An improved material removal model for robot polishing based on neural networks

Yu Yi[1], Kong Lingbao[1], Zhang Haitao[2], Xu Min[1], Wang Liping[2]

(1. Shanghai Engineering Research Center of Ultra-precision Optical Manufacturing, Department of Optical Science and Engineering, Fudan University, Shanghai 200433, China; 2. State Key Laboratory of Applied Optics, Changchun Institute of Optics, Fine Mechanics and Physics, Chinese Academy of Sciences, Changchun 130033, China)

Abstract: A strategy for improving the precision of material removal model based on deep neural networks was proposed. A deep learning algorithm with ability of feature selecting was proposed. A series of simulation samples composed of a material removal rate and corresponding polishing parameters were generated based on the model of material removal rate for robot polishing. The deep learning algorithm learned both the simulation samples and practical samples and then a deep learning model was established. The error between material removal depth of the test samples and material removal depth estimated by polishing parameters by using proposed deep learning model was calculated and compared. The results show that the improved model can achieve higher accuracy than the traditional models.

Key words: robot polishing; material removal; machine learning; deep neural networks; modelling and simulation

CLC number: TP249 **Document code:** A **DOI**: 10.3788/IRLA201948.0317005

基于神经网络的机器人抛光材料去除提升模型

余 熠[1],孔令豹[1],张海涛[2],徐 敏[1],王丽萍[2]

(1. 复旦大学 光科学与工程系 上海超精密光学制造工程技术研究中心,上海 200433;
2. 中国科学院长春光学精密机械与物理研究所 应用光学国家重点实验室,吉林 长春 130033)

摘　要: 提出了一种基于深度神经网络的提高材料去除模型精度的策略。提出一种具有特征选择能力的深度学习算法。在机器人抛光的材料去除率模型的基础上,生成由材料去除率和相应的抛光参数组成的一系列仿真样本。深度学习算法学习了仿真样本和实际样本,建立了深度学习模型。通过使用所提出的深度学习模型,根据抛光参数,估测测试样本的材料去除深度,并计算估测了测试样本的材料去除深度与实际的测试样本的材料去除深度之间的误差。结果表明:改进后的模型可以获得比传统模型更高的精度。

关键词: 机器人抛光; 材料去除; 机器学习; 深度神经网络; 建模与仿真

收稿日期:2018-11-05; **修订日期**:2018-12-15

基金项目:中国科学院长春光学精密机械研究所应用光学国家重点实验室开放基金;复旦-长光所合作项目基金(FC2017-010)

作者简介:余熠(1994-),男,硕士生,主要从事基于工业机器人的光学超精密制造方面的研究。Email:yiyu17@fudan.edu.cn

导师简介:孔令豹(1980-),研究员,博士生导师,博士,主要从事光学超精密制造及检测、智能视觉、功能型结构等方面的研究。Email:lkong@fudan.edu.cn

0 Introduction

Industrial robots are widely equipped on automated production lines for their more freedom and larger operation space[1]. Typical applications of industrial robot in modern advanced manufacturing include automatic baling robots, sampling robots, labelling robots, navigation and transportation robots and so on [2]. Especially, robot polishing technology has been adopted in large-sized ultra-precision manufacturing industries.

Polishing process has low material removal efficiency but high surface precision which makes it suitable for ultra-precision manufacturing. To improve the precision of industrial robot polishing process, it requires deep understanding on material removal rate (MRR) which depends on polishing parameters as well as circumstances. Different methods are adopted to study the material removal mechanism over the past few years, including finite element method[3], molecular dynamics[4], quasi-static model[5], using fluid dynamics and probability statistics in the analysis of polishing fluid[6-7], etc.. The early investigation of material removal model can be traced back to Preston who proposed Preston′s empirical equation [8]. Buijs et al[9]. presented an MRR model by incorporating Young′s modulus, hardness and fracture toughness. Matsuo et al.[10] a modified Preston′s equation based on substituting frictional force instead of polishing pressure. Shorey′s model[11] computed the MRR using the shear stress to replace the pressure or the frictional force. Through introducing the exponents to the contact pressure and the relative velocity, Wang et al.[12] proposed a revised model.

However, theoretical models of material removal in industrial robot polishing process is far from accuracy because the interaction mechanism of polishing head/pad and workpiece is quite complex, and it is very difficult to precisely model the relationship between material removal rate and polishing parameters.

Development of machine learning provides a new strategy to establish precise material removal models. Machine learning addresses the question of how to build computers that improve automatically through experience[13-14]. Deep neural networks are able to "learn" the relationship between polishing parameters and material removal rate from previous experiences[15]. Surface topography of the workpiece is measured before and after robot polishing by interferometer, thus material removal depth of the workpiece is obtained. Material removal depth and corresponding polishing parameters are taken as a sample reflecting how polishing parameters affect material removal rate[16,17].

Although the number of experimental samples can be thousands of or more, it is still far from sufficient enough to enable deep neural networks to establish precise material removal models. Material removal rate given by the established model is close to the actual results in a certain degree, which brings new chance for deep neural networks to "learn" from samples from both actual polishing process and theoretical models.

As a result, an improved model of material removal rate is obtained. The concept of the improved model proposed will be first explained. Theoretical fundamentals about Feature-selecting deep residual neural networks are then explained in details. Based on the proposed model for material removal rate in robot polishing, a series of experimental studies are undertaken and the results are presented to validate the improved model.

1 Improvement of MRR model based on machine learning

As shown in Fig.1, regardless of random error, independent variable x and dependent variable y are two interrelated variables whose correspondence needs modeling. There must be disparity between the actual correspondence curve and the correspondence given by theoretical derivation.

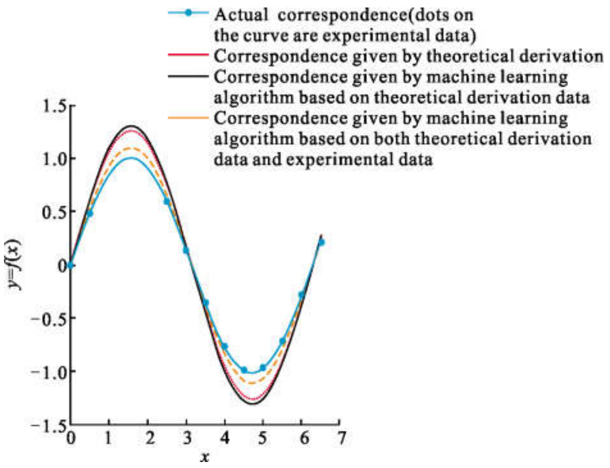


Fig.1 Principle of model improvement based on machine learning

Provided with enough samples on the actual corresponding curve of the variables x and y through actual experiments, and suitable machine learning algorithms are designed, then the algorithm will learn sufficient number of samples and the learned corresponding relationship between variables x and y will be quite close to the actual correspondence. However, due to many practical problems, the variables x and y are both multidimensional vectors and the corresponding relationship is very complicated, thus to obtain an ideal learning result requires a large number of samples as training data, while the actual situation may not be able to support such a large scale sample collection.

The limit of cost and time of actual experiment restrains the scale of actual sample collection, making machine learning algorithm unable to construct a correspondence model close enough to real correspondence by learning actual experimental data. However, the cost of collecting (calculating) samples from theoretical model is inexpensive. By acquiring large-scale samples from theoretical model and learning them using appropriate machine learning algorithms, a model is trained which can be quite close to theoretical model. Based on this learned model, appropriate weights are then assigned to a relatively smaller number of samples in the actual correspondence curve (The dots on the actual correspondence curve in Fig.1) to optimize the curve of correspondence given by machine learning algorithm based on theoretical derivation data in the graph, and the optimized model will then be obtained (Curve of correspondence given by machine learning algorithm based on theoretical derivation data and experimental data in Fig.1), which is closer to the actual correspondence curve than that given by theoretical derivation.

This is the concept of the improved model proposed in the present study. To construct an improved model based on machine learning needs three elements: a theoretical model, experiment data, and an appropriate machine learning algorithm.

2 Theoretical fundamentals

2.1 Theoretical material removal rate model

One of the three significant elements needed to build an improved material removal model for robot polishing based on machine learning algorithms is a theoretical material removal model. In the present study, Preston's empirical equation is adopted as the theoretical model for machine learning algorithms to learn from. Preston's empirical equation is described as follows

$$MRR=K\times P\times v \tag{1}$$

Where MRR is the material removal rate (material removal depth per unit time) at a certain point; K is a polishing constant related to material of polishing pad and workpiece and circumstances and so on; P is the pressure between the polishing pad and the workpiece while v is the relative speed between the polishing pad and the workpiece at the certain point.

2.2 Feature-selecting deep residual neural networks

Suppose that there exists a data training set D composed of known samples $(\vec{x}_i, y_i)$:

$$D=\{(\overrightarrow{x_1},y_1),(\overrightarrow{x_2},y_2),\cdots,(\overrightarrow{x_i},y_i),\cdots,(\overrightarrow{x_m},y_m)\} \tag{2}$$

Where $\overrightarrow{x_i}$ is a d-dimensional column vector:

$$\overrightarrow{x_i}=(x_i^{(1)},x_i^{(2)},\cdots,x_i^{(d-1)},x_i^{(d)})^{\mathrm{T}} \tag{3}$$

When it comes a new test sample $(\overrightarrow{x_{test}}, y_{test})$ with known $\overrightarrow{x_{test}}$ and unknown y_{test}:

$$\overrightarrow{x_{test}}=(x_{test}^{(1)},x_{test}^{(2)},\cdots,x_{test}^{(d-1)},x_{test}^{(d)})^{T} \tag{4}$$

Then there comes a question: based on training data set D, is there any prospect to establish a classification or regression model to predict or figure out the mostly likely y_{test} according to $\overrightarrow{x_{test}}$? Main task of machine learning, or supervised learning, specifically, is to achieve this goal. In this paper, polishing parameters such as polishing pressure, relative velocity, polishing time, and so on are dimensions of column vector $\vec{x}$ while corresponding MRR is y. A feature-selecting deep residual neural network is proposed in this paper to accomplish this goal.

Typically, a neural network has the framework similar to human neuron. An example of a simple neural network is shown as in Fig.2.

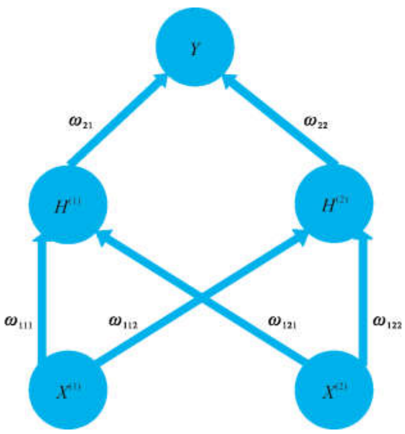


Fig.2 An example of a neural network with one hidden layer

In Fig.2, X, H and Y are input layer, hidden layer and output layer of the neural network, respectively. ω is connection weight and output of the neural network is computed by

$$H^{(1)}=X^{(1)}\times\omega_{111}+X^{(2)}\times\omega_{121} \tag{5}$$

$$H^{(2)}=X^{(1)}\times\omega_{112}+X^{(2)}\times\omega_{122} \tag{6}$$

$$Y=X^{(1)}\times\omega_{21}+X^{(2)}\times\omega_{22} \tag{7}$$

Once ω is determined, the neural network is built up. This paper determines ω by solving[18]

$$\hat{\omega}^{elastic}=\min\frac{1}{2}\{\sum_{l=1}^{m}|\overrightarrow{y_1}-\overrightarrow{\hat{y}_1}|^2+\lambda\sum_{i=1}^{d}\sum_{j=1}^{k}\omega_{1ij}^2+\mu\sum_{i=1}^{d}\sum_{j=1}^{k}|\omega_{1ij}|\} \tag{8}$$

Where $\overrightarrow{y_i}$ is output of the neural network if inout of the neural net work is $\overrightarrow{x_i}$. The first item is root-sum square loss, the second item is rigid regression loss and the third item is least absolute shrinkage and selection operator (LASSO). The second and third items are called regularization items preventing neural network from being unstable. It is noticed that if λ or μ is appropriately set, some of the ω_{1ij} will be quite small or even zero, which means that corresponding dimensions of the input have no effect on the output of the nerual network-in other words, the neural network has feature-selecing function(in Fig.3).

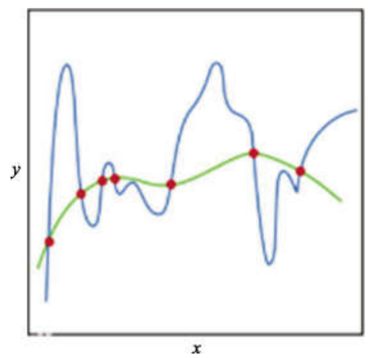


Fig.3 Regularization: an example of unstable model, where the dots are training examples, the green curve is ideal regression model while the blue curve is regression model based on root-sum square loss function without regularization

It is difficult to solve Eq.(8). Methods frequently used to solve Eq.(8) include random gradient descent, simulated annealing algorithm, error back-propagation algorithm and so on. However, when the neural network becomes deeper (more neuron layers), which means increase of learning ability of the neural network, non-convergence issue in the calculation for gradient is given rise to. In this paper, the neural network is turned to a residual topological structure to solve the problem[19].

As is shown in Fig. 4 (a), ReLu (·) is the activation function which aims to attach nonlinearity to the neural network.

$$H^{(1)}=\mathrm{ReLu}(X^{(1)}\times\omega_{111}+X^{(2)}\times\omega_{121}+X^{(3)}\times\omega_{131}) \quad (9)$$

$$H^{(2)}=\mathrm{ReLu}(X^{(1)}\times\omega_{112}+X^{(2)}\times\omega_{122}+X^{(3)}\times\omega_{132}) \quad (10)$$

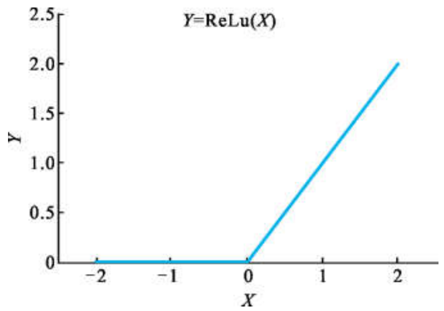
$$H^{(3)}=\mathrm{ReLu}(X^{(1)}\times\omega_{113}+X^{(2)}\times\omega_{123}+X^{(3)}\times\omega_{133}) \quad (11)$$

$$Y^{(1)}=\mathrm{ReLu}(H^{(1)}\times\omega_{211}+H^{(2)}\times\omega_{221}+H^{(3)}\times\omega_{231}+X^{(1)}) \quad (12)$$

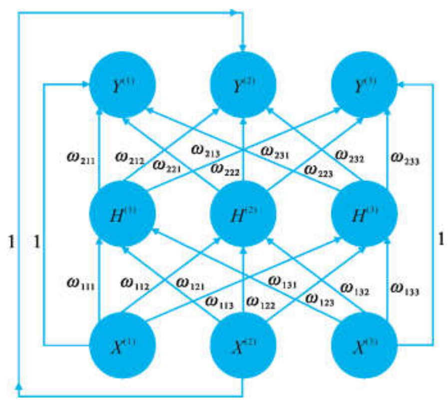
$$Y^{(2)}=\mathrm{ReLu}(H^{(1)}\times\omega_{212}+H^{(2)}\times\omega_{222}+H^{(3)}\times\omega_{232}+X^{(2)}) \quad (13)$$

$$Y^{(3)}=\mathrm{ReLu}(H^{(1)}\times\omega_{213}+H^{(2)}\times\omega_{223}+H^{(3)}\times\omega_{233}+X^{(3)}) \quad (14)$$

This paper adopts a feature-selecting deep residual neural network whose weights are determined by Eq.(8) with similar framework of Fig.4 (b) but having 100 hidden layers and 100 neurons each hidden layer.



(a) Rectified linear unit (ReLu) as activation function



(b) Feature-selecting deep residual neural network with 3 layers and 3 neurons each layer

Fig.4 An example of a feature-selecting deep residual neural network

2.3 Performance test for material removal model

MRR at each point of the training workpiece is derived from material removal depth(MRD) of training workpieces and polishing parameters related to each point under the circumstance that all polishing parameters, except polishing time, for any certain point of the training workpiece are constants throughout the whole polishing process:

$$MRR=\frac{\mathrm{d}MRD}{\mathrm{d}t}=\frac{MRD}{\Delta t} \quad (15)$$

So a number of experimental samples (Polishing parameters and corresponding material removal rate) is obtained. Meanwhile, 100 thousand of simulation samples (Polishing parameters and corresponding material removal rate) are built up based on Preston's empirical equation.

The feature-selecting deep residual neural network learns the polishing-parameters-to-MRR samples coming from both training workpiece and Preston's empirical equation. Then polishing parameters of each point of the test workpiece are put into the trained neural network, the output is material removal rate of each point of the test workpiece predicted by the neural network.

Material removal depth ($\hat{\mathrm{MRD}}$) at each point of the test workpiece predicted by the neural network are derived from material removal rate($\hat{\mathrm{MRR}}$) and polishing parameters related to each point under the circumstance that all polishing parameters, except polishing time, for any certain point of the training workpiece are constants throughout the whole polishing process

$$M\hat{R}D=\int_{t=0}^{T}M\hat{R}R\mathrm{d}t=MRR\times T' \quad (16)$$

The error between material removal depth of test workpiece predicted by nerual network ($\widehat{MRD}$) and actual MRD of test workpiece is defined as:

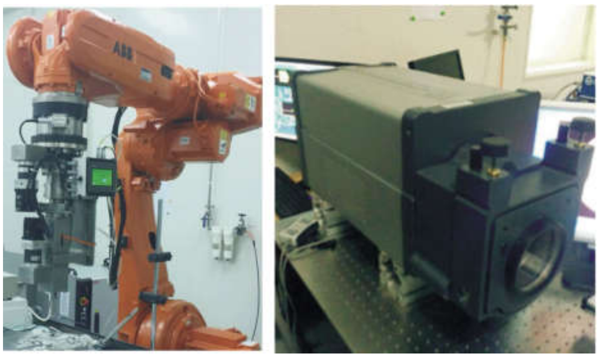
$$\mathrm{error}=\iint_{S,MRD\neq 0}\frac{|M\hat{R}D-MRD|}{|MRD|} \quad (17)$$

The error illustrates the disparity between material removal model constructed by the proposed feature-selecting deep residual nerual network and actual correspondence of material removal rate and polishing parameters.

3 Experimental studies and results

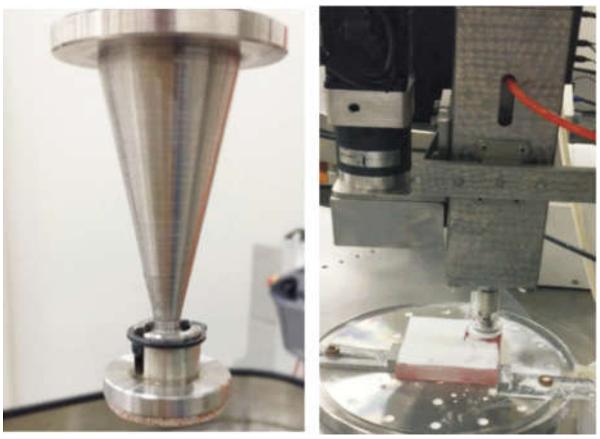
3.1 Experimental design

Two 120 mm×120 mm glass workpieces are marked as training workpiece and test workpiece, respectively. The two workpieces are polished with front-placed planetary polishing tool which is carried by ABB IRB-6620 six-axis industrial robot (Fig.5(a)). Polishing parameters applied to training workpiece and test workpiece are shown in Tab.1.



(a) ABB IRB-6620 six-axis industrial robot and front-placed polishing tools

(b) Zygo gpi xp/d interferometry



(c) Polishing pad at the end of front-placed polishing tools

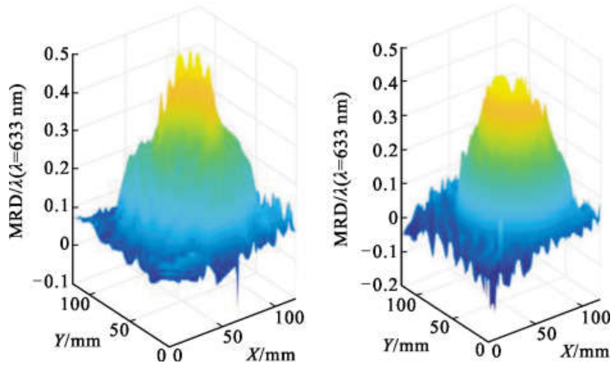
(d) Workpiece to be polished

Fig.5 Experimental system

Surface topography of the two workpieces are measured with Zygo GPI XP/D interferometry (Fig.5(b)) before and after polishing process, respectively. The MRDs of both workpieces (Fig.6) are got by computing the difference of surface topography before and after polishing process, respectively.

Tab.1 Polishing parameters applied to training workpiece and test workpiece

Polishing parameter	Training workpiece	Test workpiece
Revolution radius/mm	30	40
Rotation speed/rad·s^{-1}	20	10
Polishing pressure/kgf	1	2
Polishing time/s	30	30



(a) Material removal depth of training workpiece

(b) Material removal depth of test workpiece

Fig.6 MRD in experimental studies

MRR at each point of the training workpiece are derived from MRD of the workpieces and polishing parameters related to each point with Eq.(15), so a number of experimental samples (Polishing parameters and corresponding material removal rate) are obtained. On the other hand, 100 thousand of simulation samples are got based on Preston's empirical equation. Constant K is concerned in material of polishing pad and workpiece, polishing fluid, temperature, humidity and other factors as well as unit of MRD, polishing pressure and relative velocity. In this paper, K is determined by minimizing Eq.(17), K=4.73e-5 (λ·s/kgf·mm).

The feature-selecting deep residual neural network learns the polishing-parameters-to-MRR samples coming from both training workpiece and Preston's empirical equation. Polishing parameters of each point of the test workpiece are put into the trained neural network, then the output is material removal rate of each point of the test workpiece predicted by the neural network.

$M\hat{R}D$ at each point of the test workpiece are derived from $M\hat{R}R$ and polishing parameters related to each point according to Eq.(16).

3.2 Results and discussions

The error of Preston′s empirical equation and material removal model given by the neural network are computed based on Eq. (17) respectively. The result is shown in Fig.7. It indicates that the error between based on Preston′s empirical equation and MRD of test workpiece is 36.73% while the error between based on the feature-selecting deep residual neural network and MRD of test workpiece is 25.16%.

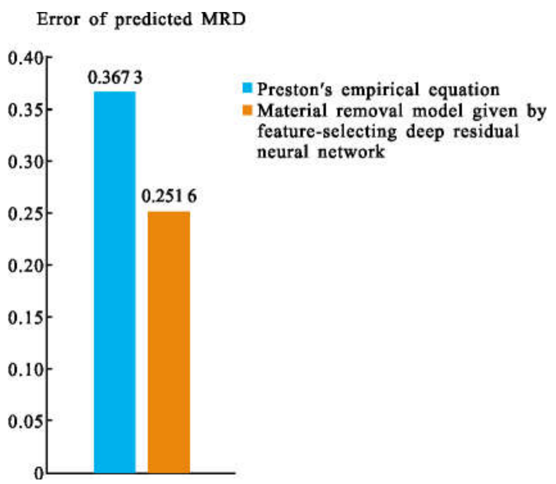


Fig.7 Error of predicted material removal depth

Compared with Preston′s empirical equation, the error based on model given by neural network has a 31.5% drop. In the field of machine learning, whether the regression or classification error can controlled less than 10% is a standard to judge whether the regression model is good. The result shows that, although the performance of the both two models is not satisfactory enough, strategy proposed in this paper do have the ability to build up an improved material removal model much better than the theoretical model which the neural network learns from with a 31.5% error drop.

From the comparison between the prediction of the algorithm proposed and the actual testing result, although the method performs better than Preston′s equation does, there are still 25.16% relative errors, which might be caused by:(1) the number of practical samples used for training is limited; (2) the Preston equation itself is not satisfied enough; (3) random error in polishing process.

In the future research, more suitable learning algorithms with stronger learning ability are going to be designed to learn theoretical polishing models more advanced than Preston′s empirical equation, and to achieve accurate material removal depth prediction of polishing methods more complex than planetary polishing.

4 Conclusion

Polishing process with industrial robot has a significant role in modern advanced manufacturing, therefore constructing a material removal model of robot polishing is important. This paper proposes an improved material removal model for robot polishing based on Preston′s empirical equation and a feature-selecting deep residual neural network. The feature-selecting deep residual neural network learns samples from both a training workpiece and Preston′s empirical equation, and then build up an improved material removal model. The experimental studies show that the proposed improved model provides more accurate prediction results than the traditional models, which will be helpful for the more precise control of polishing process by an industrial robot.

References:

[1] Cully A, Clune J, Tarapore D, et al. Robots that can adapt like animals[J]. ***Nature***, 2014, 521(7553): 503-507.

[2] Peng Lu, Man Chen. Analysis of the application of industrial robot in intelligent manufacturing [J]. ***Metallurgical Automation***, 2018(S1): 134.

[3] Seok J, Sukam C P, Kim A T, et al. Material removal model for chemical-mechanical polishing considering wafer flexibility and edge effects[J]. ***Wear***, 2004, 257(5-6): 496-508.

[4] Eder S J, Cihak-Bayr U, Pauschitz A. Nanotribological simulations of multi-grit polishing and grinding [J]. ***Wear***, 2015, 340–341: 25–30.

[5] Xu H, Komvopoulos K. A quasi-static mechanics analysis of three-dimensional nanoscale surface polishing [J]. ***Journal of Manufacturing Science & Engineering***, 2010, 132(3): 321–333.

[6] Cao Z C, Chi F C. Theoretical modelling and analysis of the material removal characteristics in fluid jet polishing [J]. ***International Journal of Mechanical Sciences***, 2014, 89: 158–166.

[7] Tichy J. Contact Mechanics and lubrication hydrodynamics of chemical mechanical polishing[J]. ***Tree Physiology***, 1999, 25 (10): 1243–1251.

[8] Preston F W. The theory and design of plate glass polishing machines[J]. ***J Soc Glass Tech***, 1927, 11: 214.

[9] Buijs M, Houten K V. A model for lapping of glass [J]. ***Journal of Materials Science***, 1993, 28(11):3014–3020.

[10] Matsuo H, Ishikawa A, Kikkawa T. Role of frictional force on the polishing rate of Cu chemical mechanical polishing [J]. ***Japanese Journal of Applied Physics***, 2004, 43 (4): 1813–1819.

[11] Shorey A B. Mechanisms of material removal in magnetorheological finishing (MRF) of glass[D]. Rochester: University of Rochester, 2000.

[12] Wang C C, Lin S C, Hong H. A material removal model for polishing glass-ceramic and aluminum magnesium storage disks [J]. ***International Journal of Machine Tools & Manufacture***, 2002, 42(8): 979–984.

[13] Jordan M I, Mitchell T M. Machine learning: Trends, perspectives, and prospects [J]. ***Science***, 2015, 349 (6245): 255–260.

[14] Ghahramani Z. Probabilistic machine learning and artificial intelligence[J]. ***Nature***, 2015, 521(7553): 452–459.

[15] Lecun Y, Bengio Y, Hinton G. Deep learning [J]. ***Nature***, 2015, 521(7553): 436–444.

[16] Reza K S, Masoud G, Mohammad G, et al. Deep networks can resemble human feed-forward vision in invariant object recognition[J]. ***Scientific Reports***, 2016, 6: 32672.

[17] Yang Nan, Nan Lin, Zhang Dingyi, et al. Research on image interpretation based on deep learning [J]. ***Infrared and Laser Engineering***, 2018, 47(2): 0203002. (in Chinese)

[18] Hastie T, Tibshirani R, Friedman J. The Elements of Statistical Learning[M]. New York: Springer, 2009.

[19] He K, Zhang X, Ren S, et al. Deep residual learning for image recognition [C]//Proceedings of the IEEE Conference on Computer Vision, 2016: 770–778.