Real-time defect detection of laser additive manufacturing based on support vector machine

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Abstract. Laser additive manufacturing is an advanced digital manufacturing technology used to build or repair metal parts layer by layer. However, monitoring and in-process defect diagnosis lag behind advances in other key technologies, which makes product quality control a challenging problem. In this paper, a novel real-time monitoring system is proposed to automatically detect defects using principal component analysis and support vector machine. A camera is used in the image acquisition system to capture molten pool image. Ten molten pool features were extracted and principal component analysis was used to reduce the dimensions of the feature set. Support vector machine is used to build a classifier to detect defects in the deposited layer. The experimental results show that the SVM method can achieve high defect detection rate when identifying both slag and bulge defects. The support vector machine has a more satisfactory performance than the RBF neural network method. It is proved that the support vector machine method can be used more accurately and more universally in the in-situ monitoring system of laser additive manufacturing for defect diagnosis.

1. Introduction
Laser additive manufacturing can transforms CAD model into physical products by layer-by-layer deposition, and has the advantages of short manufacturing cycle and high material utilization [1]. Therefore, it plays an important role in many fields, such as aerospace and automotive. Despite its significant advantages, quality problems constrain further development of additive manufacturing technology. In order to obtain high-quality components, the defects of parts should be detected firstly. Post-processing testing is a non-destructive testing technique including magnetic particle testing and ultrasonic testing, but it adds additional cost and extends component production time [2]. In addition, finite element modeling method requires high computational cost, and the prediction results may deviate from the actual manufacturing process. Therefore, it is necessary to establish a real-time monitoring system for laser additive manufacturing.

Zhang et al. [3] proposed a photodiode multi-photodetector divisional detection method, which can detect three defects including the delay of scanner, edge effect and unstable temperature field. Barua et al. [4] used a SLR camera to obtain the temperature gradient of molten pool, which in turn can detect
defects caused by interference in heat transfer process. In general, the quality information obtained by
the above method is limited, and fewer extracted features may affect the defects detection.

With the development of artificial intelligence technology, machine learning has been widely used
to monitor the manufacturing process. Song et al. [5] proposed a method using support vector
regression to predict the concentration of Al in the laser additive manufacturing process in real time.
Ye et al. [6] used a microphone to collect acoustic signals and processed the features extracted from
the sound signals using a deep belief network method. This method can detect both spheroidization
and overheating of selective laser melting.

However, more research needs to be done regarding utilizing machine learning to automatically
detect defects in laser additive manufacturing. In this work, the molten pool images of the laser
additive manufacturing process were captured by a CCD camera. After image processing, ten features
of the molten pool were extracted. Then, principal component analysis method was used to reduce the
dimension of the feature set, and a support vector machine model is established to evaluate the quality
of additive manufacturing parts. Finally, the experiment results are recorded and analyzed.

2. Experiment

2.1. Experimental setup

Figure 1 shows a schematic diagram of the laser additive manufacturing monitoring system. A YLS-
6000 laser was used as the laser source, and a laser cladding head was mounted on a three-axis CNC
table. The metal powder is transported into the molten pool by a powder feeding device, and a single
track is deposited after the laser cladding head moves forward. Argon is used as a shielding gas to
prevent oxidation on the surface of the deposited track. A CCD camera is used to capture the molten
pool image, which is mounted coaxially on the laser cladding head. In order to obtain high-definition
images, neutral dimmer films and filters are placed in front of the camera.

![Schematic diagram of the monitoring system.](image)

In this study, the metal powder used was AlSi12 and the substrate was the 2024 aluminum plate
with a size of 120 × 60 × 5 mm. The optimum process parameters are as follows: laser power 1800W,
powder feeding rate 0.6L/min, scanning speed 600mm/min, and shielding gas flow rate 10L/min.

2.2. Image processing

Image processing plays an important role in this study because it affects the accuracy of the next
extracted feature. After image processing, a region of interest (ROI) can be obtained and unnecessary
information can be filtered out.

In this paper, the molten pool image captured by the CCD camera is shown in Figure 2(a). The
molten pool image is often affected by the imaging equipment and the external environmental noise
during digitization and transmission, so image denoising is necessary. Some image denoising methods
have been developed, such as mean filtering, median filtering and wavelet transform [7]. The mean
filtering is applied in this work, and the filtered molten pool image is shown in Figure 2(b). In order to reduce the amount of calculation and save processing time, RGB images are converted into grayscale images. Figure 2(c) shows the grayscale image of molten pool. After grayscale transformation, threshold segmentation is used to further distinguish the ROI from the background. More specifically, the grayscale image is converted into a binary image according to the set threshold. Points on a grayscale image with a pixel value greater than the threshold are considered to be molten pool regions and are defined as 1, one of which is a white pixel. The rest of the points on the grayscale image are considered to be background regions and are defined as 0, one of which is a black pixel. The Otsu threshold segmentation method is used in this study, which is a method of adaptively calculating the optimal threshold [8]. Figure 2(d) shows the binary image of molten pool by threshold segmentation.

![Figure 2. Image processing schematic diagram: (a) original image; (b) denoising image; (c) grayscale image; (d) binary image.](image)

2.3. Feature extraction

The extracted features are the basis of a classifier for classification. In this study, ten features are extracted from the molten pool image, as shown in Table 1, and their definitions are as follows:

- **Area**: The area is calculated by counting the number of white points in the binary image.
- **Perimeter**: A point in a binary image surrounded by two types of points (white and black) is marked as a boundary point. The perimeter of molten pool is calculated by counting the number of boundary points.
- **Compactness**: The compactness of molten pool is calculated by:
  \[
  C = \frac{P^2}{A}
  \]
  where \(P\) represents the perimeter of molten pool and \(A\) represents the area of molten pool.
- **Centroid**: The centroid of molten pool can be calculated by:
  \[
  x = \frac{\sum_{j=1}^{n} \sum_{i=1}^{m} g(i, j) \times i}{\sum_{j=1}^{n} \sum_{i=1}^{m} g(i, j)}, \quad y = \frac{\sum_{j=1}^{m} \sum_{i=1}^{n} g(i, j) \times j}{\sum_{j=1}^{n} \sum_{i=1}^{m} g(i, j)}
  \]

\[(2)\]
where \( g(i, j) \) represents the gray value of the point \((i, j)\) in the grayscale image.

**Height**: The height of molten pool is the vertical distance between the highest point and the lowest point in the binary image.

**Width**: The width of molten pool is the horizontal distance between the leftmost point and the rightmost point in the binary image.

**Average grayscale value**: The average grayscale value of molten pool can be calculated by:

\[
\bar{g} = \frac{\sum_{i=1}^{n} \sum_{j=1}^{m} g(i, j)}{n \times m}
\]

**Number of pixels**: The number of pixels of molten pool is calculated by counting the number of points in the grayscale image whose grayscale value is greater than the average grayscale value.

**Average temperature**: The average temperature of molten pool can be calculated by:

\[
\bar{T} = \frac{\sum_{i=1}^{n} \sum_{j=1}^{m} c_2 \left( \frac{1}{\lambda_g} - \frac{1}{\lambda_b} \right) \ln \left( \frac{B(i, j)}{G(i, j)} \right) - 5 \ln \left( \frac{\lambda_g}{\lambda_b} \right)}{n \times m}
\]

where \( c_2 \) represents the second radiation constant. \( \lambda_g \) and \( \lambda_b \) represent the wavelengths of the blue and green light, respectively. \( G(i, j) \) and \( B(i, j) \) respectively represent the blue and green pixel values of the points \((i, j)\) in the RGB color image.

| No. | Feature       | No.  | Feature               |
|-----|---------------|-----|-----------------------|
| 1   | Area          | 6   | Height                |
| 2   | Perimeter     | 7   | Width                 |
| 3   | Compactness   | 8   | Average grayscale value |
| 4   | Centroid (x)  | 9   | Number of pixels      |
| 5   | Centroid (y)  | 10  | Average temperature   |

### 2.4. Feature dimension reduction and classification

In this work, two types of defects were explored, namely slag inclusion and bulge. The slag inclusion is simulated by simultaneously depositing AlSi12 and 316L metal powder. Figure 3 shows two deposited tracks of different quality. The height and width of the track 1 are large and the surface is relatively flat, which means that it has high quality. The height and width of the track 2 that produces slag inclusion are relatively small and the surface fluctuates in a bigger range, which means that it has inferior quality. The bulge is simulated by lifting the middle substrate to deposit track. Figure 4 shows the deposited tracks with bulge. This track can be divided into three parts, namely region A, B and C. The height of region A and C are relatively large, while the height of the region B is relatively small. Thus, tracks having high quality are denoted as class G, and the rest tracks are denoted as class B.
In this paper, 1100 images are respectively extracted from each of track 1 and 2, and a total of 2,100 images are extracted from the three regions. There may be linearly related variables in the dataset that affect the accuracy and classification time. In this study, principal component analysis is used to reduce the number of data dimensions. A data set consisting of newly generated variables which are named the principal component is used in the next classification recognition. Support vector machine is used to build a classifier model, and 10-fold cross validation is used to evaluate the performance of SVM classifier.

3. Results and discussion

3.1. Classification performances

For the slag inclusion defect, the cumulative contribution rate of the first and second principal component is 88.193%, so the first two principal components can be used to build the classifier. The relationship between these two principal components and the ten features is shown in Figure 5. The magnitude of the principal component coefficient directly reflects the strength degree of the relationship between the principal component and the feature. Thus, it can be considered that the first principal component represents a composite component of the molten pool size and shape. The second principal component represents the composition of the molten pool cooling rate, which may be due to the slag inclusion presence that causes the heat transfer process to be disturbed. For the bulge defect, the first three principal components can be used to build a SVM classifier, which together explain 87.442% of a total variance. The relationship between three principal components and ten original features is shown in Figure 6. It can be inferred from the histogram that the first principal component represents the composition of the molten pool size, and the other two principal components represent the composition of the molten pool temperature and shape, respectively.

For the slag inclusion defect, the classifier is established by using the first two principal components, and the classification accuracy reaches 99.95%. For the bulge defect, the classifier is established by using the first three principal components, and its classification accuracy is 86.81%. Therefore, the results of the SVM model to identify both defects are satisfactory. To further explore
the relationship between classification accuracy and the number of principal components, more experimental results were analyzed. Figure 7 shows the classification accuracy of the different number of principal components in the experiment of slag inclusion. Among them, the accuracy of class B has always been 100%, which means that the track of inferior quality is relatively easy to identify. When the first principal component is used to build the SVM model, the classification accuracy can reach 100%. As can be seen from the figure, as the number of principal components increases, the overall accuracy will be reduced firstly and then remain unchanged. This may be because the added principal components and the principal components have redundant information or noise. Figure 8 shows the classification accuracy of the different number of principal components in the experiment of bulge defect. It can be seen from the figure that as the number of principal components increases, the overall accuracy rate will be increased. However, starting from the first seven components, the overall accuracy gradually stabilized. This also reveals that principal component analysis is necessary in the defect detection process. Under the condition that the number of principal components is less than or equal to two, the accuracy of the class G is higher than that of the class B, which reveals that the high quality track is easier to identify. However, when the number of principal components is greater than two, this is the opposite. Therefore, the overall accuracy is the result of the two class combination.

3.2. Comparison with RBF neural network

Due to their close relation to the SVM in defect detection, radial basis function (RBF) neural network recognition method is implemented for a comparison of the results. In this study, the number of hidden layer units in the RBF neural network is equal to the number of input data, and the training number is 1000. For the slag inclusion defect, the classification accuracy of RBF model based on the first two principal components is 99.91%, while that of the SVM model is 99.95%. The ability of the two methods to identify slag inclusions is basically the same. For the bulge defect, the classification accuracy of RBF model based on the first three principal components is 80.05%, while that of the SVM model is 86.81%. The ability of the SVM model to identify bulge defect is better than the RBF model. The reason for this difference may be that RBF neural network requires a larger number of data and more features to solve complex classification problems.

4. Conclusions

In this paper, a coaxially mounted camera is used to capture the molten pool image and ten extracted molten pool features are converted into a new feature set by principal component analysis. Support vector machine method is used to build a classifier to automatically detect two kinds of defects: slag inclusion and bulge. The experimental results show that the SVM model generated by the principal
component with a cumulative contribution rate of 85% has satisfactory performance. The accuracy of identifying two defects is 99.95% and 86.81%, respectively. It is proved that this method is feasible and can be used in real-time monitoring system for laser additive manufacturing.

The relationship between the classification accuracy of the classifier and the number of principal components is complex. Adding additional principal components does not improve the classification accuracy, and even reduces the classification accuracy. Therefore, it is necessary to select the first few principal components with a cumulative contribution rate of 85%. The experimental results show that principal component analysis effectively reduces the number of features dimensions.

Support vector machine performs superior compared with the utilities of RBF neural network method. Although the two methods have basically the same ability to identify the slag inclusion defect, the SVM method has stronger ability to identify the bulge defect. Thus, the SVM method may be used to detect more types of defect without a large amount of feature data and training times. Hence, this research provides a convenient and possible solution to realize the process monitoring and defect detection during the laser additive manufacturing process.

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References
[1] Chua, Z.Y. Ahn, I.H. Moon, S.K. (2017) Process monitoring and inspection systems in metal additive manufacturing: Status and applications. International Journal of Precision Engineering and Manufacturing-Green Technology, 4: 235-245.
[2] Lu, Q.Y. Wong, C.H. (2017) Applications of non-destructive testing techniques for post-process control of additively manufactured parts. Virtual and Physical Prototyping, 12: 301-321.
[3] Zhang, K. Liu, T. Liao, W. Zhang, C. Du, D. Zheng, Y. (2018) Photodiode data collection and processing of molten pool of alumina parts produced through selective laser melting. Optik, 156: 487-497.
[4] Barua, S. Liou, F. Newkirk, J. Sparks, T. (2014) Vision-based defect detection in laser metal deposition process. Rapid Prototyping Journal, 20: 77-86.
[5] Song, L. Huang, W. Han, X. Mazumder, J. (2017) Real-Time Composition Monitoring Using Support Vector Regression of Laser-Induced Plasma for Laser Additive Manufacturing. IEEE Transactions on Industrial Electronics, 64: 633-642.
[6] Ye, D. Hong, G.S. Zhang, Y. Zhu, K. Fuh, J.Y.H. (2018) Defect detection in selective laser melting technology by acoustic signals with deep belief networks. The International Journal of Advanced Manufacturing Technology, 96: 2791-2801.
[7] Gupta, S. Meenakshi. (2014) A review and comprehensive comparison of image denoising techniques. In: International Conference on Computing for Sustainable Global Development. New Delhi. pp. 972-976.
[8] Liu, Q. Zhao, L. Zhang, L. (2013) Image Feature Extraction of Moment of Inertia Based on Otsu Threshold Segmentation[J]. Advanced Materials Research, 756-759: 3157-3161.