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ARTICLE

Prediction for Geometric Characteristics of Single Track of Deposition Layer and Surface Roughness in Thin Wire-Based Metal Additive Manufacturing Process

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Abstract: Machine learning prediction models for thin wire-based metal additive manufacturing (MAM) process were proposed, aiming at the complex relationship between the process parameters and the geometric characteristics of single track of the deposition layer and surface roughness. The effects of laser power, wire feeding speed and scanning speed on the width and height of the single track and surface roughness were experimentally studied. The results show that laser power has a significant impact on the width of the single track but little effect on the height. As the wire feeding speed increases, the width and height of the single track increase, especially the height. The faster the scanning speed, the smaller the width of the single track, while the height does not change much. Then, support vector regression (SVR) and artificial neural network (ANN) regression methods were employed to set up prediction models. The SVR and ANN regression models perform well in predicting the width, with a smaller root mean square error and a higher correlation coefficient R^2. Compared with the ANN model, the SVR model performs better both in predicting geometric characteristics of single track and surface roughness. Multi-layer thin-walled parts were manufactured to verify the accuracy of the models.

Key words: thin wire-based; metal additive manufacturing; machine learning; SVR; ANN

The metal additive manufacturing (MAM) process is widely used in equipment manufacturing in aviation, aerospace and other fields due to its advantages of rapid fabrication speed and low cost[1–6]. The material forms of MAM are mainly metal powder and wire, and the wire-based MAM is highly concerned due to its low cost, high material utilization rate and no dust pollution[7–8]. The accuracy and roughness of the fabricated parts are greatly affected by the geometric characteristics of the single track of the deposition layer[9]. The quality of the single track of the deposition layer will be poor and even discontinuous, due to the factors such as inappropriate power, wire feeding speed or scanning speed ratio, which not only affect the deposition of the current layer, but also have adverse effects on subsequent deposition layers, and even make the deposition process unable to continue. Therefore, studying the influence of process parameters on single track deposition of wire-based MAM is of great significance for obtaining high-quality parts.

Numerous researchers found that the geometric characteristics of single track deposited by wire-based MAM, such as the width, height and wetting angle, have complicated relationships with process parameters such as laser power, wire feeding speed and scanning speed. Ayed et al[10] used a direct energy deposition wire-laser with Precitec coax printer station to melt a metallic filler wire to build titanium parts, and the process parameters were optimized, by which wire feeding speed, travel speed and laser beam power were defined as predominant process parameters governing the layer deposition. Liu et al[11] proposed a comprehensive quality investigation framework based on learning from experimental

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data to obtain high quality microstructural properties of the parts and to control the desired part geometry. These studies show that the scanning speed and laser power have the most significant effects on the width of the single track, and the wire feeding speed has more obvious effects on the height. Wang et al[12–13] studied a novel wire-based plasma transferred arc-laser hybrid additive manufacture process to fabricate large-scale titanium parts. In order to improve the deposition rate and near-net shape, the processing conditions, including the heat source configuration, wire feeding speed, arc-to-laser separation distance and travelling speed, were optimized. The results show that laser power and travelling speed have more significant influence on the deposition layer of the parts than other processing parameters.

Based on the research of the single track of deposition layer, many scholars have investigated the influence of the processing parameters on the surface roughness of the desired parts. Xiong et al[14] proposed a methodology based on a laser vision system to view the surface appearance on the side face of the parts deposited by gas metal arc welding (GMAW)-based additive manufacturing, and the influential mechanisms and evaluation methods of the effect of process parameters, such as the ratio of wire feeding speed to travel speed and the wire feeding speed, on the surface roughness were set up. Xia et al[15] developed a laser sensor based surface roughness measuring method for wire arc additive manufacturing (WAAM) process, and in order to improve the surface integrity of deposited layers, different machine learning methods were invested to predict the surface roughness. Their studies also provided guidance for surface roughness modeling in multi-pass arc welding and cladding. Wu et al[16] presented a data fusion approach to predict surface roughness in fused deposition modeling processes, which were trained by the machine learning algorithms such as random forests, support vector regression (SVR), ridge regression and least absolute shrinkage and selection operator. Experimental results show that these predictive models are capable for predicting the surface roughness of additively manufactured parts with very high accuracy.

In order to obtain higher surface roughness of parts, using thinner wire for MAM based on wire feeding is a good choice. However, the diameter of the wire also affects the selection of process parameters. Based on the above studies, it can be seen that the geometric characteristics of the deposition morphology of single track have complex relationships with laser power, wire feeding speed and scanning speed. However, existing predict models are all obtained for thicker wire, for example, the diameter of the wire used in Ref. [12 – 13] and Ref. [10 – 11] was 1.2 and 1.5 mm, respectively. Most of the roughness of the parts prepared by MAM with thicker wire is above 0.1 mm, which is unable to fabricate parts with lower roughness. Therefore, it is necessary to study the influence of process parameters on the geometric characteristics of deposition morphology under thinner metal wire. Machine learning methods, such as random forest, SVR and artificial neural network (ANN), must be used to fit the nonlinear relationship between input process parameters and output index variables, so as to establish a prediction model to guide the selection of process parameters to obtain better surface roughness.

In this research, a thin wire-based MAM process, with the wire diameter of only 0.3 mm, was proposed to obtain manufactured parts with lower surface roughness. Based on a single track process experiment, a multi-layer thin-wall part was prepared. Predictive models derived from machine learning algorithms (SVR and ANN regression) were used to establish the relationships between the process parameters and geometric characteristics of single track and surface roughness of deposited parts, so as to provide a strong basis for choosing optimal process parameters for high-quality 3D printed parts.

1 Experiment

1.1 Experiment setup

The experimental system for thinner wire-based MAM process is shown in Fig. 1, including IPG-QW150 fiber laser, working table, wire feeding system, current preheating system, industrial camera, etc. During the deposition process, the whole system was placed in the argon protection environment box, in which the oxygen content in the environment box was less than 10 μL/L.

Preliminary experiments have shown that high power is adverse to the preparation of thin wire-based MAM process. Therefore, the metal deposition process in this work employed a laser as the main heating source and a resistance preheating system as the assisted heating source. The assisted heating source heated the wire to a half-melt state, making it easy to adhere to the substrate or each other. The main heating source, a low-power laser, was used to heat the half-melt wire until it was totally melted, thereby completing the multi-layer deposition and the manufacturing of the desired part.

The preliminary experiments found that the angle between the laser beam and the printing direction has a significant impact on the single deposition track. If the angle is too small, the energy is too concentrated and it is easy to produce spheroidization phenomenon; if the angle is too large, energy is dispersed and the wire cannot melt. So the angle was set as about 110°, and the diameter of the laser spot was 0.3 mm. The substrate and the metal wires were all made of Ti-6Al-4V alloy with a diameter of 0.3 mm. In the process of wire deposition additive manufacturing, the working table, including the *X*-axis and *Y*-axis, drove the substrate to complete the filling motion of wire deposition. After a layer of deposition was completed, the *Z*-axis descended by thickness of one layer, and the filling motion was repeated until the entire deposition process of the part was completed.

1.2 Geometric characteristics of single track of deposition layer

The typical single track of the deposition layer is shown in Fig.2, and its main geometric features can be characterized by three parameters: the width of the single track D, the height of the single track H and wetting angle θ. With the assumption

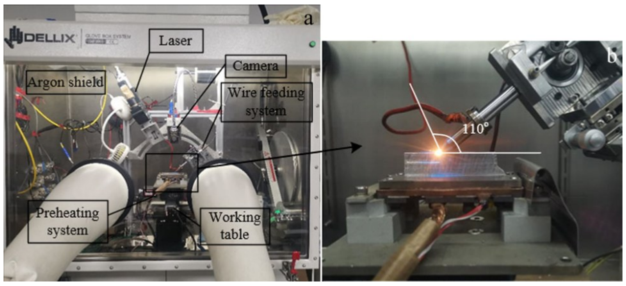

Fig.1 Experimental system for thinner wire-based MAM process: (a) vacuum chamber and (b) feeding angle between the laser beam and the printing direction

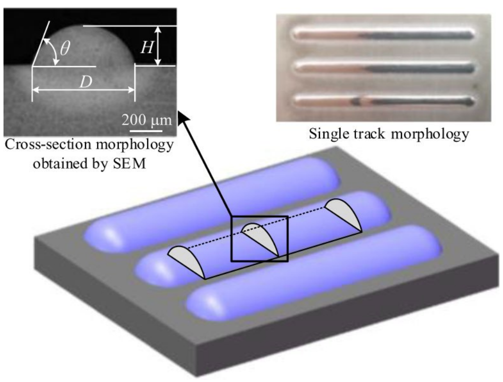

Fig.2 Geometric characteristics of the single track

that the cross-section of the track is an arc, the wetting angle can be characterized by the width and height, which is considered as a dependent parameter and will not be discussed in this research. The width D and height H of the single track determine the minimum formed element, which stably control the shape accuracy of the current layer and the layer in stacking direction.

In addition, the features of the single track also have a significant impact on the surface quality of the manufactured parts. A deposition layer with an ideal width/height ratio is more conducive to the deposition of the next layer on the basis of the current layer, which reduces the step effect between two layers. Therefore, it is necessary to study the complicated relationships between the geometric characteristics of single track and process parameters, in order to control the size of deposition element and to ensure the stable forming.

1.3 Deposition element

The process parameters affecting the single track of the deposition layer mainly include laser power, wire feeding speed and scanning speed. The parameters given in the experiments are shown in Table 1, and a total of 27 sets of process experiments were carried out. The main chemical composition of the wire material, Ti-6Al-4V, is shown in Table 2.

When the laser power is low (<100 W), the input energy is insufficient to melt the wire, or it is in a semi-molten state and cannot be bonded to the substrate tightly. Meanwhile, if the laser power is too high, that is, the input energy is excessive, the resulting formed element has a larger width-to-height ratio and a smaller wetting angle, which not only reduces the manufacturing efficiency, but also causes excessive remelting between multi-layers due to heat accumulation. Therefore, the range of the laser power is 100–200 W. When the wire feeding speed and scanning speed are constant, the basic relationships between laser power and the width/height of single track of the deposition layer are shown in Fig. 3a. It can be seen that the laser power has a more significant impact on the width with a linear positive correlation relationship, and slightly affects the height with an inverse correlation relationship. This is mainly because the higher the laser power, the better the flowability of the wire after melting, resulting in the increase in the width of the single track and decrease in its height.

Under a certain laser power (175 W) and scanning speed (120 mm/min), as the wire feeding speed increases, more

Table 1 Parameters of thin wire-based MAM process

Parameter	Value
Laser power/W	100, 125, 150, 175, 200
Wire feeding speed/mm·min^{-1}	60, 120, 180, 240, 300, 360
Scanning speed/mm·min^{-1}	150, 180, 210, 240, 270, 300

Table 2 Chemical composition of wire material Ti-6Al-4V (wt%)

Al	Si	Fe	V	C	O	N	Ti
5.40	0.15	0.30	3.41	11	0.15	0.15	Bal.

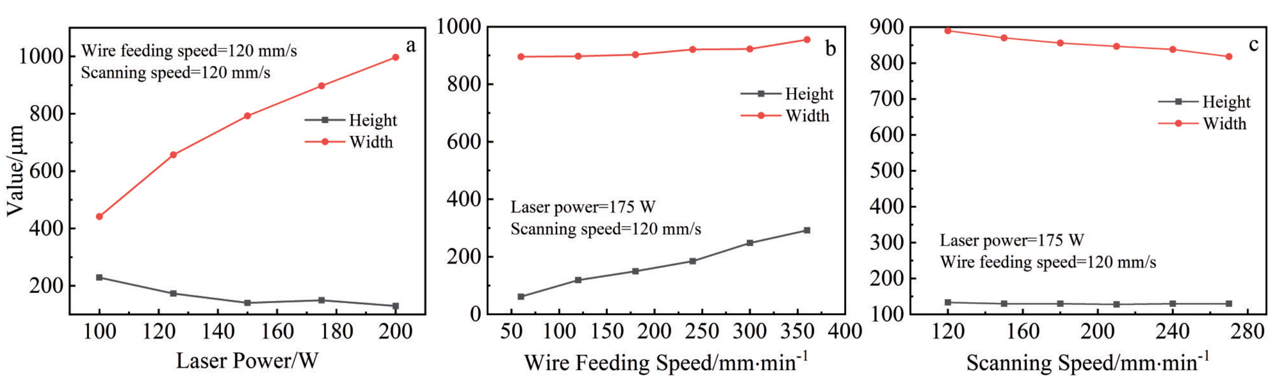

Fig.3 Relationships of laser power (a), wire feeding speed (b) and scanning speed (c) with respect to the width and height of single track of the deposition layer

material enters the melt pool, resulting in an increase in the width and height of the single track, especially the height, as shown in Fig.3b.

When the laser power and wire feeding speed are constant, the faster the scanning speed, the less energy input into the molten pool and the less material entering the molten pool per unit time. Therefore, the width of the single track of deposition layer decreases, and the height changes slightly, as shown in Fig.3c.

1.4 Roughness of multi-layer parts

On the basis of single track process experiments, multi-layer stacking experiment was carried out to prepare thin-walled parts. 50 layers are deposited, with a total length of 30 mm, as shown in Fig.4. Confocal microscope is employed to measure the roughness R_a of a set of 2 mm×2 mm surface in the middle of thin-walled parts. 6 sets of R_a values are adopted for each surface, the average of all measuring results is used as the final surface roughness, and the standard deviation is taken as the error range, as shown in Fig.5–7. Overall, the higher the laser power, the lower the surface roughness, and an approximately linear relationship is observed. The relationship of the wire feeding speed and scanning speed with respect to surface roughness is the same as that of the laser power.

1.5 Inter-layer temperature

Inter-layer temperature affects the microstructure and grain size of metal parts. Higher temperatures promote grain growth, while lower temperatures result in smaller grain sizes. Proper control of inter-layer temperature helps to achieve the desired microstructure, thereby influencing the mechanical properties and heat resistance of the material. Fig.8 shows scanning electron microscope (SEM) images of the cross-section of thin-walled part. It can be observed that the cross-section of the thin-walled component is dense. Due to the repeated increase and decrease in temperature during the printing process, the internal grains of the component are small, resulting in good mechanical performance.

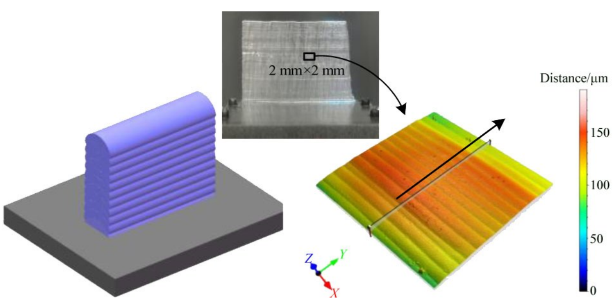

Fig.4 Roughness measurement for multi-layer thin-walled parts

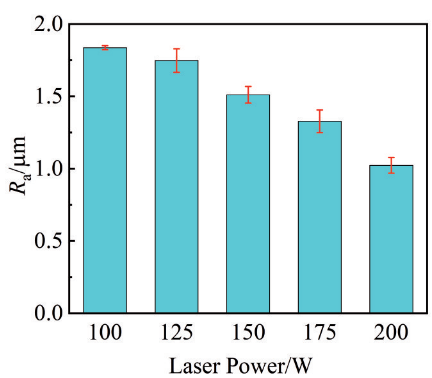

Fig.5 Influence of laser power on surface roughness R_a

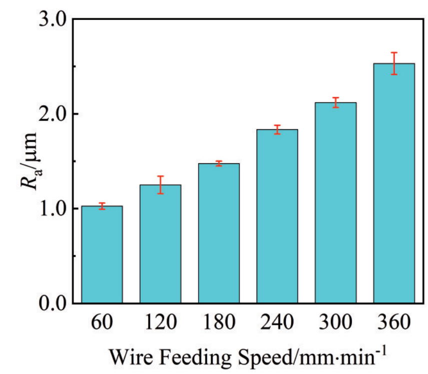

Fig.6 Influence of wire feeding speed on surface roughness R_a

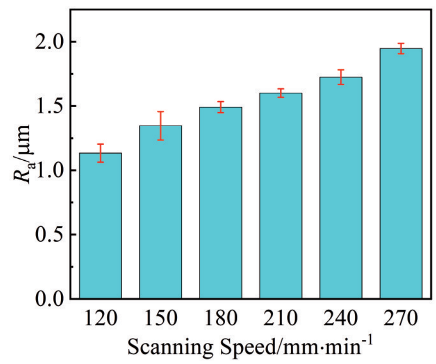

Fig.7 Influence of scanning speed on surface roughness R_a

2 Machine Learning Prediction Models

According to the research on the influence of process parameters on the geometric characteristics of single track and

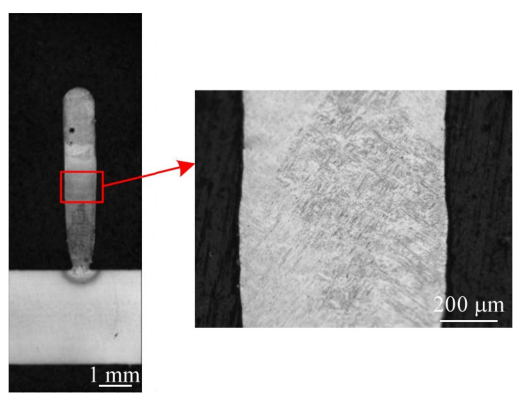

Fig.8 SEM image of the cross-section of thin-walled part

surface roughness of the parts deposited by multi-layer mentioned above, it is very difficult to choose appropriate process parameters to obtain desired parts with high accuracy and low surface roughness. Predicting the geometric features and surface roughness through process parameters is essentially a regression problem based on machine learning, so in this work, SVR and ANN methods are used to establish regression prediction models.

2.1 SVR

It is well known that the aim of support vector machine is to find a separation hyperplane by maximizing the interval, so that the majority of sample points are located outside the two decision boundary, as shown in Fig. 9a. Although SVR also seeks to maximize the interval, it considers the points within the decision boundary, so as to make as many sample points as possible within the interval and thus the hyperplane is the regression prediction model, which is shown in Fig.9b.

SVR can be formulated as a convex optimization problem, which can be expressed by Eq.(1).

$$\min_{w} \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{N}\left(\xi_i + \hat{\xi}_i\right)$$
$$\text{s.t. } y_i - \omega^T x_i - b \leqslant \varepsilon + \xi_i,\ \omega^T x_i + b - y_i \leqslant \varepsilon + \hat{\xi}_i \tag{1}$$

where $C>0$ is the trade-off parameter; ξ and $\hat{\xi}$ are relaxation factors; both ξ and $\hat{\xi}$ are lager than 0.

2.2 ANN regression

ANN is widely used to fit nonlinear relationships and it is mainly composed of input layer (3 nodes in this study, including laser power, wire feeding speed and scanning speed), hidden layer (10 layers, Sigmoid function is chosen as the activation function) and output layer (1 node, i. e. the width/height of single track or the surface roughness), as shown in Fig. 10. The input layer variables enter the hidden layer node after linear combination $w_i x_i + b_i$, and the hidden layer nodes enter the output layer nodes after the activation of the Sigmaid function. When neural network is applied to regression analysis, ReLU function is employed to calculate the sum of the output as the final value to obtain the predicted width, height or surface roughness.

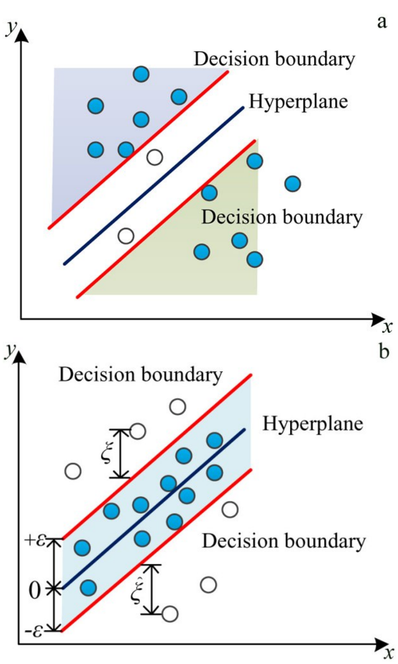

Fig.9 Schematics of support vector machine (a) and SVR (b)

2.3 Data for model training

When predicting the width and height of single track, additional 10 sets of data are added to the previous 17 sets of process experiments mentioned in Section 1.3, so a total of 27 sets of experimental data under different laser powers, wire feeding speeds and scanning speeds are used as training and testing data, as shown in Table 3. When predicting the surface roughness, 17 sets of data mentioned in Section 1.4 are still used, as shown in Table 4.

The correlation coefficient R^2 and root mean square error (RMSE) are taken as performance indicators of the regression models, and the calculation formula for R^2 is as follows:

$$R^2 = 1 - \frac{\text{SSE}}{\text{SST}} \tag{2}$$

where SSE is the sum of squared residuals, representing the error between the observed values and the predicted values in the model, and its calculation formula is as follows:

$$\text{SSE} = \sum\left(y_i - \hat{y}_i\right)^2 \tag{3}$$

where y_i is the actual observed value, and $\hat{y}_i$ is the predicted value. *SST* is the total sum of squares, representing the total deviation between the observed values and their mean values ($\bar{y}$, in Eq(4)) which can be calculated as:

$$\text{SST} = \sum\left(y_i - \bar{y}\right)^2 \tag{4}$$

The calculation formula for RMSE is as follows:

$$\text{RMSE} = \sqrt{\frac{\sum\left(y_i - \hat{y}_i\right)^2}{n}} \tag{5}$$

3 Prediction Model Analysis Results

3.1 Regression model for the morphology of single track

Fig. 11 shows the actual value and the regression model prediction for the width of single track using SVR and ANN, in which the diagonal lines are the perfect prediction values, and the blue spots are the observed values, i. e. the experimental data points. It can be seen that both SVR and

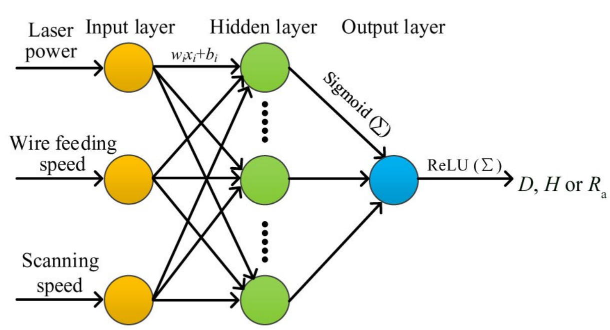

Fig.10 Schematic of ANN model

Table 3 Training data for the prediction of width and height of single track

No.	Laser power/W	Wire feeding speed/mm·min^{-1}	Scanning speed/ mm·min^{-1}	Width/ μm	Height/ μm
1	100	120	120	441.464	228.831
2	125	120	120	656.896	172.994
3	150	120	120	792.826	140.552
4	175	120	120	897.362	149.617
5	200	120	120	997.025	129.686
6	175	60	150	895.524	61.268
7	175	120	150	897.299	118.974
8	175	180	150	902.573	149.560
9	175	240	150	920.700	184.688
10	175	300	150	922.361	247.828
11	175	360	150	954.970	291.914
12	175	120	120	890.090	133.346
13	175	120	150	870.198	129.730
14	175	120	180	855.873	129.742
15	175	120	210	846.632	127.928
16	175	120	240	837.869	129.730
17	175	120	270	818.026	129.730
18	150	180	180	800.338	142.561
19	150	240	180	806.877	143.252
20	150	180	150	798.363	139.551
21	125	240	180	676.951	189.457
22	125	180	180	656.324	147.369
23	125	240	210	667.653	186.567
24	100	300	150	587.965	236.369
25	100	180	210	479.862	152.645
26	200	60	210	950.235	65.556
27	200	60	270	955.530	70.232

ANN methods perform well in predicting the width of single track, and this conclusion can also be seen in Fig. 12, which shows the errors of the width regression models using the two methods. The predicting accuracy of SVR is slightly better than that of ANN, with RMSE=33.50 and R^2=0.95, as shown in Table 5. This indicates that the regression models for the width of single track have strong correlation and obvious patterns.

Fig. 13 shows that the regression model ANN has better accuracy in predicting the height of single track than the SVR, with RMSE=22.9 and R^2=0.83, indicating that ANN model for the height of single track has low correlation and poor pattern. The SVR has the same problem, with R^2=0.72, as shown in Table 5.

Similarly, the errors of the two regression models are large at some experimental data points, as shown in Fig.14, which is because the height of single track has a significant positive relationship with the wire feeding speed, while the influence of laser power and scanning speed is not as significant as that of the wire feeding speed, which can be seen from Fig. 3, so the SVR and ANN regression models for the height are less patterned than that for the width.

Table 4 Training data for the prediction of surface roughness

No.	Laser power/W	Wire feeding speed/mm·min^{-1}	Scanning speed/ mm·min^{-1}	Surface roughness/μm
1	100	180	120	1.836
2	125	180	120	1.747
3	150	180	120	1.511
4	175	180	120	1.327
5	200	180	120	1.023
6	125	60	150	1.025
7	125	120	150	1.249
8	125	180	150	1.475
9	125	240	150	1.833
10	125	300	150	2.119
11	125	360	150	2.530
12	150	120	120	1.133
13	150	120	150	1.346
14	150	120	180	1.491
15	150	120	210	1.600
16	150	120	240	1.724
17	150	120	270	1.946

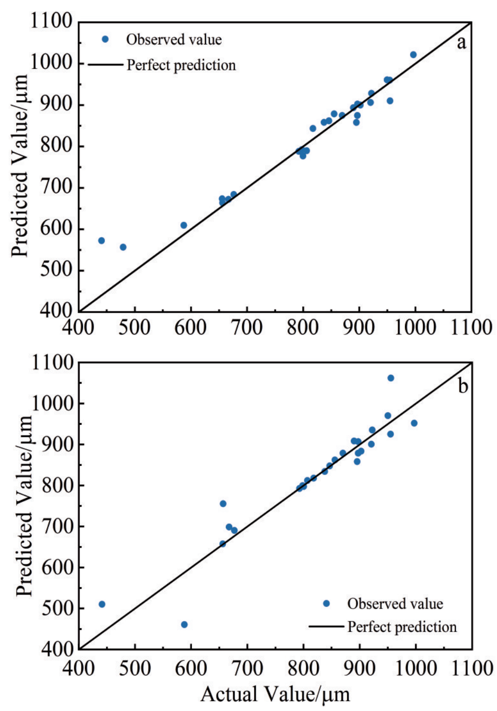

Fig.11 Actual value and the regression model prediction for the width of single track using SVR (a) and ANN (b)

3.2 Regression model for surface roughness

Fig.15 shows the actual value and regression model predic-

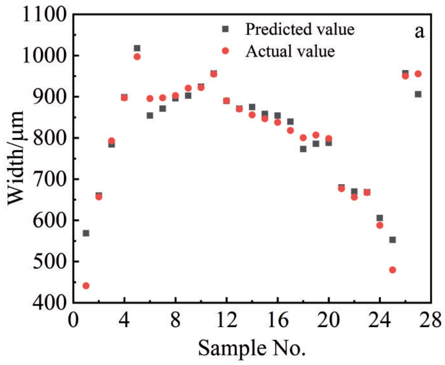

Fig.12 Error response diagrams of the regression model SVR (a) and ANN (b) for the prediction of width of single track

Table 5 RMSE and R^2 of the regression model SVR and ANN in predicting width and height of single track

Parameter	RMSE		R^2	
	SVR	ANN	SVR	ANN
Width	33.50	46.50	0.95	0.90
Height	29.40	22.90	0.72	0.83

tion for the surface roughness of thin-walled parts using SVR and ANN. Fig. 16 is the error response diagrams of the two methods, and the comparison of the RMSE and R^2 is shown in Table 6. It can be seen that the accuracy of the regression model SVR is much better than that of ANN, with the RMSE= 0.15 and R^2=0.86, and the R^2 of regression model ANN is only 0.53, which indicates that the patternity of the

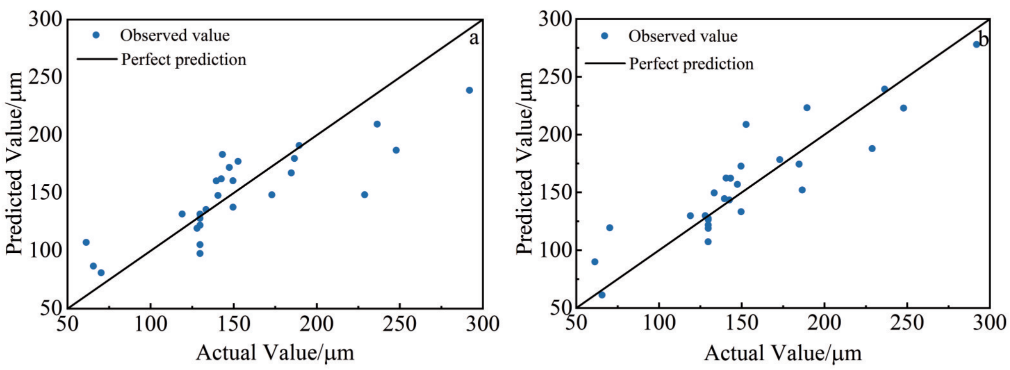

Fig.13 Actual value and the regression model prediction for the height of single track using SVR (a) and ANN (b)

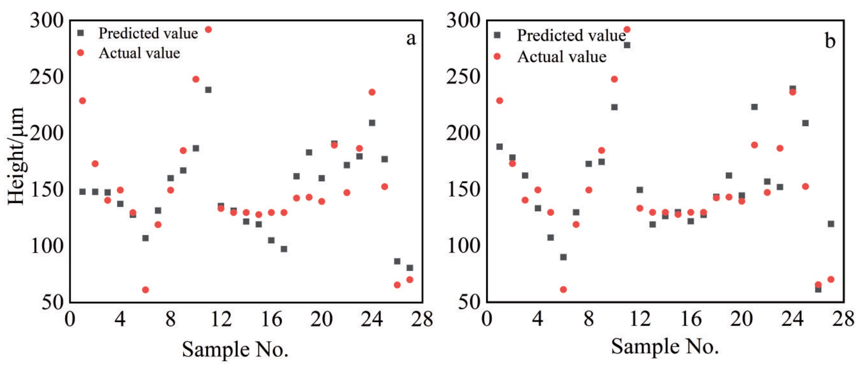

Fig.14 Error response diagrams of the regression model SVR (a) and ANN (b) for the prediction of height of single track

regression model SVR is more obvious than that of ANN.

Overall, SVR and ANN methods perform better in predicting the width and height of single track than in predicting surface roughness. The reason for this phenomenon is that the relationship between the surface roughness of parts and process parameters is not stable. Other interfering factors, such as the consistency of the silk material and the degree of curling, can cause changes in surface roughness, which are difficult to quantify and can only be eliminated as much as possible.

4 Production of Thin-Walled Parts

Based on the above regression models, suitable process parameters are selected, by which multi-layer thin-walled

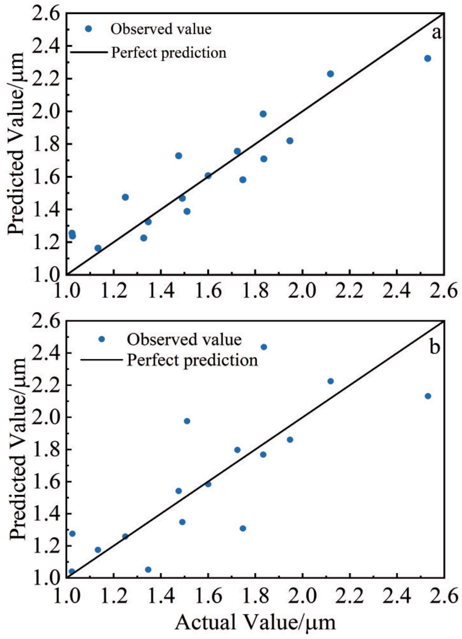

Fig.15 Actual value and regression model prediction for the surface roughness using SVR (a) and ANN (b)

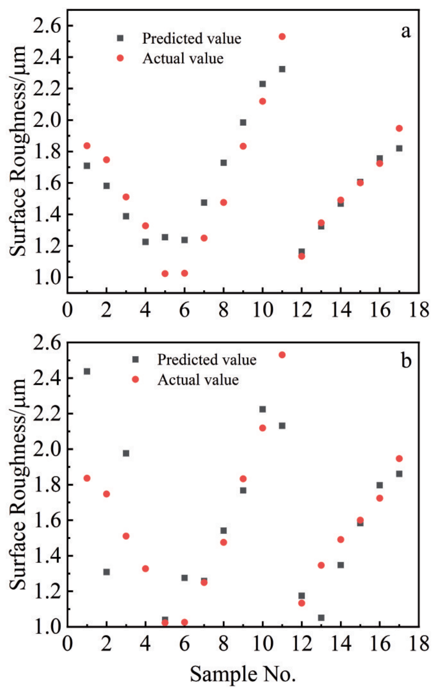

Fig.16 Error response diagrams of the regression model SVR (a) and ANN (b) for the prediction of surface roughness

Table 6 RMSE and R^2 of the regression model SVR and ANN in predicting surface roughness

Model	RMSE	R^2
SVK	0.15	0.86
ANN	0.27	0.53

parts are produced, as shown in Fig.17 and Fig.18, which effectively verify the accuracy of the model.

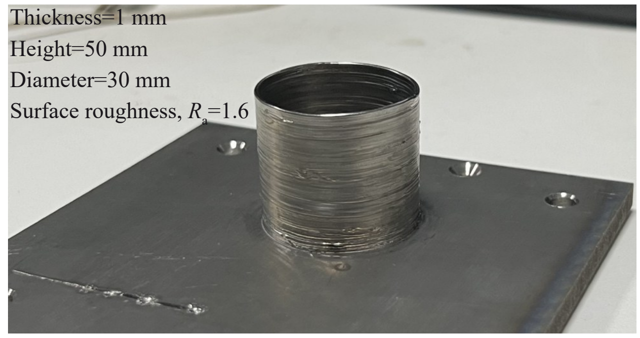

Fig.17 Multi-layer annular parts prepared under process parameters of laser power=125 W, wire feeding speed=180 mm/min and scanning speed=180 mm/min

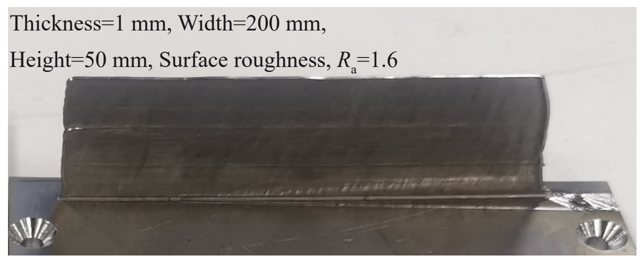

Fig.18 Multi-layer annular walled parts under process parameters of laser power=125 W, wire feeding speed=200 mm/min and scanning speed=200 mm/min

5 Conclusions

1) The laser power has a significant impact on the width of single track of deposition layer, showing a linear positive relationship with width, while it slightly affecting the height of a single channel, showing an inverse proportional relationship with height.

2) At a certain laser power and scanning speed, as the wire feeding speed increases, more material enters the melt pool, and the width and height of the single track increase, especially the height.

3) When the laser power and wire feeding speed are constant, the faster the scanning speed, the smaller the width of the single track, and the height changes little.

4) Due to the repeated increase and decrease in temperature during the printing process, the internal grains of the component are small, resulting in high mechanical performance.

5) The higher the laser power, the lower the surface roughness, showing an approximately linear relationship between the laser power and the surface roughness, and the relationship between wire feeding speed/scanning speed and surface roughness is similar.

6) The SVR and ANN regression models predict the width of the single track more effectively than they predict the height, with a smaller RMSE and a higher correlation coefficient R^2. Compared with the ANN model, the SVR model performs better both in predicting geometric

characteristics of single track and surface roughness.

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细丝基金属增材制造沉积层单道几何特征及粗糙度的预测

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摘　要：针对细丝基金属增材制造（MAM）工艺参数与沉积层单道几何特征和表面粗糙度之间的关系，提出了基于MAM工艺的机器学习预测模型。实验研究了激光功率、送丝速度和扫描速度对单道轨宽度、高度和表面粗糙度的影响规律。结果表明，激光功率对单道宽度影响显著，对高度影响不大。随着送丝速度的增加，单道的宽度和高度增加，特别是高度。扫描速度越快，单道宽度越小，而高度变化不大。采用支持向量回归（SVR）和人工神经网络回归（ANN）方法建立预测模型。SVR和ANN回归模型均具有较好的预测效果，均方根误差较小，相关系数R^2较高。与ANN模型相比，SVR模型在预测单道几何特性和表面粗糙度方面都有更好的效果。在此基础上制造了多层薄壁零件，验证了模型的准确性。

关键词：细丝基；金属增材制造；机器学习；支持向量回归；人工神经网络回归

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