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Surface roughness stabilization method based on digital twin-driven machining parameters self-adaption adjustment: a case study in five-axis machining

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Abstract
Surface roughness, which has a significant influence on fatigue strength and wear resistance, is an important technical parameter. In practical machining, it is unstable and may be larger than the acceptable surface roughness due to unstable machining process. This will seriously deteriorate the surface performance of the workpieces. Therefore, an effective surface roughness stabilization method is of great significance to improve machining efficiency and reduce machining cost. In this paper, a surface roughness stabilization method is proposed and illustrated by taking five-axis machining as an example. A self-learning surface roughness prediction model based on Pigeon-Inspired Optimization and Support Vector Machine is firstly constructed and its prediction error is only 8.69% in the initial stage. This model has the self-learning ability that the prediction accuracy can be improved with the increase of training data. Furthermore, a machining parameters self-adaption adjustment method based on digital twin is proposed to make the machined surface quality stable. In this method, considering the feasibility of practical machining operation, the cutter posture (i.e. lead angle and tilt angle in five-axis machining) and spindle speed are selected as the adjustable parameters. When the predicted surface roughness doesn't meet the requirements, the Gradient Descent algorithm is applied to recalculate the new parameters for adjustment. According to the experimental results, the proposed method can stabilize surface roughness and improve the surface quality, which is vital for the precision manufacturing of complex workpiece. Meanwhile, it also greatly improves the intelligence level of manufacturing and production.

Keywords Surface roughness stabilization · Pigeon-Inspired Optimization and Support Vector Machine (PIO–SVM) · Self-learning · Machining parameters self-adaption adjustment · Digital twin

Introduction

The surface quality usually directly affects the physical, chemical and mechanical properties of the workpiece, such as friction performance, fatigue resistance, wear resistance, lubrication ability etc. Surface roughness, the most important index to evaluate the surface quality, is therefore selected as a key technology requirement for parts production (Liu et al. 2016). Although the usage of multi-material components is increased with the sustainable development of modern manufacturing, the most parts are mono-material components at present. In the machining of mono-material components, arithmetic average height (Ra) is widely used as an important technical index to characterize the surface roughness; while in the machining of multi-material components, Ra cannot fully represent the surface quality (Ullah et al. 2015). This paper focuses on the surface roughness of mono-material components, so the Ra can be used as an evaluation criterion. The surface roughness is continually changing in practical machining, and often has an increasing trend due to tool vibration, tool wear and plastic deformation of workpiece material. In consequence, an effective surface roughness stabilization method is needed to get better surface performance of the workpiece. Meanwhile, the measurement of surface roughness is a very time-consuming process. It should be pointed out that surface roughness prediction model with

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high precision is not only the basis of controlling and stabilizing surface roughness but also can avoid the high cost and longtime measurement process. Over the past decades, many researchers have been carried out for establishing surface roughness prediction model, which can be approximately fall into three categories: theoretical method, experimental design method, and artificial intelligence (AI) method.

In the first category, based on the machining theory, surface roughness prediction model (usually a mathematical equation for machined surface) is established by considering cutter shape, workpiece material properties, installation error, machining dynamics (Benardos and Vosniakos 2003). Munoz-Escalona and Maropoulos (2015) proposed a surface roughness prediction model based on cutter trail geometric analysis for any combination of workpiece and tool. Similarly, Lu et al. (2017) established a cutter flexible deformation model based on cutting force, and uses this model to build a surface topography simulation model for predicting surface roughness. To reduce the non-uniformity of surface roughness, Sun et al. (2018) proposed a relative standard deviation of surface roughness (RSDS) method based on relative tool sharpness to predict the surface non-uniformity. To predict the in-process surface roughness during machining, Tangjitsitcharoen et al. (2017) developed a prediction model based on the dynamic cutting force ratio. In this model, the effects of spindle speed, feedrate cutter diameter, cutting depth and dynamic cutting force ratio on surface roughness are considered simultaneously. Liang et al. (2017) analyzed the influence of cutter path orientations on surface roughness and found that the horizontal upward direction of cutter path was beneficial to the surface quality. In addition, considering the effect of machining parameters on surface roughness, Chen et al. (2011) developed a new surface roughness prediction model integrating path-interval and feed-interval scallops.

In the second category, the surface roughness model is established in various machining by experimental design method. The common experimental design methods include Taguchi method, full factorial design method, response surface methodology (RSM) and so on. Compared to other methods, RSM is usually applied to surface roughness prediction due to requiring only a small number of experiments. Karkalos et al. (2016) researched the optimal machining parameters of Ti-6Al-4 V titanium alloy for minimum surface roughness with RSM. Noordin et al. (2004) researched the performance (mainly surface roughness and cutting force) of tungsten carbide tool by RSM. The study find that the feed speed is the main influence factor of surface roughness. Similarly, under dry drilling condition, Cicek et al. (2015) used RSM method to optimize drilling parameters to improve the surface quality of holes.

In addition to the above two methods, AI method, a powerful prediction tool with self-learning and self-adaption ability, is also widely applied to predict surface roughness. Ghosh et al. (2019a, b) proposed a surface roughness prediction model in keyway milling based on artificial neural network (ANN), and used genetic algorithm (GA) and particle swarm optimization (PSO) to find the optimal cutting conditions. In grinding, Ullah et al. (2010) divides 3D surface finish into three features (trend, irregularity, burst) and models them with different mathematical procedure. Pan et al. (2020) presented a surface roughness modelling method based on back propagation neural network (BPNN) and an activation function selection approach for grinding to improve the prediction accuracy and efficiency. To achieve the prediction and monitoring online of surface roughness, Huang et al. (2017) establish a Grey online modeling surface roughness monitoring (GOMSRM) system based on the Grey theory and bilateral best-fit method. In the high speed milling process, Xu et al. (2020) proposed a novel improved case based reasoning method to predict the surface roughness. Pimenov et al. (2018) applied random forest (RF), multilayer perceptron (MLP), regression tree (RT), radial basis function (RBF) to establish the relationship between cutter wear, cutting power and surface roughness, among which RF has the highest prediction accuracy and followed by RT. To improve the surface quality of workpiece in additive manufacturing (AM), Li et al. (2019) introduced a data-driven surface roughness prediction method. The implementation of this method is by using ensemble learning algorithm to train data extracted from sensors. In Rao and Murthy (2016), RSM, support vector machine (SVM) and ANN are employed to predict the surface roughness in steel boring. The machining parameters are optimized for minimal surface roughness through multi response optimization approach. Ullah (2017) used the improved Q-Sequence to build a surface roughness prediction model, which could regenerate the surface height (i.e., the surface contour).

Under the same machining conditions (including cutter, workpiece, machining parameters etc.), the surface roughness predicted by the above all models is constant value. However, in practical machining, surface roughness of the machined workpiece can't be stable due to the influences of tool wear, vibration, heterogeneity of material properties, stability of process system and other factors. Therefore, dynamic factors should be considered to accurately predict surface roughness. Cutting force is usually considered as one of the most important dynamic factors that affect surface roughness and machining accuracy (Geng et al. 2015). This paper proposed a prediction model considering dynamic cutting force and machining parameters, which can effectively reflect the influence of geometry and machining dynamics on surface roughness.

Further, the surface roughness usually fluctuates in a very short time, which may cause the machined workpiece to fail to meet the actual needs, thus increasing the manufacturing cost and machining time. Therefore, a real-time and effective surface roughness control method is very important. Digital twin, as an important approach to realize intelligent interconnection and interaction fusion of manufacturing physical world and virtual information world, is an effective method to solve this problem. Many scholars have explored the application of digital twins in manufacturing industry. In previous research, Tuegel et al. (2011) used digital twin to build virtual aircraft models and combined physical data with virtual data to predict fatigue life. To create virtual models in the digital twin system, Ullah (2019) proposed a method of semantic modeling, and took cutting force as an example to verify the effectiveness of the method. Redelinghuys et al. (2019) developed a six-layer architecture for the digital twin which including physical twin, local data layer, IoT Gateway layer, cloud-based databases layer and emulation and simulation. To improve the efficiency and accuracy of prognostics and health management (PHM), Tao et al. (2018) established a 5-dimension digital twin model for complex equipment. To improve the intelligence of manufacturing, Tong et al. (2020) presented a real-time machining data application and service based on digital twin technique and take 5-axis machine tool as example to build a twin model of dynamic characteristics. Ghosh et al. (2020) proposed the definition of a digital twin system, which consists of input, processing and output components. Taking surface roughness as an example, the process of modeling, simulation and verification in digital twin system is introduced in detail. In Lim et al. (2019), the application of digital twin in different fields, the current development bottleneck and future research perspectives are introduced comprehensively.

Five-axis machining is one of the most widely used machining approaches for sculpture surface due to its advantages of flexibility, high efficiency and high quality (Liu et al. 2018). Therefore, the proposed surface roughness stabilization method based on digital twin is illustrated by the case study in five-axis machining. The rest of this paper is organized as follows. "Construction of self-learning surface roughness prediction model based on PIO–SVM" section proposes a self-learning surface roughness prediction model based on Pigeon-Inspired Optimization and Support Vector Machine (PIO–SVM). In "Experimental validation and discussions" section, the proposed prediction model is validated by a series of experiments. "Digital twin-driven parameters self-adaption adjustment method towards surface roughness stabilization" section describes the method of combining this model with digital twin to maintain surface roughness stable. The conclusion of this paper is described in "Conclusion" section.

Construction of self-learning surface roughness prediction model based on PIO–SVM

In this section, a self-learning surface roughness prediction model based on PIO–SVM is developed. The basic principle of SVM is briefly introduced, which is the basis for the establishment of surface roughness prediction model. To improve the prediction accuracy, PIO algorithm is applied to optimize the parameters of SVM model.

The basic theory of SVM

Support vector machine (SVM) is a machine learning method based on structural risk minimization principle proposed by Vapnik (2000) using statistic studying theory. Compared with the traditional machine learning approaches represented by neural network, SVM has obvious advantages in theoretical basis, training process, node number, weight vector and global optimal solution (Vapnik 1999). The basic idea of SVM is to simplify searching the optimal linear hyperplane to a convex programming problem. The sample space is nonlinear mapped to a feature space with high- or infinite-dimension. In this way, the linear learning machine can be applied to solve the nonlinear problems (including classification and regression) in high-dimensional feature space.

Its regression function can be written as follows:

$$\begin{cases} f(x) = \sum_{i=1}^{N} \omega_i \boldsymbol{K}(x_i, x) + b \\ \omega_i = \alpha_i - \alpha_i^*, \ 0 \le \alpha_i, \alpha_i^* \le C \\ b = y_i - \sum_{i=1}^{N} \left(\alpha_i - \alpha_i^*\right) \boldsymbol{K}\left(x_i, x_j\right) + \varepsilon \end{cases} \tag{1}$$

where α_i and α_i^* are Lagrangian multipliers, C is penalty factor and its role is to adjust the error of model, $\boldsymbol{K}\left(x_i, x_j\right)$ is kernel function, x_i, x_j are arbitrary support vectors corresponding to $\left(\alpha_i - \alpha_i^*\right) \neq 0$ and $\left(\alpha_j - \alpha_j^*\right) \neq 0$, respectively.

Establishment of surface roughness prediction model based on SVM

The selection of training set and test set

The training set is used to describe how the influencing factors affect surface roughness and established the decision function. The test set is used to evaluate the accuracy of decision function established by the training set. In this paper, lead angle (L), tilt angle (T), cutting depth (a_p), spindle speed (n), feedrate (f) and average cutting force $(\bar{F})$ are considered as the influencing factors. Please refer to Wang (2015) for the detailed descriptions of these factors.

Data pre-processing (normalization)

In order to shorten the training time and improve the prediction accuracy of regression model, the training sample set need to be normalized. In this paper, the training set is normalized into [0, 1]. Its calculation formula is as follows:

$$x_i' = \frac{x_i - x_i^{\min}}{x_i^{\max} - x_i^{\min}} \tag{2}$$

where x_i' and x_i are the sample data before and after normalization, respectively; $x_i^{\max}$ and $x_i^{\min}$ are the maximum and minimum of the influencing factor i of surface roughness.

The selection of kernel function

Kernel function is an important part of establishing regression prediction model in SVM, and its reasonable selection is helpful to improve the accuracy of prediction model. The function of kernel function is to transform the problem of linear inseparability in low-dimension space into the problem of linear separability and linear regression in high-dimension space. The radial basis kernel function (RBF) has a relatively simple calculation form with less input parameters and stronger learning ability (Shamshirband et al. 2016). Therefore, the RBF should be selected as the kernel function of regression prediction model and can be described as follows:

$$\boldsymbol{K}\left(x_i, x_j\right) = \exp\left\{-g\left|x_i - x_j\right|^2\right\}, \quad (g > 0) \tag{3}$$

The optimization for parameters *C* and *g* of the SVM using PIO

The selection of parameter C penalty factor and parameter g kernel bandwidth has important influence on the accuracy of regression prediction model. Compared with PSO algorithm and GA algorithm, PIO has faster convergence speed, higher accuracy and stability (Qiu and Duan 2020). Hence, it is used to select the best C and g in this paper.

Duan and Qiao (2014) first proposed the PIO algorithm, inspired by the navigation behavior of the pigeon. In PIO, each pigeon is a solution to a problem and the optimal solution is the pigeon with the highest fitness value. This algorithm consists of two parts: Map and compass operator and Landmark operator. The mathematical models for each part are described as follows:

Map and compass operator

The pigeons use their field-sensing abilities to form maps in their brains and then sense the earth's magnetic field. Meanwhile, they adjust their flight direction according to the altitude of the sun. As the pigeons get closer to their destinations, they become less dependent on the sun and earth's magnetic field. The pigeon population is N_g and the number of iterations for map and compass operator is $N_{t,1}$. Define pigeon i with its location $L_i = [l_{i,1}, l_{i,2}, \ldots, l_{i,n}]$ and velocity $V_i = [v_{i,1}, v_{i,2}, \ldots, v_{i,n}]$, where n is the dimension of search space. In map and compass operator, the new location L_i and velocity V_i of each pigeon can be updated according to the following rules:

$$\begin{aligned} V_i(k) &= V_i(k-1)\cdot e^{-fk} + rand\cdot(L_b - L_i(k-1)) \\ L_i(k) &= L_i(k-1) + V_i(k) \end{aligned} \tag{4}$$

where k represents the number of iterations and $k \in \left[1, N_{t,1}\right]$, f is the map and compass factor, and $rand$ is a random value in [0, 1], and L_b represents the optimal solution for the current iterations.

Landmark operator

When the pigeons are near their destination, they switch from relying on the sun and earth's magnetic field to relying on nearby landmarks. If they know well nearby landmarks, they would fly directly to their destination. Otherwise, the unfamiliar pigeons will follow the familiar pigeons familiar with landmarks to their destination. In this process, the number of pigeons decreased by half in each iteration and the number of iterations for landmark operator is $N_{t,2}$. Similarly, the location and velocity of the pigeons are calculated by the following equations:

$$\begin{aligned} N_g &= \frac{N_g}{2}, k \in \left(N_{t,1}, N_{t,2}\right] \\ L_C(k) &= \frac{\sum L_i(k)\cdot fitness(L_i(k))}{N_g\cdot\sum fitness(L_i(k))} \\ L_i(k) &= L_i(k-1) + rand\cdot(L_C(k) - L_i(k-1)) \end{aligned} \tag{5}$$

where $fitness$ is a function of each solution's quality, and this function represents the mean square error (MSE) corresponding to each parameter C, g. When dealing with a minimization problem, the $fitness(L_i(k))$ can be expressed as $\frac{1}{fit(L_i(k))}$; When dealing with a maximization problem, the $fitness(L_i(k))$ can be expressed as $fit(L_i(k))$. Each pigeon's optimal location at the kth iteration can be denoted as $L_o = \min\left(L_{i,1}, L_{i,2}, \ldots, L_{i,k}\right)$.

The complete flowchart of the SVM model parameters optimized by PIO is shown in Fig. 1. The experimental data

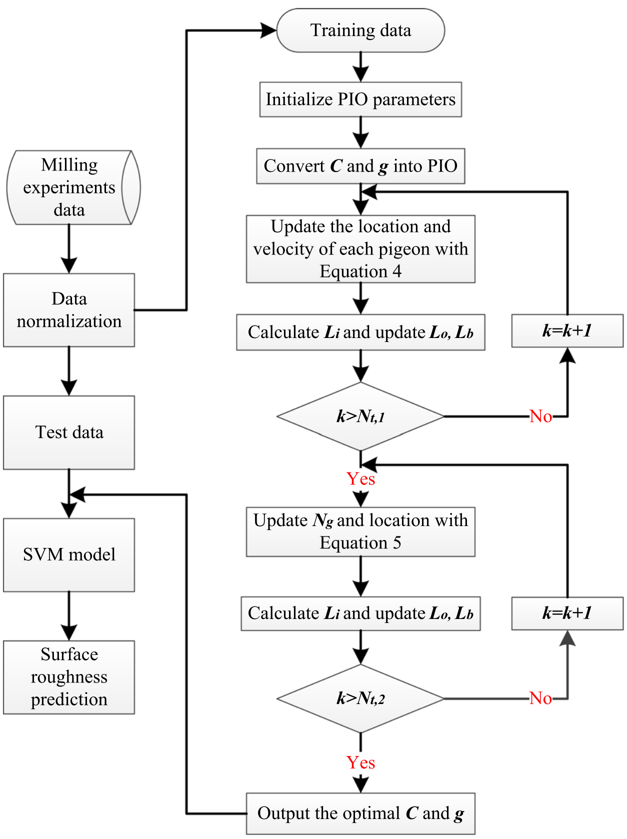

Fig. 1 The complete flowchart of PIO–SVM

is firstly normalized. Then, the prediction accuracy is selected as the fitness function and the training data is input into the PIO algorithm to obtain the optimal C and g, which is used for the construction of surface roughness prediction model.

Experimental validation and discussions

The experiment design

In experiments, the workpiece material is AL7075 which is usually used in aerospace industry. The 5-axis machine tool is Mazak INTEGREX e-1060 V/8 S. The cutting force is measured using a Kistler 9139A dynamometer (see Fig. 2a). A Mitsubishi carbide ball-end cutter (helix angle: 30°; diameter: 10 mm) is used for slot milling. Surface roughness R_a is measured by FTS Intra (see Fig. 2b). In order to reduce the measurement error as much as possible, R_a is the mean value of five evenly distributed measured points whose measurement positions are marked by a marker-pen. Meanwhile, each experiment (including the training and test set) is carried out twice repeatedly.

The experiment results and discussion

For each group of experiments, the R_a are basically the same in the two repeated experiments. The final R_a is the mean value of two experiment results. To build the prediction model, a total of 50 experiments were designed and conducted, including two sets of two-factor four-level full factorial experiments, and two sets of three-factor three-level orthogonal experiments. 40 experiments are randomly selected as the training set, and the remaining 10 experiments are selected as the test set. The training set are shown in Table 1. The initial parameters of PIO algorithm are set as: $N_g = 100$, $n = 2$, $f = 0.3$, $N_{t,1} = 100$, $N_{t,2} = 150$. The optimal C and g are 0.5 and 1 respectively.

The machining parameters and predicted results of test set are shown in Table 2. The column below R_a^{pre-P} represents the predicted surface roughness calculated by the proposed model, while the column below R_a is the measured surface

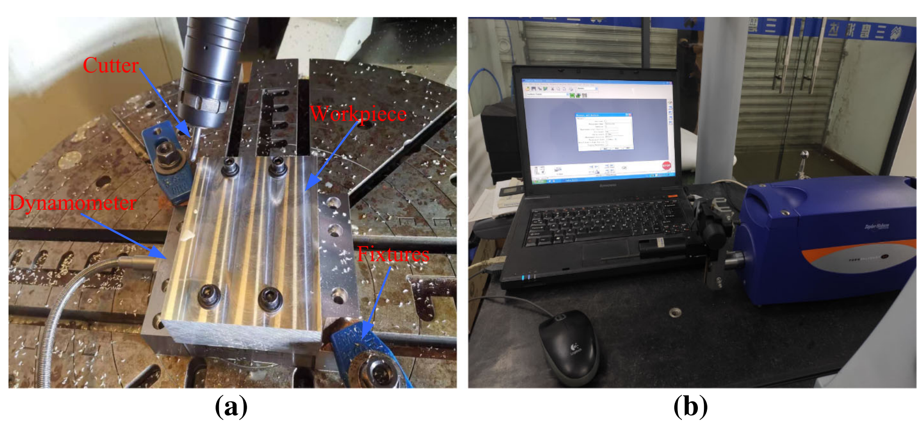

Fig. 2 The experimental details. **a** 5-axis machine tool, **b** surface roughness measuring instrument

Table 1 Experimental results of the training set

No.	L (°)	T (°)	a_p (mm)	f (mm/min)	n (rpm)	$\bar{F}$ (N)	R_a(μm)
1	0	0	1.5	600	4800	155.00	0.2906
2	15	0	1.5	600	4800	149.51	0.1794
3	30	0	1.5	600	4800	121.23	0.3855
4	45	0	1.5	600	4800	93.85	0.2553
5	0	15	1.5	600	4800	104.75	1.3363
6	15	15	1.5	600	4800	93.64	0.3695
7	30	15	1.5	600	4800	85.25	1.6502
8	45	15	1.5	600	4800	75.51	1.1773
9	0	30	1.5	600	4800	78.80	1.9792
10	15	30	1.5	600	4800	77.71	0.9771
11	30	30	1.5	600	4800	71.85	1.1421
12	45	30	1.5	600	4800	68.82	1.3591
13	0	45	1.5	600	4800	71.33	1.4831
14	15	45	1.5	600	4800	71.13	1.2840
15	30	45	1.5	600	4800	80.04	1.0445
16	15	0	2.5	800	6000	190.99	0.2591
17	30	0	2.5	800	6000	186.25	0.7390
18	45	0	2.5	800	6000	177.34	2.7680
19	0	15	2.5	800	6000	171.56	1.5793
20	30	15	2.5	800	6000	154.12	1.1183
21	0	30	2.5	800	6000	152.23	0.5848
22	15	30	2.5	800	6000	138.09	0.3905
23	30	30	2.5	800	6000	132.64	1.3162
24	45	30	2.5	800	6000	158.68	2.3047
25	15	45	2.5	800	6000	130.45	0.5599
26	30	45	2.5	800	6000	131.75	0.5207
27	45	45	2.5	800	6000	148.41	0.8290
28	0	0	1.25	800	6000	143.60	0.1748
29	0	0	1.5	600	6000	139.14	0.1832
30	0	0	1.5	800	7200	158.46	0.2331
31	0	0	1.5	1000	4800	219.31	0.4342
32	0	0	1.75	600	7200	144.30	0.5604
33	30	30	1.25	600	4800	144.30	0.7357
34	30	30	1.25	800	6000	98.17	1.5216
35	30	30	1.25	1000	7200	68.71	2.2689
36	30	30	1.5	600	6000	57.03	1.1494
37	30	30	1.5	800	7200	57.16	0.3273
38	30	30	1.5	1000	4800	154.00	0.9971
39	30	30	1.75	600	7200	108.65	2.1557
40	30	30	1.75	1000	6000	130.19	2.0400

roughness. To testify the validation of the proposed model, the Prediction Error (P_e) of each set of experiments is calculated with the formula as follows:

$$P_e = \frac{\left|R_a^{pre-P} - R_a\right|}{R_a} \tag{6}$$

It can be seen that the predicted R_a^{pre} is basically consistent with the actual measured R_a. The average prediction error (APE) is only 8.69%, which has a high prediction accuracy at the initial stage. Compared with the traditional surface roughness prediction model, the proposed model considers the influence of cutter posture (i.e. lead angle and tilt angle)

Table 2 Comparison between the measured and predicted R_a

No.	L (°)	T (°)	a_p (mm)	f (mm/min)	n (rpm)	$\bar{F}$ (N)	R_a (μm)	R_a^{pre-P} (μm)	P_e (%)	APE	R_a^{pre-G} (μm)	P_e (%)	APE
1	45	45	1.5	600	4800	88.61	1.0260	1.1921	16.18	8.69%	1.0432	1.68	11.65%
2	0	0	2.5	800	6000	199.06	0.4451	0.4647	4.40		0.5096	14.49	
3	15	15	2.5	800	6000	159.59	0.6131	0.6879	12.20		0.7209	17.58	
4	45	15	2.5	800	6000	174.38	1.2759	1.1685	8.41		1.3560	6.27	
5	0	45	2.5	800	6000	136.62	0.6304	0.6169	2.14		0.5618	10.88	
6	0	0	1.25	600	4800	140.44	0.3496	0.3793	8.49		0.3536	1.15	
7	0	0	1.25	1000	7200	138.74	0.6980	0.5963	14.57		0.5656	18.97	
8	0	0	1.75	800	4800	218.54	0.2914	0.2679	8.06		0.3577	22.77	
9	0	0	1.75	1000	6000	194.07	0.3820	0.3848	0.74		0.4371	14.42	
10	30	30	1.75	800	4800	107.11	0.9923	1.1084	11.70		1.0750	8.33	

and dynamic cutting force on surface roughness. There are two reasons for this consideration. On the one hand, in our previous research (Zhao et al. 2019), it is found that cutter posture changes the distribution of cutting force and thus affects surface roughness. On the other hand, the cutting force is unstable due to cutter vibration and the heterogeneity of material, which will lead to poor surface quality (Wang et al. 2015). Meanwhile, on-line measurement of cutting forces is very easy. Therefore, surface roughness can be predicted online by inputting real-time data of cutting forces into the proposed prediction model. In addition, this model also has the ability of self-learning. Parameters C, g of the model will be updated continuously with the increase of the training data to improve the prediction performance. Compared with Grid Search (GS) technology, the prediction performance of C and g obtained by PIO is better. To prove this, with the same training data, the C and g obtained by GS is 0.45 and 1.9 respectively. Its predicted results are shown at the column below R_a^{pre-G} in Table 2. It can be observed that the maximum P_e and APE predicted by GS method are 22.77% and 11.65% respectively, which are much larger than that of the PIO. This fully proves that the proposed model can predict surface roughness effectively and quickly when the machining parameters and dynamic average cutting force are known.

In addition, surface roughness of the machined workpiece is unstable due to instability of the cutting force. As a result, under the given the machining parameters (obtained by the workers' machining experience), surface roughness may not meet the technology requirements. According to our prediction model, the variation trend of surface roughness can be monitored online to judge its stability. Meanwhile, the spindle speed and cutter posture can be adjusted online in machining considering the machine tool's operational feasibility. So, the surface roughness can be stabilized and controlled by adjusting spindle speed and cutter posture. In order to prove the effectiveness of this method, a set of simulation results is carried out. The simulation is selected for two reasons: (1) The proposed prediction model is accurate enough to take the predicted surface roughness as the actual value; (2) The simulation can reduce the machining cost and save the machining time. The simulation results are shown in Table 3.

Table 3 Comparison of experimental results under different adjustable parameters

No.	L (°)	T (°)	a_p (mm)	f (mm/min)	n (rpm)	$\bar{F}$ (N)	R_a (μm)
1	0	0	1.0	600	7200	107.49	0.4882
2	0	0	1.0	600	5200	118.84	0.3692
3	5	0	1.0	600	7200	105.73	0.4760
4	5	0	1.0	600	4400	129.49	0.3346
5	15	0	1.0	600	4400	122.32	0.2995
6	15	5	1.0	600	4400	108.85	0.4341

According to the experimental results, the surface roughness decreased markedly from 0.4882 μm to 0.2995 μm by adjusting the adjustable parameters (cutter posture and spindle speed). This means that the workpiece only needs to be machined once to obtain the desired surface quality, which greatly improves the machining efficiency and reduces the machining cost.

However, it is possible to obtain satisfactory surface roughness with many adjustable parameter combinations, which means that the optimal one needs to be selected effectively and simply. Therefore, a parameter adjustment strategy based on Gradient Descent (GD) is proposed. When the initial machining parameters (obtained by the manual of machining process and worker's machining experiences) can't meet the machining requirements, the GD is used to identify the optimal parameter adjustment steps and output the new adjustable machining parameters to ensure surface roughness stability. The complete parameters adjustment strategy

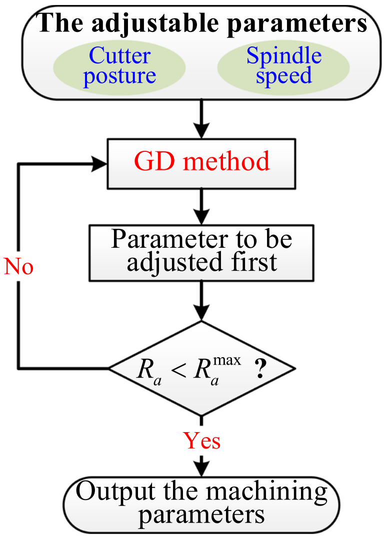

Fig. 3 The parameter adjustment strategy based on GD

is shown in Fig. 3. It should be noted that if the current surface roughness is still larger than the acceptable surface roughness after 4 times adjustment, this indicates that only adjusting the cutter posture and spindle speed cannot meet the machining requirements, and other parameters (the cutting depth, feedrate, etc.) also need to be adjusted.

Digital twin-driven parameters self-adaption adjustment method towards surface roughness stabilization

Based on the above prediction model, the surface roughness can be accurately predicted in real time and its stability trend can be monitored. The simulation results in Table 3 has proved the effectiveness of the surface roughness stabilization method, that is, the surface roughness can be reduced obviously by adjusting the adjustable parameters. This is of great significance for the control of surface roughness. If the surface roughness is larger than a preset threshold (R_a^{max}, the acceptable surface roughness), the adjustable machining parameters (cutter posture and spindle speed) need to be adjusted to reduce surface roughness to an acceptable criteria. This is a very complex dynamic change problem, which involves the real-time interaction and fusion of various machining information. Therefore, new and effective approaches are need to solve the problem. Digital twin is a simulation process that reflects the whole life cycle process of physical equipment by using physical model, sensor update and operation history data (Lu et al. 2020). With the help of digital twin, it can be realized that surface roughness can be predicted online based on the real-time input data and the parameters of machine tool can be adjusted simultaneously based on the feedback information of prediction model and parameter adjustment strategy. Therefore, a novel surface roughness stabilization method based on digital twin-driven parameters self-adaption adjustment is proposed in this paper. The traditional digital twin system structure usually includes modeling, simulation, verification and other steps (Ghosh et al. 2019a, b). As the surface roughness prediction model has been established and its accuracy has been verified by experiments, it only needs to be embedded into the digital twin system and conduct online prediction based on real-time data. The driving mode of digital twins is shown in Fig. 4. The models and data are the core of digital twins. The data is the foundation of the model, and the model is the embodiment of the data. In this paper, data are divided into two categories: (1) static data: geometric dimensions of workpiece, material properties, cutter parameters, etc.;

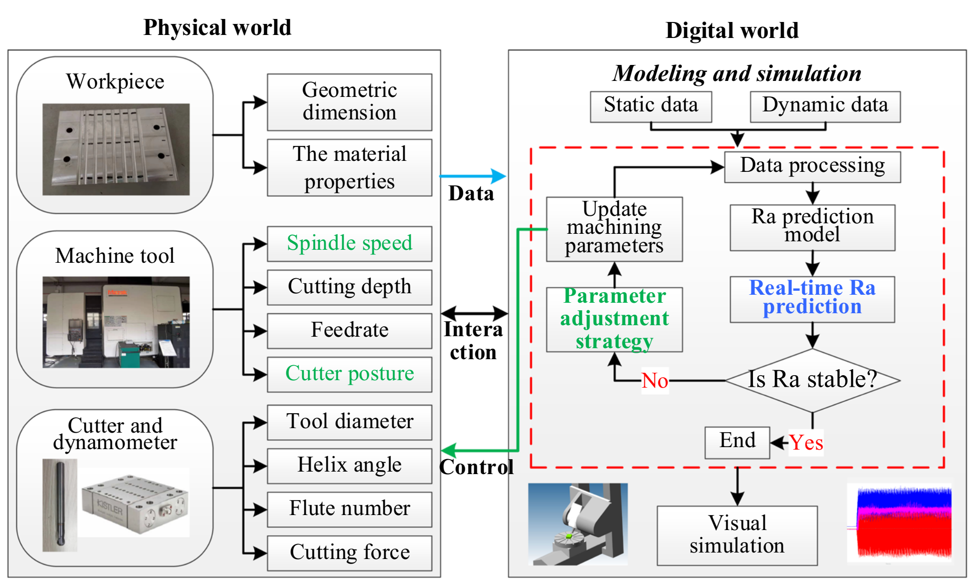

Fig. 4 Surface roughness stabilization method based on digital twin

(2) dynamic data: machining parameters, cutting force, etc. These data are used for modeling and prediction of surface roughness in digital world. Meanwhile, the adjusted parameters need be fed back to the machine tool in the physical world for adjustment.

The complete optimization method as follows:

(1) The initial machining parameters should be determined firstly.
(2) The cutting force is measured in real time and the average cutting force over a period is calculated. The surface roughness is then calculated based on the proposed prediction model.
(3) If surface roughness is a stable trend (i.e., $R_a \leq R_a^{\max}$), it is proved that the current machining parameters meet the machining demands; Otherwise, it is necessary to recalculate the machining parameters through parameter adjustment strategy and feedback it to the machine tool.
(4) The whole process is repeated until the end of the machining.

Conclusion

In this paper, a surface roughness stabilization method based on digital twin-driven machining parameters self-adaption adjustment is proposed to obtain stable surface quality in five-axis machining. Some significant conclusions are shown as follows:

(1) A novel self-learning surface roughness prediction model based on Pigeon-Inspired Optimization and Support Vector Machine (PIO–SVM) is proposed, which takes the influence of cutter posture and cutting force on surface roughness into consideration. The average prediction error of the proposed model is only 8.69% at the initial moment. In addition, the model will be updated automatically with the increased training data to enhance the accuracy of prediction.
(2) A parameter adjustment strategy based on Gradient Descent (GD) for surface roughness stability is proposed. Considering the feasibility of practical operation, the cutter posture (i.e. lead angle and tilt angle in five-axis machining) and spindle speed are considered as the adjustable parameters. Based on GD method, the reasonable parameters are selected to adjust to meet the machining requirements.
(3) To make the whole machined surface meet the surface roughness technology requirements, a surface roughness stabilization method combining the proposed prediction model and digital twin technology is proposed. In this method, the adjustable parameters are adjusted automatically in real time to keep the surface roughness stable according to the trend of surface roughness, which is very important to improve the intelligence level of the whole machining system.

Using the proposed method, the surface roughness of the workpiece is stable and meets the final machining requirements, which is greatly to improve the machined surface properties, machining efficiency and reduce manufacturing cost. This is of crucial importance for the machining of complicated and precise workpiece with sculptured surfaces. In the future work, the idea of surface roughness stabilization method will be applied to other machining technology.

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References

Benardos, P. G., & Vosniakos, G. C. (2003). Predicting surface roughness in machining: A review. *International Journal of Machine Tools and Manufacture, 43*(8), 833–844.

Chen, J. S., Huang, Y. K., & Chen, M. S. (2011). A study of the surface scallop generating mechanism in the ball-end milling process. *International Journal of Machine Tools and Manufacture, 45*(9), 1077–1084.

Cicek, A., Kivak, T., & Ekici, E. (2015). Optimization of drilling parameters using Taguchi technique and response surface methodology (RSM) in drilling of AISI 304 steel with cryogenically treated HSS drills. *Journal of Intelligent Manufacturing, 26*(2), 295–305.

Duan, H. B., & Qiao, P. X. (2014). Pigeon-inspired optimization: A new swarm intelligence optimizer for air robot path planning. *International Journal of Intelligent Computing & Cybernetics, 7*(1), 24–37.

Geng, L., Liu, P. L., & Liu, K. (2015). Optimization of cutter posture based on cutting force prediction for five-axis machining with ball-end cutters. *International Journal of Advanced Manufacturing Technology, 78*(5–8), 1289–1303.

Ghosh, G., Mandal, P., & Mondal, S. C. (2019a). Modeling and optimization of surface roughness in keyway milling using ANN, genetic algorithm, and particle swarm optimization. *The International Journal of Advanced Manufacturing Technology, 100*(5), 1223–1242.

Ghosh, A. K., Ullah, A. M. M. S., & Kubo, A. (2019b). Hidden Markov model-based digital twin construction for futuristic manufacturing systems. *Artificial Intelligence for Engineering Design, Analysis and Manufacturing, 33*(3), 317–331.

Ghosh, A. K., Ullah, A. M. M. S., Kubo, A., Akamatsu, T., & D'Addona, D. M. (2020). Machining phenomenon twin construction for industry 4.0: A case of surface roughness. *Journal of Manufacturing and Materials Processing, 4*(1), 11.

Huang, P. T. B., Zhang, H. J., & Lin, Y. C. (2017). Development of a Grey online modeling surface roughness monitoring system in end milling operations. *Journal of Intelligent Manufacturing, 30,* 1923–1936.

Karkalos, N. E., Galanis, N. I., & Markopoulos, A. P. (2016). Surface roughness prediction for the milling of Ti–6Al–4 V ELI alloy with the use of statistical and soft computing techniques. *Measurement, 90,* 25–35.

Li, Z. X., Zhang, Z. Y., Shi, J. C., & Wu, D. Z. (2019). Prediction of surface roughness in extrusion-based additive manufacturing with machine learning. *Robotics and Computer-Integrated Manufacturing, 57,* 488–495.

Liang, T., Yao, C. F., Ren, J. X., & Zhang, D. H. (2017). Effect of cutter path orientations on cutting forces, tool wear, and surface integrity when ball end milling TC17. *International Journal of Advanced Manufacturing Technology, 88*(9–12), 1–14.

Lim, K., Zheng, P., & Chen, C. H. (2019). A state-of-the-art survey of Digital Twin: Techniques, engineering product lifecycle management and business innovation perspectives. *Journal of Intelligent Manufacturing, 31,* 1313–1337.

Liu, Y., Wan, M., Xing, W. J., Xiao, Q. B., & Zhang, W. H. (2018). Generalized actual inverse kinematic model for compensating geometric errors in five-axis machine tools. *International Journal of Mechanical Sciences, 145,* 299–317.

Liu, N., Wang, S. B., Zhang, Y. F., & Lu, W. F. (2016). A novel approach to predicting surface roughness based on specific cutting energy consumption when slot milling Al-7075. *International Journal of Mechanical Sciences, 118,* 13–20.

Lu, X. H., Hu, X. C., Jia, Z. Y., Liu, M. Y., Song, G., Qu, C. L., et al. (2017). Model for the prediction of 3D surface topography and surface roughness in micro-milling Inconel 718. *International Journal of Advanced Manufacturing Technology, 94*(1), 1–14.

Lu, Y. Q., Liu, C., Wang, K. K., Huang, H. Y., & Xu, X. (2020). Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues. *Robotics and Computer-Integrated Manufacturing, 61,* 101837.

Munoz-Escalona, P., & Maropoulos, P. G. (2015). A geometrical model for surface roughness prediction when face milling Al 7075-T7351 with square insert tools. *Journal of Manufacturing Systems, 36,* 216–223.

Noordin, M. Y., Venkatesh, V. C., Sharif, S., Elting, S., & Abdullah, A. (2004). Application of response surface methodology in describing the performance of coated carbide tools when turning AISI 1045 steel. *Journal of Materials Processing Technology, 145*(1), 46–58.

Pan, Y. H., Wang, Y. H., Zhou, P., Yan, Y., & Guo, D. M. (2020). Activation functions selection for BP neural network model of ground surface roughness. *Journal of Intelligent Manufacturing*. https://doi.org/10.1007/s10845-020-01538-5.

Pimenov, D. Y., Bustillo, A., & Mikolajczyk, T. (2018). Artificial intelligence for automatic prediction of required surface roughness by monitoring wear on face mill teeth. *Journal of Intelligent Manufacturing, 29*(5), 1045–1061.

Qiu, H. X., & Duan, H. B. (2020). A multi-objective pigeon-inspired optimization approach to UAV distributed flocking among obstacles. *Information Sciences, 509,* 515–529.

Rao, K. V., & Murthy, P. B. G. S. N. (2016). Modeling and optimization of tool vibration and surface roughness in boring of steel using RSM, ANN and SVM. *Journal of Intelligent Manufacturing, 29*(7), 1533–1543.

Redelinghuys, A. J. H., Basson, A. H., & Kruger, K. (2019). A six-layer architecture for the digital twin: A manufacturing case study implementation. *Journal of Intelligent Manufacturing, 31*(6), 1383–1402.

Shamshirband, S., Mohammadi, K., Khorasanizadeh, H., Yee, P. L., Lee, M., Petković, D., et al. (2016). Estimating the diffuse solar radiation using a coupled support vector machine–wavelet transform model. *Renewable and Sustainable Energy Reviews, 56,* 428–435.

Sun, Z. W., To, S., Zhang, S. J., & Zhang, G. Q. (2018). Theoretical and experimental investigation into non-uniformity of surface generation in micro-milling. *International Journal of Mechanical Sciences, 140,* 313–324.

Tangjitsitcharoen, S., Thesniyom, P., & Ratanakuakangwan, S. (2017). Prediction of surface roughness in ball-end milling process by utilizing dynamic cutting force ratio. *Journal of Intelligent Manufacturing, 28*(1), 13–21.

Tao, F., Zhang, M., Liu, Y. S., & Nee, A. Y. C. (2018). Digital twin driven prognostics and health management for complex equipment. *CIRP Annals, 67*(1), 169–172.

Tong, X., Liu, Q., Pi, S. W., & Xiao, Y. (2020). Real-time machining data application and service based on IMT digital twin. *Journal of Intelligent Manufacturing, 31*(5), 1113–1132.

Tuegel, E. J., Ingraffea, A. R., Eason, T. G., & Spottswood, S. M. (2011). Reengineering aircraft structural life prediction using a digital twin. *International Journal of Aerospace Engineering*, *2011*, 154798. https://doi.org/10.1155/2011/154798.

Ullah, A. M. M. S. (2017). Surface roughness modeling using Q-sequence. *Mathematical & Computational Applications, 22*(2), 33.

Ullah, A. M. M. S. (2019). Modeling and simulation of complex manufacturing phenomena using sensor signals from the perspective of Industry 4.0. *Advanced Engineering Informatics, 39,* 1–13.

Ullah, A. M. M. S., Fuji, A., Kubo, A., Tamaki, J., & Kimura, M. (2015). On the surface metrology of bimetallic components. *Machining Science & Technology An International Journal, 19*(2), 339–359.

Ullah, A. M. M. S., Tamaki, J., & Kubo, A. (2010). Modeling and simulation of 3D surface finish of grinding. *Advanced Materials Research, 126–128,* 672–677.

Vapnik, V. N. (1999). An overview of statistical learning theory. *IEEE Transactions on Neural Networks, 10*(5), 988–999.

Vapnik, V. N. (2000). *The nature of statistical learning theory*. New York: Springer.

Wang, S. B. (2015). *Automated five-axis tool path generation based on dynamic analysis*. Singapore: National University of Singapore.

Wang, S. B., Geng, L., Zhang, Y. F., Liu, K., & Ng, T. E. (2015). Cutting force prediction for five-axis ball-end milling considering cutter vibrations and run-out. *International Journal of Mechanical Sciences, 96–97,* 206–215.

Xu, L., Huang, C., Li, C., Wang, J., & Wang, X. (2020). An improved case based reasoning method and its application in estimation of surface quality toward intelligent machining. *Journal of Intelligent Manufacturing*. https://doi.org/10.1007/s10845-020-01573-2.

Zhao, Z. Y., Wang, S. B., Wang, Z. H., Liu, N., Wang, S. L., Ma, C., et al. (2019). Interference- and chatter-free cutter posture optimization towards minimal surface roughness in five-axis machining. *International Journal of Mechanical Sciences, 171,* 105395.