Research on aircraft skin damage identification method based on image analysis

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Abstract. In the field of civil aviation maintenance, it is necessary to identify aircraft skin damage, and then formulate a maintenance plan. The traditional detection method process is more complicated. This paper proposes an image-based skin damage recognition method. After pre-processing the samples to form a unified sample library, the eigenvalues of the samples are obtained by wavelet packet decomposition and gray-level co-occurrence matrix, and finally the c and g values in the optimal RBF kernel function are selected to construct a support vector machine training model and the test results show that with a low sample size, the constructed model is more accurate in identifying normal skins and accidental impacts, and the overall system recognition rate is 81.5%.

1. Introduction

At present, aircraft skin damage can be roughly divided into three categories: cracks, corrosion, and accidental impact[1]. The skin detection methods used at home and abroad are mostly manual inspections, using fluorescent agents, ultrasound, radiation, electromagnetic induction, etc. to produce different reactions to the skin[2]. But some of these methods are more complicated in detection process, and some are more labor-intensive and time-consuming[3]. To cure the above problems, this article mainly studies the aircraft skin damage recognition method based on image analysis. The method is mainly divided into four steps: aircraft skin damage sample acquisition, sample pre-processing, feature value extraction and feature value analysis.

2. Acquisition and pre-processing of aircraft skin samples

The acquisition and pre-processing of skin damage image samples include three processes: image cropping, grayscale processing and noise reduction processing, ensuring the unity and clarity of the samples, and preparing for the feature value extraction of subsequent image samples.

2.1. Aircraft skin damage sample acquisition

The aircraft skin damage sample acquisition work is mainly composed of two parts, one is to autonomously acquire images of the aircraft, and the other is to collect related images through the Internet. Autonomous sample acquisition was carried out on more than 20 aircraft parked on the apron of Civil Aviation University of China, such as B707, B737, Y7, MD82, etc., using iPhone 11 mobile phones. In order to reduce the reflection effect of the sample surface caused by sunlight, the backlight surface should be selected as far as possible; The network selects relevant images as a supplement to the sample set, which provides a strong guarantee for improving the accuracy of the final detection. Since there are fewer images of accidental crashes on the tarmac, this type of sample library mainly...
comes from the network to simplify the model. The training algorithm only analyzes the damage of the hole shape on the accidental impact image, and does not involve pits and other situations.

In order to increase the sample capacity of self-collected samples, the literature [4] pointed out that the capacity can be expanded by rotation. This article uses 90° rotation, flipping up and down along the central axis of the picture, and flipping left and right. The processing of some accidental impact samples is shown in Figure 1.

![Fig.1 The rotated and flipped accidental crash image](image)

The collected pictures are manually classified according to the four categories of normal, crack, corrosion and accidental impact, and a sample library of different types of damage is assembled to ensure that the pictures in each library are clear and the number is enough to make 30 pictures for the later period. Some samples of different types of skinning picture are shown in Figure 2.

![Fig 2 Samples of different types of skinning picture](image)
2.2. Pre-processing of aircraft skin damage samples

The collected sample images are color images with different sizes and a lot of background noise. It is more complicated to directly process the original image. Therefore, the main task of pre-processing is to unify the size of the image, and then process the color image in grayscale. Carrying out noise reduction filtering processing, where sample segmentation is needed for samples that contain various types of skin damages. The sample pre-processing procedure is shown in Figure 3.

![Sample image pre-processing procedure](image)

**Fig 3 Sample image pre-processing procedure**

2.2.1. Sample segmentation. Before extracting the sample feature values, the sample pictures need to be cropped to the same size. All the pictures are taken to the size of 256×256 pixels. The damaged part is mainly cut off and put into the sample library as the segmented skin sample picture. The skin crack damage sample library is shown in Figure 4.

![The skin crack damage sample library](image)

**Fig 4 The skin crack damage sample library**

2.2.2. Sample Grayscale processing. A picture can be represented by RGB color components. The color can be changed by adjusting the RGB color components. This article uses matlab to read the picture first, and then adjusts the RGB so that the values of the three channels are equal.

2.2.3. Noise reduction processing of samples. Considering the size of samples with strong edge effects such as cracks in the detection object, this paper uses a 3×3 median filter algorithm for noise reduction. The core of this algorithm is to select a 3×3 matrix pixel around the current pixel to be processed, sort the gray values in the matrix pixels from small to large, and replace the original pixel value with the middle gray value. The comparison between the original picture the grayscale image and the image after noise reduction is shown in Figure 5.

![Original image Grayscale image and noise reduction image comparison](image)

**Fig 5 Original image Grayscale image and noise reduction image comparison**
3. Feature extraction of skin samples

In order to improve the recognition accuracy of the skin sample, two methods are used in the feature value extraction of the skin sample. The feature value extracted by the two methods is used as the feature value of an image, and the feature points of the image are increased. One method is to perform three-layer wavelet packet decomposition on the image samples, make a wavelet packet tree, obtain the 8 nodes of the third layer, extract the wavelet packet decomposition coefficients and normalize them to calculate the average value; another method is to make the gray co-occurrence matrix of the sample in the directions of 0°, 45°, 90°, 135° and normalize it to synthesize the total co-occurrence matrix, and then calculate the texture coefficient energy, entropy, correlation and moment of inertia.

3.1. Wavelet packet decomposition to extract sample eigenvalues

3.1.1. Wavelet packet decomposition. Wavelet packet decomposition is a further optimization of wavelet transform, also known as the optimal subband tree structure. Wavelet packet decomposition is based on wavelet transform. In each level of signal decomposition, in addition to decomposing low frequency subbands, it also decomposes high frequency subbands. Finally, by minimizing a cost function, the information entropy function, the optimum is calculated Signal decomposition path. Wavelet packet decomposition is more precise and meticulous when analyzing signal characteristics. It can divide the time-frequency plane into finer divisions, and the resolution of wavelet packet decomposition on the high frequency part of the signal is higher than that of wavelet decomposition. Therefore, wavelet packet decomposition which belongs to the field of signal analysis has a wide range of application value.

3.1.2. Wavelet packet decomposition to extract eigenvalues. The sample is decomposed by wavelet packet to obtain the wavelet packet decomposition coefficients of each node. These coefficients contain the signal characteristics of the sample, so the wavelet packet decomposition coefficients can be used as the characteristic value of the sample. The working process is to first read in the sample picture, then set the sampling frequency, then use the wpdec program to decompose the picture into a wavelet packet tree, and then use the wpcoef function to extract the wavelet packet decomposition coefficients of each node, and finally normalize the data And save the average value, as shown in Figure 6.

![Fig 6 The process of extracting eigenvalues by wavelet packet decomposition](image)

Read the picture data in matlab and set the sampling frequency to 64. After the 3-layer wavelet packet decomposition, In the third layer of the wavelet packet tree, 8 nodes can be obtained, and the wavelet packet decomposition coefficient of each node is calculated and recorded. Since the image features are distributed differently at different frequencies, the wavelet packet decomposition coefficients will differ greatly. At this time, the data is normalized and the average value of the normalized data is obtained, which can clearly reflect the image feature value. Record the feature values of the skin image samples of different damage types in the table as the feature value database. Part of the data is shown in Table 1.
Table 1 Wavelet packet decomposition coefficients of different damage types

| Damage type   | Wavelet 1 | Wavelet 2 | Wavelet 3 | Wavelet 4 | Wavelet 5 | Wavelet 6 | Wavelet 7 | Wavelet 8 |
|---------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| Normal        | 0.4885    | 0.0466    | 0.0779    | 0.1966    | 0.1273    | 0.1521    | 0.1164    | 0.2125    |
| Crack         | 0.5941    | 0.0359    | 0.0828    | 0.1862    | 0.0268    | 0.1536    | 0.1160    | 0.2177    |
| Corrosion     | 0.4897    | 0.0653    | 0.0756    | 0.1684    | 0.1822    | 0.1422    | 0.1170    | 0.2205    |
| Accidental impact | 0.0909 | 0.0422    | 0.0920    | 0.3424    | 0.3245    | 0.1372    | 0.1170    | 0.4264    |

3.2. Gray-level co-occurrence matrix extracts image eigenvalues

3.2.1. Gray level co-occurrence matrix. Generation of gray-level co-occurrence matrix: take any point (x, y) in a certain \( N \times N \) image and another point \((x+a, y+b)\) that deviates from it, and set the gray value of this point \((g_1, g_2)\). Let the point \((x, y)\) make random motions in the entire \( N \times N \) image, and various gray values \((g_1, g_2)\) will be obtained. If the gray level is \( k \), then there are \( k^2 \) combinations of \((g_1, g_2)\). Finally, count the number of occurrences of each gray value, and then arrange them into a square matrix, and then use the total number of occurrences of \((g_1, g_2)\) to normalize them to the probability of occurrence \( p(g_1, g_2) \), and finally form gray-level co-occurrence matrix

In order to more intuitively describe the texture condition with the co-occurrence matrix, some scalars can usually be used to characterize the characteristics of the gray-scale co-occurrence matrix \([7]\). Commonly used features are: energy, correlation, entropy, and moment of inertia. The implementation steps of the gray-level co-occurrence matrix algorithm can be summarized as four steps:

1. Extract grayscale image
2. Gray scale quantization
3. Parameter selection for calculating eigenvalues
4. Calculation of texture feature value

3.2.2. Gray level co-occurrence matrix to extract eigenvalues. In this section, a method for extracting eigenvalues of the gray-level co-occurrence matrix is written in matlab, and the co-occurrence matrix at \( 0^\circ, 45^\circ, 90^\circ \) and \( 135^\circ \) with a distance of 1 is calculated, and then the four matrices are normalized for extraction eigenvalues.

Fig. 7 Flow chart of gray level co-occurrence matrix extraction eigenvalues

As shown in Figure 7, the process of using the gray-level co-occurrence matrix can be roughly divided into six steps:

1. Use matlab to read sample pictures
2. Since the default gray level of the image is 256, in order to reduce the amount of calculation, the gray level of the original image is compressed to 16 levels
3. Calculate the gray-level co-occurrence matrix of the image in the four directions of \( 0^\circ, 45^\circ, 90^\circ \) and \( 135^\circ \) and the default distance of 1
4. Normalize the four gray-level co-occurrence matrices calculated
5. Calculate the energy, correlation, entropy and moment of inertia of the normalized gray-level co-occurrence matrix, which is convenient for statistical texture features
(6) Take the mean value and standard deviation of the four texture parameters as the feature values, obtain 8 texture feature values and record them.

Write the feature values of the picture samples of different damage types into the table and save, and some data are shown in Table 2.

Table 2 Gray-level co-occurrence matrix eigenvalues of different damage types

| Damage type     | Energy mean | Energy standard deviation | Correlation mean | Correlation standard deviation | Entropy mean | Entropy standard deviation | Mean moment of inertia | Standard deviation of moment of inertia |
|-----------------|-------------|----------------------------|------------------|--------------------------------|--------------|---------------------------|------------------------|----------------------------------------|
| Normal          | 0.3270      | 0.1676                     | 1.3436           | 0.0555                         | 0.0845       | 0.0172                    | 1.8815                 | 0.0350                                 |
| Crack           | 0.3146      | 0.0077                     | 1.5858           | 0.0557                         | 0.1098       | 0.0370                    | 1.0974                 | 0.0233                                 |
| Corrosion       | 0.2860      | 0.1774                     | 2.0897           | 0.0921                         | 0.2420       | 0.0671                    | 0.4854                 | 0.0091                                 |
| Accidental impact | 0.3200   | 0.3677                     | 2.6049           | 0.0830                         | 0.1741       | 0.0403                    | 0.2291                 | 0.0009                                 |

Integrate the texture eigenvalues extracted using the gray-level co-occurrence matrix with the eigenvalues extracted from the wavelet packet decomposition coefficients using wavelet packet decomposition in the previous part to prepare for the next step of using support vector machines to analyze the eigenvalues.

4. Analysis of eigenvalues of skin samples

Perform feature value analysis after feature value extraction, mainly using the method of constructing a support vector machine (SVM) in matlab. After the feature value is input and the established three-dimensional vector, the feature value is divided into training set and test set, and then Select the optimal values of c and g, establish a support vector machine training model, and finally test and observe the results.

4.1. Support vector machine(SVM) analysis eigenvalue

4.1.1. SVM. Support vector machine(SVM)is a two-classification model. A linear classifier with the largest interval is established in the feature space. The largest interval makes it different from the perceptron. The linear classifier established is the support vector machine; the nonlinear classifier is also Contains nuclear skills and can be widely used in signal analysis. The learning strategy of SVM is to maximize the interval, which can be formalized as a problem of solving convex quadratic programming, which is also equivalent to the problem of minimizing the regularized hinge loss function [8].

Reasonable use of support vector machines can quickly identify and classify two types of samples. There are four types of aircraft skin damage samples to be classified in this study, so four classifications of support vector machines should be performed at this time to construct C\{2,4 \}=6 support vector machine classifiers, each support vector machine classifier can be divided into two categories, put four groups of skin damage samples into the support vector machine for pairwise classification, and finally four groups can be identified and classified Skin sample.

4.1.2. Support vector machine analysis eigenvalue. First, create a three-dimensional vector with feature values, and then select training data and test data, as well as the category identification of the two types of data. After selection, normalize the training set and test set data to find the kernel function parameters and build the training model. Finally, the test classification is performed to obtain the results, and the specific flow chart is shown in Figure 8.
In order to enable the support vector machine to read the eigenvalue data, create a three-dimensional variable and group it, the first dimension is the number of sample categories to be divided. In this study, normal skin, cracked skin, and corroded skin are analyzed. And accidental impact on the skin, so the number of categories is 4; the second dimension is all the skin damage characteristic values entered, and 120 characteristic value data can be imported from the established table; the third dimension divides the category boundary line.

After successfully reading the imported eigenvalues, first among the 30 eigenvalues of each category, the first 10 eigenvalues are classified as the training set, the last 20 eigenvalues are classified as the test set, and the data is normalized in the interval [0, 1]. Treatment. Use the cross-validation method to find the c/g parameters in the optimal RBF kernel function, and use the kernel function RBF to build a support vector machine training model, and finally test and classify the test set data, observe the prediction of the test set classification and the actual test set classification Images, the analysis results of different types of damage are shown in Figure 9.

It can be seen from the figure that from bottom to top are the identification of normal skin, cracked skin, corroded skin, and accidental impact skin. Normal skin and accidental impact are recognized
more accurately, and there are errors in cracked skin and corroded skin. The overall recognition rate is 81.428%.

5. Conclusion

Nowadays, aircraft transportation is used more and more in the field of transportation, and long-term flight and climate change can easily cause damage to the aircraft. Inspection work should not be underestimated. In view of the complex process of traditional detection methods and the high cost of manpower and material resources, this article studies the method of using image analysis to recognize aircraft skin damage, which provides a reference idea for skin damage detection. The experimental results show that with a low sample size, the constructed model is more accurate in identifying normal skins and accidental impacts, without identification errors, and there are misjudgments in the identification of cracks and corrosion with higher accuracy requirements. The overall recognition rate of the system is close to 81.5%.

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