Defects Recognition in Selective Laser Melting with Acoustic Signals by SVM Based on Feature Reduction

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Abstract. Defects among the selective laser melting (SLM) part hinder the development of the SLM process. This work provides an approach to conduct the monitoring and defect diagnosis by support vector machines (SVM) model using extracted features from acoustic signals. After training and testing with the linear SVM model, the result from the Fisher discriminant analysis (FDA) feature reduction performs optimal compared with those from the original features and the principal component analysis (PCA) feature reduction. The melted state monitoring and classification can be realized by simple discriminant model of SVM with extracted features after dimension reduction. The proposed method can be applied in the SLM process monitoring and defect diagnosis by acoustic signals with generalization.

1. Introduction

Defects occur within selective laser melting (SLM) additive manufacture parts, which interfere with the product applications among aerospace, health care and industry. The defects are mainly from the underheating and overheating melting process over overhang structures or unsteadily melting sections. Process monitoring of the SLM process is the premise for process feedback control to solve defects [1]. Therefore, it is necessary to implement the SLM process monitoring technique for improving the SLM part quality.

SLM process is accompanied with optical, acoustic, electron, and other weak signals. Many researches have been conducted to monitor the SLM process. Kruth’s group developed a series of coaxial monitoring and control approaches with combined cameras and photodiodes. The melt pool size and thermal dynamics were analysed to match the SLM process [2, 3]. Lane’s group executed the thermography measurement process with multiple off-axial optical sensors. Temperature and brightness of the melt pool as well as the spatter observation were captured for the process monitoring [4]. Rieder et al. demonstrated an online ultrasonic monitoring system to investigate the dynamic layer building process. The residual stresses and possible porosity were indicated by evaluating the backwall signals and ultrasonic velocities [5]. Ye et al. collected the acoustic signal for monitoring the characteristics by a microphone. There is a good mapping between audible signals and laser power as
well laser scanning speed during the SLM process [6]. Melted states have been recognized by deep learning algorithm [7].

All the signals from image or acoustic information can represent the status of the melting. Monitoring with coaxial optical setups easily affects the captured signals by lens characteristics, while monitoring with off-axial optical setups is influenced by the sensor installation site of clamping position, angle, and distance. The acoustic signal can predict the penetration state during processing since there is a relationship between acoustic signal features and penetration states [8]. As a flexible setup and non-destructive method, acoustic methods offer a wide variety of detectability and provide information on defect location and shape [9]. Acoustic signals have been successfully applied in the monitoring of the SLM process using deep belief networks, while more accurate and simpler algorithms can be used to detect the defects.

In terms of acoustic signals during the processing, the modes are time-varying signals due to the changing of spatters on the powder, temperature around the melt pool, and formations around the melting site. Acoustics signals are non-stationary signals. Both low frequency and high frequency bands have information from acoustic signals. Wavelet package transform (WPT) can decompose acoustic signals into approximations and details. Acoustic signal features in each frequency range indicate the relationship between failure modes and components [10]. Components of the decomposed acoustic signals are analyzed by parameter statistics. To make less computation and robust representation for different melted states, feature selection for feature dimension reduction is necessary. Principal component analysis (PCA) and Fisher linear discriminant analysis (FDA) are used to make the feature dimension reduction. Comparisons methods with original features, PCA feature selection and FDA feature selection are carried out to evaluate the present approach. In the final, conclusions are provided for this work.

2. Feature extraction

2.1 Wavelet packet decomposition of acoustic signals
Acoustic signals from the SLM process are time varying and non-stationary. With the non-stationary signal from the melting conditions, WPT can decompose signals into different frequency bands with different resolutions. Features of acoustic signals in different depths are sensitive to different melted states and insensitive to the stationary working conditions. The acoustic signal measurement is $x(t)$ for the WPT analysis and parameter statistics. With different decomposed depths of the WPT, the measurement is [11]

$$W_{x_n}(l,k) = \langle x(t),\mu_{n}(t,l,k) \rangle = \int_{-\infty}^{\infty} x(t)\mu_n(t,l,k)dt$$

where $\mu_n$ is the $n_{th}$ wavelet packet function with $n = 0,1,2...2^l$, $l$ is the level and $k$ is the location parameter. $\langle$, $\rangle$ donates the inner product. The melting condition is able to be reflected with different wavelet packet decomposed signals $W_{x_n}(l,k)$.

2.2 Feature parameter statistics
Melting condition can be reflected by the acoustic signal information included in different wavelet packet nodes. Statistical parameters are useful indicators for extracting the melting condition. In this work, absolute mean amplitude ($F_i$), variance value ($F_s$), skewness factor ($F_3$), kurtosis($F_4$), square root amplitude($F_5$), crest factor($F_6$), impulse indicator($F_7$), shape factor($F_8$), and cepstrum factors($F_9$ and $F_{10}$) for signals in each frequency range are calculated respectively. In the non-stationary signal processing, ten parameter statistical methods with physical meaning are applied [12-14].

$$F_i(l,n) = \frac{1}{K} \sum_{k=1}^{K} [W_{x_n}(l,k)]^i, F_s(l,n) = \frac{1}{K} \sum_{k=1}^{K} (W_{x_n}(l,k))^2, F_3(l,n) = \frac{1}{K} \sum_{k=1}^{K} (W_{x_n}(l,k))^3, F_4(l,n) = \frac{1}{K} \sum_{k=1}^{K} (W_{x_n}(l,k))^4$$
\[ F_i(l,n) = \left( \frac{1}{K} \sum_{k=1}^{K} W_{x_i}(l,k)^2 \right)^{\frac{1}{2}} \]  
\[ F_i(l,n) = \left( \frac{1}{K} \sum_{k=1}^{K} (W_{x_i}(l,k))^2 \right)^{\frac{1}{2}} \]  
\[ F_i(l,n) = \frac{1}{K} \sum_{k=1}^{K} \log |\Phi^q(\omega)|^{2\max}/K \]  
\[ F_{i\alpha}(l,n) = 1 \sum_{\alpha} \log |\Phi^q(\omega)|^{2\max}/K \]

where \( \Phi^q(\omega) \) is Fourier transformations of wavelet packet decomposing signals \( W_{x_i}(l,k) \). With the WPT decomposition and parameter statistics, the melting measurement \( x(t) \) can be extracted as

\[ F_i = (F_1, F_2, F_3, F_4, F_5, F_6, F_7, F_8, F_9, F_{10}) \]

3. Feature selection and classification

3.1 PCA for feature selection

After wavelet packet decomposition and feature statistical analysis, the total number of features extracted by acoustic signals is 160 dimensions. To decrease the computation complexity and increase the robust classification ability, the extracted feature dimension needs to be reduced for realizing the SLM process monitoring. PCA method uses the covariance of the input vector to project the features from high-dimensional space into the low-dimensional space. It finds the projection method that best represents the original data in the minimum mean square sense.

The normalized feature is \( \hat{F} = F - \bar{F} \), where \( \bar{F} \) is the mean values of feature \( F_i \). Sample covariance matrix \( C \) is \( \hat{F}^T \hat{F}/T \), where \( T \) is the feature number of measured acoustic signals. By PCA, \( \hat{F} \) was transferred into \( S = Z^T \hat{F} \), where \( Z \) is \( N \times N \) orthogonal matrix and \( z_j \) is the \( j \)-th eigenvector of the sample covariance matrix \( C \). The eigenvalue \( \lambda_j \) of the covariance matrix \( C \) is \( \lambda_j = \lambda_{ij}, j = 1,...,N \).

PCA ratio \( \eta \) represents that the principal component dominants the whole information

\[ \eta = \left( \sum_{j=1}^{M_q} \lambda_j / \sum_{j=1}^{N} \lambda_j \right)^{\frac{1}{2}} \]

3.2 FDA for feature selection

The PCA is to find the direction to represent the principal information effectively. FDA method is carried out to direct the output of effective classification. It distinguishes various classes with maximizing the between-class distance and minimizing the within-class distance. The mean vectors of the \( p_a \) features of different samples are calculated by \( m^q = n^q \sum_{k=0}^{K} F^k, \ q = 1,2,..., \) where \( \omega_q \) belongs to class \( q \). The summary of the within-class covariance matrix is \( S_q = \sum_{k=0}^{K} (F^k - m^q)^T (F^k - m^q)^T \). The between-class covariance matrix is \( S_b = \max(m^a - m^b)^T, \ a,b \in q \).

For making the two classes as far as possible and the same class as clustered as possible, the ratio of between-class distance and within-class distance is defined \( J = S_b/S_a \). Rank \( J \) from the largest to the smallest and select the top \( M_s \) between-class distance and within-class distance ratios. The FDA ratio \( \varepsilon \) is taken with \( J \) as \( \varepsilon = \sum_{j=1}^{M_s} J_j / \sum_{j=1}^{K} J_j \)

3.3 Classification with Support Vector Machines (SVM)

The SVM algorithm searches for an optimal hyperplane that separates the data into classes. The discriminant function for the optimal hyperplane is
\[ f(x) = \text{sign} \left( \sum_{i=1}^{D} \gamma_i y_i G(x, x_i) + b \right) \]  
(4)

where \( y_i \) is the observation corresponding to the sample \( x_i \). \( D \) is the sample number and \( \gamma_i \) is the Lagrange multipliers. \( G(x, x_i) \) is the kernel functions and \( b \) is a bias term. The function is solved by

\[
\max \left( \sum_{i=1}^{D} \gamma_i y_i G(x, x_i) + b \right), \quad 0, \quad 0 \leq \gamma_i \leq E
\]

where \( E \) is the normalization value for separating classes.

4. Experiment setup

Experiments are conducted with an own designed SLM system as shown in Figure 1(a). The SLM system is composed by a laser, a powder spreading facility, and a controller panel. The acoustic monitoring system for experiments includes a 3780C1 PCB microphone and a SIRUSm data acquisition system. The frequency response of the acoustic signal acquisition system is 0~200 KHz and is mounted 2cm above the platform (Figure 1(b)). Single tracks are conducted on 50\( \mu \)m-thickness 304L stainless steel powder. Parameters are changed to obtain the states of overheating, normal, and underheating.

![Figure 1](image1.png)

**Figure 1.** (a) SLM machine for the melting process, and (b) experiment setups with an acoustic signal acquisition system.

All the single tracks are observed with an Olympus microscope with 200 times enlargement. There are three typically features of the single tracks as shown in Figure 2. Balls take shape due to underheating caused by lack of energy input as illustrated in Figure 2(a). In Figures 2(b) and 2(c), satellites on the single tracks come from the powder and liquid spatter separately. The wettability is good from the energy density and satellites are mostly from the powder spatter that has no effect on the adjacent remelting. Melted tracks as Figure 2(b) are normal melted states.

![Figure 2](image2.png)

**Figure 2.** Melted states of single tracks from different melting conditions.
Satellites larger than $50\mu m$ cannot be sufficiently melted and tend to hinder the paving roller movement or affect the following layer. Single tracks with larger than $50\mu m$ satellites are defined as medium overheating states. The melted tracks with energy density larger than that for medium overheating ones are overheating states. The melted states between normal and underheating states are medium underheating ones. Single tracks are conducted from different energy input to obtain underheating, medium underheating, normal, medium overheating, and overheating states separately.

Figure 3 shows the acoustic signals and the corresponding appearance of the quality of one melted track from the SLM process. The single-track image has been multiplied by 50 times. In this work, $10mm$ single tracks are conducted with each melted state for 7 $s$. Test experiments are conducted with different scanning speed and laser power for 2.3 $s$ as listed in Table 1.

![Acoustic signal detected in the PBF-L process.](image)

**Figure 3.** Acoustic signal detected in the PBF-L process.

| Test | Scanning speed ($mm/s$) | Laser power ($W$) | Melted state         |
|------|-------------------------|------------------|---------------------|
| 1    | 100                     | 50              | Underheating        |
| 2    | 700                     | 100              | Medium underheating |
| 3    | 110                     | 100              | Normal              |
| 4    | 100                     | 150              | Medium overheating  |
| 5    | 40                      | 100              | Overheating         |

Table 1. Parameters for the test experiments.

5. Experiment results and discussions
In order to recognize the melted states, the sample window is set with 10 $k$ signal points. 140 train samples and 46 test samples are obtained for each melted state. Acoustic signals are decomposed with 4-level WPT of Daubeches 3 wavelet and signals reconstructed from the fourth-level wavelet package coefficient are chosen as the features for parameter statistics (Figure 4). Statistical parameters have 160 dimensions after feature extraction. PCA and FDA are performed for the feature dimension reduction.

![Wavelet package decomposing after 4-level WPT of Daubeches 3 wavelet.](image)

**Figure 4.** Wavelet package decomposing after 4-level WPT of Daubeches 3 wavelet.
34 features are selected after FDA dimension reduction with FDA ratio $\varepsilon = 0.99$ and 20 features are left after PCA dimension reduction with PCA ratio $\eta = 0.99$. Selected features are trained and tested by SVM with linear kernel function. Results of five-melted-state classification are shown as Table 2.

With empirical analysis, melted state defects diagnosis is simple and accurate with appropriate extracted features. PCA feature dimension reduction method works as a feature extraction method instead of real feature selection. Some physical nature of the acoustic signal features is lost during the PCA feature extraction. Therefore, recognition with PCA feature selection performs weak result of 55.35% classification rate in the melted state classification. With the original features, feature dimensions are larger than training samples. Although the discrimination rate is 89.13%, overfitting easily emerges and there is less generalization in the SLM process monitoring. FDA as linear discriminant method performs 77.99% rate for the classification. FDA method suits the recognition of melted state since the monitoring model has generalization in the state classification.

### Table 2. Test results with different dimension features.

| Dimension reduction method | Test result |
|----------------------------|-------------|
| Original features          | 89.13%      |
| PCA                       | 55.35%      |
| FDA                       | 77.99%      |

6. Conclusion
This work proposes an innovative method to realize the SLM process monitoring. Acoustic signals are decomposed into different frequency ranges by WPT. Signals at each frequency range are calculated with ten kinds of parameter statistical methods and extracted features are reduced by PCA and FDA. By the linear SVM classification model, the optimal result is from statistical parameters after FDA feature dimension reduction. The proposed approach with FDA feature dimension works well in the discrimination of melted states. It can be carried in the monitoring and defect diagnosis of the SLM process.

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