Research on Feature Extraction of Local Binary Pattern of SLM Powder Bed Gray Image

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Abstract: The quality of powder bed is one of the important factors that affect the quality of Selective Laser Melting (SLM) of parts. Image preprocessing method and defect identification method are proposed for recoater hopping during powder spreading by SLM. For the collected powder bed image, the Basic Mask method is designed to preprocess the image, uniform the light intensity distribution of the image and filter out the image noise. To extract the defect features accurately, different Local Binary Patterns (LBP) operators are used to classify and calculate the identification accuracy of each operator by Support Vector Machine (SVM). The recognition accuracy of this method is up to 98%.

1. Introduction
Selective Laser Melting (SLM) is an advanced metal material additive manufacturing technology. Its process is simple, the production cycle is short, the cost is low, and the forming accuracy is high. It has broad application prospects in aerospace, biomedical, automotive and military industries. The SLM device is shown in Figure 1 [1].

The powder bed quality in the SLM forming process is one of the key factors that determine the forming quality. At present, the quality of powder bed is mainly detected by manual visual inspection. This method is time-consuming and labor-intensive, relies on subjective experience, has a high false detection rate and low efficiency. In order to improve the efficiency and quality of SLM forming, this paper applies machine vision to the detection of powder bed defects, and proposes a method to automatically identify powder bed defects[2]. At present, only Zhang Peng [3] in China has developed an online monitoring system of SLM forming powder bed quality based on machine vision, which can identify four kinds of powder bed defects. Luck Scime of Carnegie Mellon University [4~5] is mainly engaged in the research of machine vision monitoring powder bed quality abroad. In 2017, he proposed a computer vision recognition technology and unsupervised machine learning algorithm, which can realize offline powder bed anomaly detection and classification; in 2018, Luck Scime proposed an improved algorithm for identifying defects in powder bed based on neural networks. The algorithm has high accuracy, but it has a huge amount of calculation and is not universal.

Common powder defects include recoater streaking, recoater hopping, incomplete spreading, super elevation, debris, etc. The most common and difficult to identify is recoater hopping. Recoater hopping occurs when the recoater blade slightly hits the place just below the powder layer during the movement or the recoater blade itself trembles during the movement, which is characterized by repeated vertical stripes (perpendicular to the direction of movement of the recoater blade) [4], as shown in Figure 2. The recoater hopping exists in the entire powder layer, the position is random, the gray scale is close to the gray value of the powder layer, the striped texture has a certain width but the thickness is uneven, and it cannot be identified by straight line detection, and its texture characteristics can be used for identification,
then handed over to the classifier for processing and classification. Based on the above characteristics of the recoater hopping, this paper proposes an image preprocessing method to enhance the characteristics of the recoater hopping, extract the defect image LBP histogram and use SVM to identify and classify.

**Fig. 1 SLM forming device**

**Fig. 2 recoater hopping (Grayscale camera)**

### 2. Image preprocessing algorithm

After analyzing the powder bed image of each layer, it is found that there is little difference in the gray value of the same position between the non-defective powder bed images (Figure 3(a)); the difference between the powder bed image with the defect of the recoater hopping and the non-defective powder bed image. There is a certain range of differences in the gray value of the defect position. Metal powder and parts produce irregular reflections under the illumination of the light source, resulting in a large amount of granular noise in the image; the long working distance of the light source leads to uneven distribution of light on the powder layer. These problems cause interferences to the direct extraction recoater hopping, as shown in Figure 3(b).

In order to eliminate noise, this paper proposes a Basic Mask method. When collecting the powder bed image \( I(x, y) \), use the defect-free powder bed image collected under the same light source and camera as the basic mask \( B(x, y) \). Set a grayscale threshold range \([G_1, G_2]\), calculate the absolute value of the grayscale difference between the collected image \( I(x, y) \) and the base mask \( B(x, y) \), and get the image \( J(x, y) \). When the gray value of a point on \( J(x, y) \) is within the range of \([G_1, G_2]\), it is considered that there is a defect at this point, and there may be a recoater hopping, and its gray level on the image is retained; When the gray value of a point on \( J(x, y) \) is less than \( G_1 \) or greater than \( G_2 \), it is considered that there is no recoater hopping at this point, and the gray value of the point is set to 0. Calculated as follows:

\[
J(x, y) = I(x, y) - B(x, y)
\]

\[
J(x, y) = \begin{cases} 
0 & J(x, y) \notin [G_1, G_2] \\
|J(x, y)| & J(x, y) \in [G_1, G_2]
\end{cases}
\]

If there is an area with a gray value that is not 0 on the image \( J(x, y) \), the image may have defects, or there may be noise similar to the gray level of the recoater hopping. Median filtering is ideal for reducing random noise, and it will not blur image features while reducing noise. Gamma transformation is a commonly used gray-scale nonlinear transformation, which can enhance the contrast of selected areas. The expression is as follows:

\[
y = (x + esp)^\gamma
\]

\( x \) is the input gray value, \( y \) is the output gray value, \( esp \) is the compensation coefficient, and \( \gamma \) is the gamma coefficient.

Therefore, according to the actual situation of \( J(x, y) \), the preprocessed image \( K(x, y) \) can be obtained by performing median filtering and gamma transformation, as shown in Figure 3(c).

The basic mask method can uniform the image light intensity, so that the image is not restricted by the light intensity distribution, and lays the foundation for subsequent defect feature extraction.
3. Local Binary Patterns

Local Binary Patterns (LBP) is a kind of texture description operator, which has a strong ability to describe image texture, strong classification ability, high calculation efficiency and invariance to monotonous grayscale changes.

The application process of LBP operator is shown in Figure 4. In a progressive scan image, for each pixel in the image, the gray value of the pixel is used as the threshold, and the gray value of its surrounding 3×3 neighborhood pixels is compared and binarized, and the binary value is determined in a certain order. The result of the transformation constitutes an 8-bit binary number, and the decimal value of the binary number is used as the response at this point to obtain an LBP response image. The histogram of this response image is called the LBP statistical histogram, which is used as a feature of subsequent recognition work. It is called LBP feature.

As an extension of the basic LBP operator, the circular neighborhood LBP operator can obtain any radius and any number of neighborhood pixels, as shown in Figure 5. The unified LBP operator is an improvement on this basis. For a local binary mode, the 8-bit binary number after its binarization contains no more than two transitions from 0 to 1 or from 1 to 0, then this local binary mode is called a unified mode. For example, 10000001 is the unified mode (2 transitions), and 01100001 is the non-uniform mode (3 transitions). There are a total of 2^8 8-bit binary numbers after binarization, of which 58 are in unified mode, and the rest are in non-unified mode; in general, unified mode is a mode that reflects important information of the image, rather than a unified mode. Many jumps are caused by noise, which increases the amount of calculation of the entire image, which is not statistically significant; therefore, when calculating the LBP histogram, only the binary numbers of the 58 unified modes are counted separately, and the binary numbers of the non-unified modes All statistics together. In this way, the unified LBP operator can reduce the number of redundant features, while retaining sufficient feature depiction capabilities. Figure 6 is the feature histogram of the unified LBP operator for the recoater hopping.

The unified LBP operator can finely describe the local texture information of the image, but it is susceptible to noise interference and lacks the grasp of the main frame of image features. MB-LBP (Multi-Block Local Binary Patterns) can solve this problem. Select n×n pixels to form a pixel block, and calculate the average value of n×n pixels, so that the comparison between the pixel values of the traditional LBP operator is replaced by the average gray value between the pixel blocks, making the main structure of the image more characteristic clear, as shown in Figure 7. The stripes of the recoater hopping are obvious, the MB-LBP calculation can be used to enhance the main structure of the stripes, filter out unnecessary defect information, and highlight the defect characteristics [6].

The LBP histogram is only the statistics of grayscale changes, and cannot describe the structural features of the image, and the local features of each area of the image are often different. If only one LBP histogram is generated for the entire image, these local differences information will be lost. Partition LBP extraction of the image can make up for this deficiency. The specific method is to appropriately divide an image into M×N partitions, then calculate the histogram features of each image partition, and finally connect the histogram features of all the regions into a composite vector as the LBP
4. Experimental process and analysis

In order to verify the accuracy of the algorithm, this paper uses a self-built recoater hopping powder bed defect image database. The defect images are all from the real grayscale images of the powder spreading process of the SLM forming equipment. The database has a total of 547 samples, and each image has a size of 900*900. It contains two types of images, including 351 images without defects and 196 images with defects caused by the blade impact. 216 non-defective samples were randomly selected, 150 recoater hopping samples were used as training set images; 135 non-defective image samples, 46 recoater hopping samples were used as test set images. The program algorithm verification environment is Matlab R2019a. The classifier uses a support vector machine(SVM), the accuracy of the classifier uses a confusion matrix to judge [7].
During the experiment, the defect image is divided into 1×1, 3×3, 10×10, 30×30 partitions, and the recognition accuracy of different LBP operators is shown in Table 1.

### Table 1 The recognition accuracy of different LBP operators SVM

| Image Partition | LBP Operator | Pixel Block Size | Feature Dimension | Classifier Accuracy (%) |
|-----------------|--------------|------------------|-------------------|-------------------------|
| 1×1             | circular LBP | 1×1              | 256               | 80.9                    |
|                 | unified LBP  | 1×1              | 531               | 90.4                    |
| 3×3             | unified LBP  | 1×1              | 59                | 88.3                    |
|                 | MB-LBP       | 3×3              | 531               | 93.7                    |
|                 | MB-LBP       | 5×5              | 531               | 97.5                    |
| 9×9             | unified LBP  | 1×1              | 59                | 96.2                    |
|                 | MB-LBP       | 3×3              | 4779              | 98.0                    |
|                 | MB-LBP       | 5×5              | 4779              | 92.5                    |
| 10×10           | unified LBP  | 1×1              | 59                | 98.3                    |
|                 | MB-LBP       | 3×3              | 23600             | 95.5                    |
|                 | MB-LBP       | 5×5              | 23600             | 90.3                    |
| 30×30           | unified LBP  | 1×1              | 59                | 95.4                    |
|                 | MB-LBP       | 3×3              | 53100             | 92.5                    |
|                 | MB-LBP       | 5×5              | 53100             | 90.3                    |

From the above results, it can be seen that the traditional circular LBP operator has poor recognition ability, the unified LBP operator's recognition ability has been improved to a certain extent, and the image partition unified LBP operator can improve the recognition accuracy of the classifier to more than 90%. When the number of partitions increases to a certain extent, the dimension of the feature vector is too high, and the recognition ability of the classifier decreases. For MB-LBP operation, when the number of image partitions is small and the feature vector dimension is low, the larger the pixel block, the higher the recognition ability of the classifier; when the number of image partitions is large, the feature vector dimension is high, the larger the pixel block, the image details may be lost, resulting in a decline in the recognition ability of the classifier.

### 5. Conclusion

In this paper, the image preprocessing method based on the basic mask method effectively solves the problems of uneven light intensity distribution and more granular noise, and lays the foundation for defect feature extraction. Experiments show that the unified LBP operator after dimensionality reduction has better recognition ability for the entire image, and the recognition rate is improved by nearly 10% compared with the circular LBP operator. Within a certain range of the number of partitions, the more partitions, the better the image detail information is retained, and the recognition rate can reach more than 95%; when the number of partitions is too large, the image feature vector dimension becomes higher, the LBP histogram is too sparse, and the recognition rate decreases. When the image partition is small and the pixel block is larger, the MB-LBP can extract the main structure of the recoater hopping better, and the recognition rate is higher, and the highest recognition rate reaches 98%; when the image partition is large, the pixel block is larger, and the defect features if it becomes fuzzy, the recognition rate will decrease.

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