.1052        | 9.0594        | 55.0407      | 0.05837| 2.8275   | 0.8925       | 4.9956  | 0.8529 | burn-through |
| 98.9348        | 7.7736        | 59.4908      | 0.00777| 8.4832   | 0.7341       | 7.3995  | 0.3397 | ablation    |
| 96.6967        | 7.6054        | 65.1879      | 0.0488 | 7.5639   | 0.8126       | 5.2735  | 0.8344 | drop block  |
| 95.6412        | 12.0436       | 64.0749      | 0.0173 | 5.0355   | 0.8722       | 6.6855  | 0.4971 | drop block  |
| 97.0433        | 6.7279        | 66.9045      | 0.0469 | 9.7213   | 0.7677       | 5.3636  | 0.8191 | drop block  |
| 106.4187       | 6.9893        | 61.5982      | 0.0068 | 8.7235   | 0.7506       | 7.5113  | 0.3386 | perforation |
| 98.4885        | 8.5429        | 59.4548      | 0.0138 | 5.3788   | 0.8317       | 6.7651  | 0.4707 | perforation |
| 108.8065       | 6.9618        | 61.6739      | 0.0068 | 8.7999   | 0.7493       | 7.5277  | 0.3368 | perforation |

**Table 2.** The basic characteristics of damage images database.

| Damage site          | Damage types     | Training samples size | Test samples size |
|----------------------|------------------|-----------------------|-------------------|
| fuel nozzle baffle   | burn-through     | 78                    | 20                |
| HPT blade            | ablation         | 90                    | 23                |
| HPC blade TE         | drop block       | 78                    | 20                |
| combustion chamber   | perforation      | 93                    | 23                |

3. The improved PSO algorithm

PSO is a heuristic swarm random search algorithm. Since it was proposed in 1995, because of its simple mathematical expression, clear mathematical interpretation and less parameter adjustment, it has been widely used in engineering optimization problems, and has become one of the most popular intelligent optimization methods [14]. Like other swarm optimization algorithms, PSO also has an inherent defect, in the iterative process, it is easy to trap into the local optimal region, which results in
premature convergence [15]. In order to overcome this inherent defect, this paper proposed an improved double-mutations PSO (DMPSO) based on iteration mutation strategy and self-regulation mutation strategy. By enhancing the population diversity, balancing the exploitation and exploration in the iterative process, the DMPSO can enhance the population global optimization ability and provides the optimal parameters for SVM.

3.1. DSPO algorithm
For the detailed theory of traditional PSO algorithm, please refer to [14]. The improved strategies proposed in this paper includes two aspects. Iteration mutation strategy can improve the particle update formula. And self-regulation mutation strategy is used to mutate these particles that can't optimize the global extremum.

3.1.1. Iteration mutation strategy.
Formula (14) shows the redesigned particle update formula based on iteration mutation strategy, mutation vector is introduced into update formula, the expression is as follows:

\[
\begin{align*}
    v_i^{k+1} &= \omega \cdot v_i^k + c_1 \cdot r_1 \cdot \alpha \left( p_{ie}^k - p_i^k \right) + c_2 \cdot r_2 \left( p_{ge}^k - p_i^k \right) \\
    p_i^{k+1} &= p_i^k + \alpha \cdot v_i^{k+1}
\end{align*}
\]

where \( k \) denotes the current iteration number; \( p_i \) is the \( i \)th particle; \( p_{ie} \) is the individual extremum, which is a historical optimal position experienced by particle; \( p_{ge} \) is the global extremum, which is optimal position experienced by population; \( v_i \) is the velocity vector; \( \omega \) is the decreasing inertia weight; \( c_1 \) and \( c_2 \) are constants, usually, \( c_1=1.5 \) and \( c_1=1.7 \). \( r_1 \) and \( r_2 \) are two independent random numbers in \([0, 1]\). Tradition update formula doesn’t contain parameter \( \alpha \). \( \alpha \) is a randomly generated binary vector with the same dimension as \( p_i \). \( \alpha \) is defined as mutation vector. Its function is to reduce the dependence of particles on their own extremum, increase the population diversity, enhance the particles exploitation ability at the early stage of iteration, and it can increase the probability of particles jumping out of the local suboptimal region.

3.1.2. Self-regulation mutation strategy.
Self-regulation mutation strategy is to make a mutation to the particles that can't improve the global extremum. if a \( p_i \) can't improve the \( p_{ge} \), it will be mutated directly, which is not intervened by human in the process iteration. Conversely, if a \( p_i \) has improved the \( p_{ge} \), it will be update Continuely according to formula (14). Self-regulation mutation formula is given as follows:

\[
\begin{align*}
    p_i^{k+1} &= (1-\alpha) \cdot p_i^k + r \cdot \alpha \cdot \left( p_{ge}^k - p_i^k \right)
\end{align*}
\]

where \( r \) is also a random number in \([0, 1]\). In formula (15), the mutation vector \( \alpha \) can not only increase the population diversity, but also benefit the exploration ability at the later stage of iteration, which can increase the probability of obtaining optimal solution.

The parameters of DMPSO proposed in this paper are consistent with those of traditional PSO, and the mutation process doesn't need to be intervened by human. Furthermore, double-mutation strategy can maintain the population diversity, balance the exploitation and exploration, enrich the update mode, so that the global optimization performance of DMPSO can be enhanced significantly.

3.2. DMPSO performance verification
In order to verify the performance of DMPSO, some classic and complex test functions will be used to verify the optimization performance of different PSO variants. The relevant information of these test functions is listed in Table 3.

Some PSO variants based on different strategies will be compared with DMPSO. There are algorithms based on imitating human behavior, such as self-regulating PSO (SRPSO) [16], aging leader and challengers PSO (ALCPSO) [17]; there are algorithms based on parameter adjustment, such
as inertia weights PSO (IWPSO), shrinkage factor PSO (SFPSO) [18] There are algorithms based on neighborhood topology, such as dynamic neighborhood PSO (DNPSO) [19]; There are algorithms based on algorithm integration, such as simulated annealing PSO (SAPSO) [20], multiple agents PSO (MAPSO) [21]. The size of population in all algorithms is 60, the maximum iterations is 400, the particles are randomly initialized in the range of [-100, 100], and the velocity is randomly initialized in the range of [-2, 2]. All algorithms are run in the same computational environment.

Table 3. The characteristics of 8 test functions.

| Test function | Search range | Dimension | Optimal solution | Global extremum |
|---------------|--------------|-----------|------------------|-----------------|
| Sphere: $f_{\text{Sphere}} = \sum_{i=1}^{n} x_i^2$ | [-100, 100] | 50 | (0, 0, ..., 0)$_{50}$ | 0 |
| Schaffer: $f_{\text{Sch}} = 0.5 + \left( \left( \sin \left( \sqrt{\sum_{i=1}^{n} x_i^2} \right) \right) - 0.5 \right)$ | [-100, 100] | 50 | (0, 0, ..., 0)$_{50}$ | 0 |
| Griewank: $f_{\text{Gri}} = \sum_{i=1}^{n} \frac{x_i^2}{4000} - \prod_{i=1}^{n} \cos \left( \frac{x_i}{\sqrt{i}} \right) + 1$ | [-100, 100] | 50 | (0, 0, ..., 0)$_{50}$ | 0 |
| Ackley: $f_{\text{Ack}} = -20 \cdot e^{-\sum_{i=1}^{n} \left( \frac{x_i^2}{4} - \cos (2\pi x_i) + 1 \right)} + 20 + e$ | [-100, 100] | 50 | (0, 0, ..., 0)$_{50}$ | 0 |
| Rastrigin: $f_{\text{Ras}} = \sum_{i=1}^{n} \left[ x_i^2 - 10 \cdot \cos (2\pi x_i) + 10 \right]$ | [-100, 100] | 50 | (0, 0, ..., 0)$_{50}$ | 0 |
| Rosenbrock: $f_{\text{Ros}} = \sum_{i=1}^{n-1} \left[ 100 (x_i^2 - x_{i+1})^2 + (x_i - 1)^2 \right]$ | [-100, 100] | 50 | (1, 1, ..., 1)$_{50}$ | 0 |
| SDPF: $f_{\text{SDPF}} = \sum_{i=1}^{n} |x_i|$ | [-100, 100] | 50 | (0, 0, ..., 0)$_{50}$ | 0 |
| RHEF: $f_{\text{RHEF}} = \sum_{i=1}^{n} \left( \sum_{j=1}^{i} x_j \right)^2$ | [-100, 100] | 50 | (0, 0, ..., 0)$_{50}$ | 0 |

In this paper, the performances of PSO variants are compared by the mean of the fitness values obtained from 100 consecutively runs. Table 4 shows the optimization results of PSO variants. Obviously, table 4 proves that the DMPSO designed in this paper has excellent global optimization performance and can provide reliable optimization results in engineering optimization.

Table 4. The optimization results of PSO variants.

| function  | SRPSO | ALCPSO | IWPSO | SFPSO | DNPSO | SAPSO | MAPSO | DMPSO |
|-----------|-------|--------|-------|-------|-------|-------|-------|-------|
| $f_{\text{Sphere}}$ | 1.7591e-4 | 8.4543 | 469.3132 | 1843.34 | 0.1174 | 141.2324 | 0.0041 | 2.6565e-92 |
| $f_{\text{Sch}}$ | 0.4473 | 0.4645 | 0.4532 | 0.4864 | 0.4855 | 0.4543 | 0.3435 | 0 |
| $f_{\text{Gri}}$ | 0.0053 | 0.3654 | 1.1102 | 1.5452 | 0.0231 | 0.9563 | 0.0041 | 0 |
| $f_{\text{Ack}}$ | 21.1654 | 19.4546 | 19.5434 | 20.8652 | 20.1004 | 19.5646 | 18.7543 | 0 |
| $f_{\text{Ras}}$ | 192.8652 | 951.234 | 1126.43 | 2626.32 | 473.2345 | 1178.34 | 205.4223 | 0 |
| $f_{\text{Ros}}$ | 154.9428 | 5232.13 | 5892.74 | 2061.12 | 168.4534 | 2635.46 | 147.6532 | 43.8797 |
| $f_{\text{SDPF}}$ | 3.14e+08 | 1.21e+24 | 1.49e+38 | 1.42e+39 | 0.1564 | 9.65e+35 | 7.85e+07 | 1.3532e-11 |
| $f_{\text{RHEF}}$ | 917.6472 | 1032.76 | 10433.53 | 6846.53 | 6774.532 | 2510.42 | 1245.64 | 2.7938e-81 |
4. SVM optimized by DMPSO

SVM is a pattern recognition algorithm based on statistical learning theory. By maximizing the classification margin between hyperplanes, the optimal classification surface problem can be transformed into dual problem by Lagrange function, so that the convex quadratic programming can be solved to constructed the discriminant function. For the linearly non-separable problems, the original samples in low dimension space can be transformed into linearly separable samples in high dimension feature space by kernel function mapping, so that the linearly non-separable samples can be recognize correctly. The SVM optimization problem of the maximum classification margin can be expressed as follows:

\[
\begin{align*}
\min_{w, b, \xi} & \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{l} \xi_i \\
\text{s.t.} & \quad y_i (w \cdot \Phi(x_i) + b) \geq 1 - \xi_i, \\
& \quad \xi_i \geq 0
\end{align*}
\]  

(16)

where \(w\) is the normal vector of hyperplane; \(\xi\) is the slack variable; \(C\) is the penalty factor; \(x_i\) is the sample vector; \(y_i\) is the sample label of \(x_i\), \(y_i \in \{-1, +1\}\); \(\Phi(\cdot)\) is the mapping function that maps the samples of low dimension space into high dimension feature space.

Finally, by using the Lagrange function to construct and solve the convex quadratic programming problem, the decision functions can be obtained as follows:

\[
f(x) = \text{sgn} \left( \sum_{i=1}^{n} y_i \alpha_i^* (\Phi(x) \cdot \Phi(x_i)) + b^* \right)
\]  

(17)

where \(\alpha_i^*\) is the coefficient of the support vector; \(\alpha_i^*\) is 0 for non-support vector, \(n\) is the number of support vectors; \(x_i\) is the support vector; \(b^*\) is the classification threshold.

According to the Mercer condition, a function \(K\) can be selected to correspond to the inner product of space transformation. So let \(K(x, x_i) = \Phi(x) \cdot \Phi(x_i)\), and the function \(K(\cdot)\) is called kernel function. With the help of kernel function, the theoretical difficulty of determining \(\Phi(\cdot)\) can be effectively avoided. Then formula (17) can be changed to:

\[
f(x) = \text{sgn} \left( \sum_{i=1}^{n} y_i \alpha_i^* K(x, x_i) + b^* \right)
\]  

(18)

Radial basis function (RBF) belongs to the global kernel function. The researches have shown that the global kernel function can make the hyperplane approach the training sample as much as possible, which is conducive to improving the accuracy of classifying the samples [22]. so RBF kernel function is adopted in this paper, formula (18) can be rewritten as follows:

\[
f(x) = \text{sgn} \left( \sum_{i=1}^{n} y_i \alpha_i^* \exp \left( -\gamma \|x - x_i\|^2 \right) + b^* \right)
\]  

(19)

Because \(C\) decides the penalty for the error classification, it can adjust the confidence range of support vector and the proportion of experience risk; \(\gamma\) is the parameter of kernel function, moreover, it mainly affects the linear distribution of samples in high-dimensional feature space. Different selections of the \((C, \gamma)\) can affect the precision of SVM significantly. Therefore, it is necessary to use DMPSO to optimize \((C, \gamma)\) in order to obtain the global optimal solution, so that SVM can get the best classification results.

When DMPSO optimizes \((C, \gamma)\), cross validation (CV) is used to determine the fitness value of PSO. Generally, the training samples are divided into \(k\) groups, and \(k-1\) groups are used in turn, the remaining one group is selected as test samples, so \(k\) recognition accuracies can be obtained by SVM.
And the mean of $k$ recognition accuracies is output as the fitness value of DMPSO. Because all training samples are traversed by CV, which can ensure the stability and accuracy of SVM.

5. Verification for the damage image recognition performance

In order to verify the effect of feature extraction method based on color moment and GLCM, and to verify the damage recognition performance of DMPSO-SVM, this paper will do the following comparative verification.

5.1. The influence of different feature extraction methods on recognition accuracy

According to the characteristics of the aeroengine damage image, the feature extraction method proposed in this paper are compared with those in [10-12, 23, 24]. A HSV spatial color feature extraction method proposed in [10]; A texture feature extraction method based on GLCM statistics proposed in [11]; a feature extraction method based on Tamura is proposed in [23]; a method based on the combination of Tamura and GLCM (Tamura-GLCM) is proposed in [12]; and a method based on the combination of Tamura feature and local gray color (Tamura-GC) feature is proposed in [24]. DMPSO-SVM will be used to verify the influence of different feature methods on recognition accuracy. The size of population in PSO is 60, the maximum iterations is 200, the particles are randomly initialized in the range of $[0, 10]$, and the velocity is randomly initialized in the range of $[-1, 1]$. The $k$ of cross validation is 5. The digital features of aeroengine damage images described in section 3.2 are extracted by these different methods to train and test the recognition algorithms.

Some common intelligent algorithms based on knowledge learning, such as BP (back propagation) network [25], ELM (extreme learning machines) network [26], $k$-NN ($k$-nearest neighborhood) algorithm [27], are introduced to verify the influence of various feature extraction methods on recognition accuracy. The error of BP network is 0.005, and the number of iterations is 300. ELM network is optimized by the method proposed in [26]. The recognition accuracy of $k$-NN is taken when $k=1$. Please refer to the relevant cited references for the specific calculation process of these algorithm. Due to the influence of the random initialized weight, the outputs of BP and ELM are always uncertain, therefore, the two methods run continuously 50 times in the same computing environment, and the means of accuracies are taken as the final output.

Figure 4 shows the recognition effect comparison based on different feature extraction methods. As shown in Figure 4, for different recognition algorithms, the feature extraction method proposed in this paper has better recognition effect than other feature extraction methods. The analysis for various feature extraction algorithms shows that: the extract methods proposed in [10, 11, 23] are based on single feature extraction principle, their descriptions for the damage images are not comprehensive enough, which results in relatively poor recognition accuracy. The extraction methods proposed in [12, 24] belong to the fusion extraction principle, which is conducive to describing the image features from multiple dimensions, therefore, compared with the single extraction principle, they are relatively conducive to the damage image recognition. In addition, the method in [24] also considers the color features, and its recognition is also a relatively higher accuracy. The proposed method based on color moment and GLCM feature extraction takes color feature and texture statistical feature into account, which makes the feature extraction of aeroengine damage image more objective and comprehensive. The experimental results show that the proposed feature extraction method is more reasonable and effective.
5.2. Recognition performance Comparison of different algorithms

In this paper, a SVM optimized by DMPSO is proposed. The optimal parameters ($C$, $\gamma$) can be obtained by cross validation, so that SVM can output stable and reliable results. In order to verify the performance of the proposed algorithm in damage image recognition, the above four recognition algorithms will be compared with DMPSO-SVM. Figure 5 demonstrates the recognition performance differences of the 4 algorithms. As shown in figure 5, basically, the performance of the proposed algorithm is better than others. And table 5 shows the optimization results of DMPSO and the recognition accuracies of 4 algorithms.

![Figure 5](image_url)
Table 5. Recognition performance comparison table of 4 algorithms.

| Extraction methods   | DMPSO-SVM | BP | ELM   | k-NN  |
|----------------------|-----------|----|-------|-------|
|                      | (C, γ)best| CV mean accuracy | accuracy | accuracy | accuracy | accuracy | accuracy |
| HSV                  |           | 87.10%          | 86.04%    | 81.40%    | 84.88%    | 81.39% |
| GLCM                 |           | 74.42%          | 68.60%    | 68.60%    | 65.12%    | 66.27% |
| Tamura               |           | 84.56%          | 77.90%    | 79.06%    | 75.58% |
| Tamura-GLCM          |           | 94.01%          | 89.53%    | 82.58%    | 89.53%    | 89.53% |
| Tamura-GC            |           | 96.31%          | 95.35%    | 94.19%    | 95.34%    | 93.02% |
| CM-GLCM              |           | 96.77%          | 100%      | 97.67%    | 95.34%    | 94.18% |

Because the recognition principles of different algorithms are different, it is difficult to ensure that one algorithm is effective for all data distribution types. For example, the recognition accuracy of DMPSO-SVM is relatively lower than that of ELM network based on the data extracted by the Tamura method proposed in [23]. However, SVM can overcome the influence of randomness effectively due to the optimization ability of DMPSO, and DMPSO-SVM doesn’t have the defect of output uncertainty, such as BP network and elm network. Meanwhile, it is not as sensitive to k as k-NN. Therefore, DMPSO-SVM has good recognition performance, also provides stable and accurate output, which can provide reliable technical support for damage type recognition of civil aeroengine.

6. Conclusions
Through the research on feature extraction and recognition of a certain aeroengine damage images, the following conclusions can be drawn:

(1) The feature extraction method based on the color moments and GLCM texture features proposed in this paper is more conducive to describing the damage images of aeroengine, which can express the damage characteristics precisely. The comparison results prove this method can provide a reasonable and effective feature database for training the recognition algorithm.

(2) The iteration mutation strategy and self-regulation mutation strategy designed in this paper can make DMPSO maintain the population diversity, balance the exploitation and exploration, enrich the update mode. The double strategies improve the global optimization ability, so that DMPSO can provide the optimal SVM parameters.

(3) The SVM optimized by DMPSO can obtain the better recognition performance and stability of output.

Therefore, the feature extraction method and recognition algorithm proposed in this paper can provide automatic and reliable damage type output for the actual engine maintenance, and improve the efficiency of civil aviation safety support.

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