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ORIGINAL ARTICLE

Polishing process planning based on fuzzy theory and case-based reasoning

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Abstract Process planning is a key step for obtaining high machine quality and efficiency in the polishing. By studying the polishing process planning idea of the skilled technician, a novel process planning method combining with artificial intelligence principle is proposed in this paper. Polishing planning model based on fuzzy theory and case-based reasoning (CBR) technology is investigated in detail, which consists of fuzzy comprehensive evaluation of material machinability, case retrieval, case inference, and case modification. Fuzzy comprehensive evaluation standard based on material physical mechanics performance index is used for determining material cutting performance level. Specific steps are as follows: establishing the factor set, establishing the weight set, establishing evaluation set, fuzzy evaluation of single factor, and fuzzy comprehensive evaluation. The primary cases are chosen according to the grade of material cutting performance. In case retrieval, all primary cases are retrieved in terms of the nearest neighbor principle and the similarity between two cases is calculated according to Euler distance. The retrieval features include the surface roughness before polishing, material characteristics, and the surface roughness requirements after polishing. In the case inference, the method of the cross-correlation coefficient is used for reasoning all cases retrieved in order to evaluate the impact of each process parameter on the surface quality and identify the relevance of each process parameters on the surface quality. In the case modification, the methods of linear extrapolation and parameter adjustment are used for adjusting and revising the process parameters of case retrieved according to the correlation coefficients. At last, example verification is finished and the experiment results are generally acceptable. It is concluded that it is feasible to solve the problem of polishing process parameters selection using this method.

Keywords Polishing · Process planning · Fuzzy theory · Case-based reasoning

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1 Introduction

Polishing is an important finishing process and widely used as a final processing operation for many mold components. With the development of advanced manufacture technology, there are many kinds of the automatic polishing equipment at present [1]. For any automatic polishing equipment, an important problem for engineer is how to plan polishing process in order to obtain high machining quality and efficiency. Generally, the tasks of polishing process planning is determining operation steps and choosing process parameters including abrasive grit, polishing pressure, tool speed, feed rate, and the number of polishing times according to workpiece information and requirements. However, due to the complexity of polishing process, the choices of polishing steps and process parameters are still largely based on experiences of polishing technicians so that surface machine quality is not sometimes satisfactory and utilization ratio of automatic polishing equipment is low, so many researchers have been devoting to explore new polishing process planning method.

In recent years, many achievements about polishing process have been achieved by the scholars, which mostly involve process planning, polishing path planning [2–4], abrasive tool choosing [5], process parameter optimizing [6, 7], and so on. Grandguillaumea et al. proposed a method to improve the whole sequence of milling and polishing considering constraints from polishing process and machine tool in mold manufacturing field. The whole process is evaluated balancing the milling and polishing times to reduce the total manufacturing time [8]. Wu and Wang presented a neuro-fuzzy approach to generate mold/die polishing sequences that are used for mold/die polishing machine using Al_2O_3 abrasive stones on SKD61 workpiece [9]. Lai and Huang presented a new systematic data integration technique for mold-surface polishing processes planning, which is used for polishing a large area or complicated shape mold surface and can make the operations be machined economically [10]. Márquez et al. studied main steps of robotic polishing planning in detail and established automatic planning and programming system of robotic polishing based on CAD [11]. It is all known that experiences during manual polishing are very important and skilled technician can choose reasonable process parameters. Ngai et al. developed a web-based intelligent decision support system for optimization of polishing process planning and established a case-based polishing process planning with fuzzy set theory [12, 13]. Feng et al. proposed an effective planning algorithm of cutter location data in polishing for a given CNC machine tools, and validation experiments were performed on planar and curved parts [14]. Rososhansky and Xi presented a new tool path planning method for automated polishing, and it was shown here that tool path planning for polishing should be treated as a contact stress problem because of the contact action between the polishing tool and the part [15].

Huang et al. proposed a set of polishing integration process skills specifically on a special kind of plastic model steel and established a module of machining strategy process that contains the combination of cutting and polishing one kind or multi-kind machining modes and the complementary precision processing methods [16]. Aiming to a new compliant abrasive tool, Tsai et al. investigated a kind of efficient automatic polishing process that comprises many steps using different abrasive grain sizes. For each process step, an optimal set of polishing parameters that can efficiently reduce surface roughness was determined by the Taguchi method [17, 18]. Wang et al. developed a novel self-determination polishing robot finishing large mold free-form surface and proposed the process planning steps consisting of subdividing the free-form surface, choosing an abrasive tool, planning the polishing path, and optimizing machining parameters. Aiming to polishing times, the surface roughness method and polishing efficiency method were studied in detail [19]. Based on the change laws of surface roughness during polishing, Lee et al. presented the concepts of critical surface roughness and removal volume, and established a systematic finishing process model that can find the finishing process requiring the least time [20].

At present, there are many polishing process planning models based on theory and experiment results. However, these are used for special polishing equipment, workpiece material, or polishing type. It is very difficult to establish influencing relationships scientifically and accurately because polishing is a complex material removal process that is influenced by many factors such as product features, polishing force, rotating speed, feed rate, and material properties of product. Establishing a process planning system combining with artificial intelligence principle is a research trend by analyzing skilled workers' ideas. In this study, a novel polishing process planning based on fuzzy theory and case-based reasoning is proposed and investigated in detail. According to the workpiece information, the fuzzy comprehensive evaluation of material machinability is analyzed in order to determine material cutting performance grade. After some cases similar to material performance grade are retrieved from casebase, these cases retrieved are reasoned and modified. At last, some cases concluding polishing process parameters can be obtained.

2 Methodology

2.1 Process planning model

Case-based reasoning (CBR) is a kind of strategy to guide target case solution by the original paradigm in historical memory, and it is an important method of machine learning. Case-based reasoning technology, using experiences obtained by solving past problems to solve current problems, is a reasoning method developing from the field of artificial intelligence in recent decades. Therefore, it is different from rule-based reasoning and model-based reasoning. Case of reasoning is a frontier direction in the artificial intelligence and the field of machine learning. In recent years, CBR system has a wide application in fields of mechanical design, machine fixture [21, 22], fault diagnosis, and process decision [23, 24].

The working process of the example of reasoning is shown in Fig. 1. The main steps are as follows:

(1) Retrieval: put forward some questions, input the requirements of the questions, the initial conditions and other related information, and retrieval similar examples from example library
(2) Reuse: obtain the solving schemes from similar examples, if according to them, then reuse these solutions, or need correction
(3) Revise: modify the solving schemes to be suitable for the current question
(4) Saving: save new examples and its solution in example library

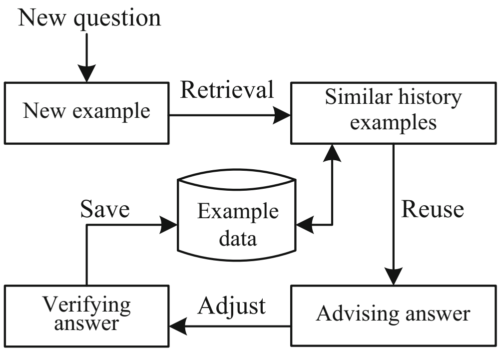


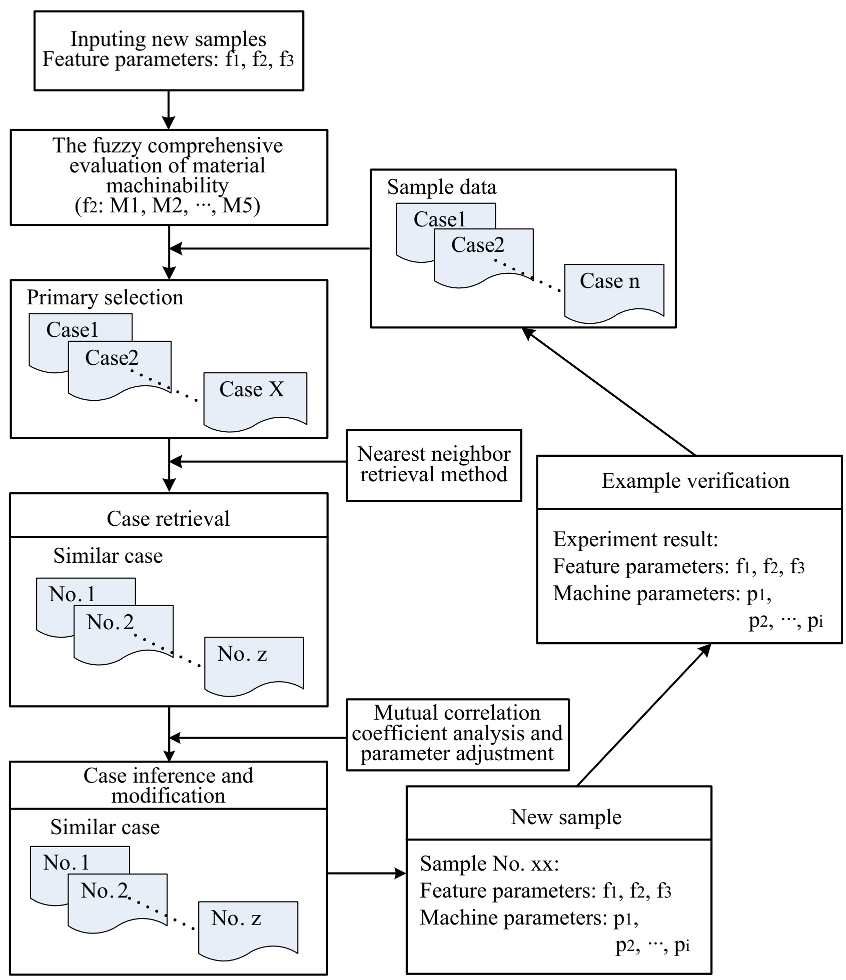
Fig. 1 The diagram of case-based reasoning

In order to reduce the scope of the search, firstly, the material cutting performance level is calculated before the case retrieval. Therefore, the fuzzy comprehensive evaluation standard based on mold material physical mechanics performance index is used for determining the mold material cutting performance level in this paper. The optimization model of polishing process based on fuzzy theory and CBR technology is established, as shown in Fig. 2. Firstly, material machinability level is given through the fuzzy comprehensive evaluation of materials, and all polishing cases of this grade are obtained from the examples in the library, then retrieval, reasoning, and modifying cases, get the new case, and finally preserving it in the library after the experimental verification.

2.2 The fuzzy comprehensive evaluation of material machinability

The material machinability is thought to be a key factor during the planning of polishing process when a skilled technician is ready to polishing mold. The main factors influencing material machinability include material chemical compositions, heat-treated conditions, and the physical and mechanical properties. The changes of material chemical composition and heat-treated conditions eventually lead to the change of the material physical mechanical properties, and the material physical mechanics performance index, generally obtained through the experiments or relevant literatures, can be quantified. Therefore, the material physical mechanics performance is chosen to estimate material machinability. Material machinability is a comprehensive performance, and it is comprehensive reflection of material basic properties. Many factors, still existing in some fuzziness,

Fig. 2 Polishing process planning model



should be chosen to evaluate. Fuzzy comprehensive evaluation refers to evaluating comprehensively a thing or phenomena affected by a variety of factors, which is used for determining the material machinability. The specific steps of fuzzy comprehensive evaluation are as follows:

(1) Establishing the factor set

Factor set is a set consisting of all kinds of factors influencing evaluation object, namely

$$U = (u_1, u_2, \cdots, u_n) \tag{1}$$

where $u_i (i = 1, 2, \cdots, n)$ represents for each factor. These factors can be vague or not be vague. Main factors influencing material machinability are hardness, tensile strength, elongation, impact toughness, and coefficient of thermal conductivity, so the factor set is $U = (u_1, u_2, \cdots, u_5)$= (hardness, tensile strength, elongation, impact toughness, coefficient of thermal conductivity).

(2) Establishing the weight set

In order to reflect the importance of each factor, a corresponding weight $a_i (i = 1, 2, \cdots, n)$ of each factor is given, which form the factor weight set, namely the weight set

$$\underset{\sim}{A} = \{a_1, a_2, \cdots a_n\} \tag{2}$$

In the weight set, each weight $a_i (i = 1, 2, \cdots, n)$ should be normalized and nonnegative, namely

$$\sum_{i=1}^{n} a_i = 1, a_i \geq 0 \tag{3}$$

According to the influence of material performance parameters on machinability and general production experiences, the weight set is determined as follows:

$$\underset{\sim}{A} = \{a_1, a_2, \cdots, a_5\} = \{0.3, 0.3, 0.1, 0.1, 0.2\} \tag{4}$$

(3) Establishing evaluation set

Evaluation set consists of all overall evaluation results of the evaluation object made by judge. It can be expressed as follows:

$$V = (v_1, v_2, \cdots, v_m) \tag{5}$$

According to the physical and mechanical performance index of material, the cutting performance level is divided into 11 levels to discriminate difficulty level of material's machinability, namely, $V = (v_1, v_2, \cdots, v_{11})$, as shown in Table 1 [25].

Table 1 The machining performance classification of workpiece material [25]

Machinability		More easy		Easy			Difficult			More difficult		
Grade number		0	1	2	3	4	5	6	7	8	9	10
Hardness	HBS	≤50	50~100	100~150	150~200	200~250	250~300	300~350	350~400	400~480	480~635	≥635
	HRC	–	–	–	–	≤24.5	24.6~31.8	31.9~37.7	37.8~43.0	43.1~50.0	51.0~60.0	>60.0
Tensile strength σ_b(GPa)		≤0.196	0.196~0.44	0.440~589	0.589~0.785	0.785~0.981	0.981~1.18	1.18~1.37	1.37~1.57	1.57~1.77	1.77~196	1.96~2.45
Elongation δ(%)		≤10	10~15	15~20	20~25	25~30	30~35	35~40	40~50	50~60	60~100	>100
Impact toughness α_k(MJ/m^2)		≤0.196	0.196~0.392	0.392~0.590	0.590~0.785	0.785~0.981	0.981~1.37	1.37~1.77	1.77~1.96	1.96~2.45	2.45~2.95	2.95~3.92
Thermal conductivity K(W/(m°C))		419~293	293~167	167~83.7	83.7~62.8	62.8~41.9	41.9~33.5	33.5~25.1	25.1~16.7	16.7~8.37	<8.37	–

(4) Fuzzy evaluation of single factor

Fuzzy evaluation of single factor refers to judging from a single factor in order to make sure the degree of membership of evaluation object to evaluation set. In factor set, evaluation set R_i of the factor u_i can be expressed

$$\underset{\sim}{R_i} = (r_{i1}, r_{i2}, \cdots, r_{im}) \tag{6}$$

In the same way, the evaluation set of each factor can be obtained in factor set, and these single factor evaluation sets can also be made into a fuzzy matrix $\underset{\sim}{R}$

$$\underset{\sim}{R} = \begin{pmatrix} R_1 \\ R_2 \\ \vdots \\ R_n \end{pmatrix} = \begin{pmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ r_{n1} & r_{n2} & \dots & r_{nm} \end{pmatrix} \tag{7}$$

where $\underset{\sim}{R}$ is for a matrix (5 × 11) in this paper.

(5) Fuzzy comprehensive evaluation

Fuzzy evaluation of single factor can only reflect the influence of a factor on the evaluation object. In order to obtain the comprehensive evaluation results, the comprehensive effect of all factors must be considered, namely fuzzy comprehensive evaluation. The method of fuzzy transformation is used for fuzzy comprehensive evaluation. It is written as

$$\underset{\sim}{B} = \underset{\sim}{A} \circ \underset{\sim}{R} = (a_1, a_2, \cdots, a_n) \circ \begin{pmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ r_{n1} & r_{n2} & \dots & r_{nm} \end{pmatrix}$$

$$= (b_1, b_2, \cdots, b_m) \tag{8}$$

where $\underset{\sim}{B}$ is comprehensive evaluation set, $b_j (j = 1, 2, 3 \cdots, m)$ is fuzzy comprehensive index, namely evaluation index, it is the membership degree of evaluation object to the jth element of evaluation set based on considering influence of all factors synthetically. According to the maximum principle of membership degree, j value of the max (b_j) is evaluation result.

2.3 Case retrieval

According to a given problem, the task of case retrieval is to find the most similar to those current problem from the casebase. CBR retrieval should reach two objectives as follows: One is the retrieval cases should be less as far as possible; second is the cases found should be related or similar to the target case as far as possible. For the given new paradigm, how to retrieve the most similar case from the case database decides the learning and reasoning performance of the example retrieving system.

There are mainly the classified network model retrieval, template retrieval, nearest neighbor search, inductive retrieval, deep retrieving based on knowledge, neural network retrieval method, rough sets retrieval ways, and fuzzy retrieval technology in CBR retrieval methods [26]. At present, the nearest neighbor algorithm is often used for example retrieval in the CBR system. Therefore, k nearest neighbor retrieval method (k-NN) is chosen in this research. Its idea is calculating the degree of similarity between examples, namely, a similarity calculation function is used for making comparison between problem case and cases in the casebase in order to find out one or more cases of maximum similarity. In k-NN method, the similarity of two examples can be obtained through evaluating the distance in the feature space of two objects.

Assuming a case $X = \{X_1, X_2, \cdots, X_n\}$, $X_i (1 \le i \le n)$ is characteristic value, W_i is weight value. X is a point in a feature space of n-dimensional space $D = (D_1 \times D_2 \times \cdots \times D_n)$, $X_i \in D_i$. For X and Y in D, the distance between X and Y is

$$\mathrm{Dist}(X, Y) = \left(\sum_i W_i {*} D(X_i, Y_i)^r\right)^{1/r} \tag{9}$$

where

$$D(X_i, Y_i) = \begin{cases} |X_i - Y_i| & \text{if } D_i \text{ is continuous} \\ 0 & \text{if } D_i \text{ is discrete, and } X_i = Y_i \\ 1 & \text{if } D_i \text{ is discrete, and } X_i \neq Y_i \end{cases} \tag{10}$$

Many common distance functions are Euler distance, Manhattan distance, and so on [26]. In the Eq. (9), if $r = 2$, then Dis(X, Y) is Euler distance. In this study, Euler distance is used for calculating the similarity between two cases as follows:

$$\mathrm{Sim}(X, Y) = 1 - \mathrm{Dist}(X, Y) = 1 - \sqrt{\sum_i w_i D^2(X_i, Y_i)} \tag{11}$$

It can be seen from above that the smaller the distance between two cases is, the greater the similarity is, and they are more similar. The case retrieval features can be described as the surface roughness prior to processing, material characteristics, and the surface roughness after processing, and the second features, namely material character, can be divided into two characteristics: material type and hardness, as shown in Fig. 3. Different characteristics play different roles in the example retrieval process. The weight coefficient method is used to reflect the importance of each feature.

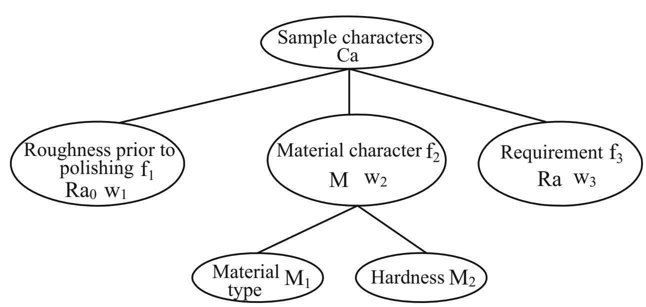


Fig. 3 Structure chart of case characteristics

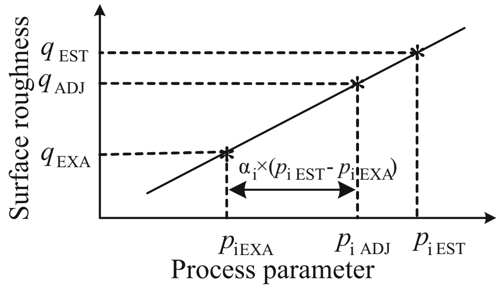


Fig. 4 Parameter adjustment diagram

If firstly, the number of the old paradigm is X through the material cutting performance levels, the similarity of the new paradigm Q and the case a is

$$\mathrm{Sim}(C_Q, C_a) = 1 - \mathrm{Dist}(C_Q, C_a) = 1 - \sqrt{\sum_{i=1}^{3} w_i D^2(C_{Qi}, C_{ai})} \tag{12}$$

where $\mathrm{Dist}(C_Q, C_a)$ is the distance between the new paradigm Q and the case a, w_i is the weight value of the ith feature, which is equal to 0.3, 0.4, 0.3, respectively.

If a feature can be divided into different sub-features, such as the second feature in Fig. 3, which includes two attribute features: material type M_1 and hardness M_2, the distance of each attribute characteristic between two cases should be firstly calculate by using Eq. (10), and then the distance of this characteristic between two cases is calculated by using formula as follows:

$$D_i(C_{Qi}, C_{ai}) = \sqrt{\frac{1}{m}\sum_{t=1}^{m} D^2\left(C_{Qi}^t, C_{ai}^t\right)} \tag{13}$$

where m is attribute characteristic quantity of a certain characteristic, $m = 2$.

2.4 Case inference

It is known that different process parameters have different influences on the surface quality. The main aim of case inference is to evaluate the influence of each process parameter on the surface quality, find out the degree of correlation of each process parameter on the surface quality. As long as the parameter of larger correlation is set to optimal value in the new paradigm, then the surface quality can be guaranteed. Therefore, the results of the evaluation of the process parameters during case inference can provide important basis for further case modification.

The method of mutual correlation coefficient analysis is used for cases inference. Firstly, the related coefficient between each process parameter and surface quality is calculated separately, which obtain the main parameter. About the solving of the related coefficient of each process parameter and surface quality in old paradigm is as follows:

If the number of the old paradigm is for X, variable $p_i = \{p_{i1}, p_{i2}, \cdots, p_{iX}\}$ is ith process parameter in examples for X, and variable $q = \{q_{i1}, q_{i2}, \cdots, q_{ix}\} = \{Ra_1, Ra_2, \cdots, Ra_X\}$ is the surface quality parameter in examples for X, so the related coefficient between p_i and q is expressed

$$\rho(p_i, q) = \left(\frac{\sum_{t=1}^{X} (p_{it} - \overline{p}_i)(q_t - \overline{q})}{\sqrt{\sum_{t=1}^{X} (p_{it} - \overline{p}_i)^2}\sqrt{\sum_{t=1}^{X} (q_t - \overline{q})^2}} \right) \tag{14}$$

where $\overline{p_i} = (\sum_{t=1}^{X} p_{it})/X$, $\overline{q} = (\sum_{t=1}^{X} q_t)/X$, $i = 1, 2, \cdots, 5$, the corresponding process parameters are grit of abrasive tools, polishing pressure, tool speed, feed rate, and polishing times. Usually, $0 \le \rho(p_i, q)^2 \le 1$, if $\rho(p_i, q)^2 = 1$, p_i is strongly related with q; if $\rho(p_i, q)^2 = 0$, p_i is not related with q.

2.5 Case modification

The task of case modification is to adjust and revise process parameters of retrieval case according to the correlation coefficients. It consists of linear extrapolation and parameter adjustment in two steps [13].

The first step is parameter linear extrapolation. The specific adjustments are finished according to the correlation

Table 2 Results of example retrieval

No.	Grit	Polishing pressure (KPa)	Tool speed (r/min)	Feed rate (mm/min)	Polishing times	Prior to polishing R_a (μm)	After polishing R_a (μm)	Similarity
1	120[a]	5	1000	180	10	1.445	0.412	0.9519
2	120[a]	3.75	1000	120	6	1.445	0.605	0.8780
3	80[a]	5	1000	180	10	1.014	0.533	0.7071
4	80[a]	3.75	1000	180	10	1.677	1.014	0.6544

[a] Granularity number

Table 3 Results of example modification

No.	Grit	Polishing pressure (KPa)	Tool speed (r/min)	Feed rate (mm/min)	Polishing times
1	120[a]	5.1	1000	179.9	10
2	150[a]	5.7	1000	119.4	6
3	80[a]	6.7	1000	179.3	10
4	90[a]	9.5	1000	178.4	9.9

[a] Granularity number

coefficient of each process parameter on the surface quality. If the related coefficient $\rho(p_i, q) \geq 0$, then

$$p_{i\mathrm{EST}} = \left(\frac{p_{i\mathrm{EXA}} \times q_{\mathrm{IDE}}}{q_{\mathrm{EXA}}}\right) \tag{15}$$

where $p_{i\mathrm{EST}}$ is the estimated value of the modified process parameters i, $p_{i\mathrm{EXA}}$ is the value of process parameters i in the retrieval example, q_{IDE} is the desirable surface roughness value in the new example, q_{EXA} is the achieved surface roughness in the retrieval example. If the related coefficient $\rho(p_i, q) < 0$, then

$$p_{i\mathrm{EST}} = \left(\frac{p_{i\mathrm{EXA}} \times q_{\mathrm{EXA}}}{q_{\mathrm{IDE}}}\right) \tag{16}$$

The second step is parameter adjustment. The parameters are further adjusted to more ideal or suitable value. Figure 4 gives the parameter adjustment schematic diagram. About calculation is as follows:

$$p_{i\mathrm{ADJ}} = p_{i\mathrm{EXA}} + \alpha_i (p_{i\mathrm{EST}} - p_{i\mathrm{EXA}}) \tag{17}$$

where $p_{i\mathrm{ADJ}}$ is the value of process parameters i after adjusting, α_i is the relevance ratio value of the process parameter i, which can reflect the importance of process parameter i on the index q. The greater important process parameters influence on index q, the greater the value α_i is.

According to Eq. (17), if $\alpha_i = 1$, process parameter i has big influence on the index, then $p_{i\mathrm{ADJ}} = p_{i\mathrm{EST}}$; if $\alpha_i = 0$, process parameter i has no influence on the index , then $p_{i\mathrm{ADJ}} = p_{i\mathrm{EXA}}$. The value α_i can be calculated by using statistical analysis method as follows:

$$\alpha_i = \frac{\rho(p_i, q)^2}{\max\left\{\rho(p_1, q)^2, \rho(p_2, q)^2, \cdots, \rho(p_i, q)^2\right\}} \tag{18}$$

Use Eqs. (15)~(18), modifying each process parameter, these new parameters reconstitute a new example.

3 Example analysis and verification

3.1 Example

The known new problem case information, the material is ZG310-570, the surface roughness prior to polishing is 1.532 μm, and the surface roughness requirement after polishing is close to 0.4 μm. The main cases in the casebase consist of the data obtained from previous experiments. The detail process is as follows:

(1) Material machinability fuzzy comprehensive evaluating

The material hardness (ZG310-570) is HBS 190, tensile strength is 570 MPa, elongation is 15 %, impact toughness is 0.49 MJ/m^2, thermal conductivity is 52.34 W/m°C. According to the machining performance classification of workpiece material in the Table 1, the fuzzy evaluation matrix is as follows:

$$\underset{\sim}{R} = \begin{pmatrix} 0.000 & 0.000 & 0.000 & 1.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 \\ 0.000 & 0.000 & 1.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 \\ 0.000 & 1.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 \\ 0.000 & 0.000 & 1.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 \\ 0.000 & 0.000 & 0.000 & 0.000 & 1.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 \end{pmatrix}$$

Using Eq. (8), calculating fuzzy comprehensive evaluation matrix is as follows:

$$\underset{\sim}{B} = \underset{\sim}{A} \circ \underset{\sim}{R} = (0.00 \quad 0.10 \quad 0.4 \quad 0.3 \quad 0.2 \quad 0.00 \quad 0.00 \quad 0.00 \quad 0.00 \quad 0.00 \quad 0.00)$$

Based on the results, in accordance with the principle of maximum membership max $(b_j) = b_3 = 0.4$, the level of this kind of material processing performance is grade 3.

Table 4 The experimental results

No.	Grit	Polishing pressure (KPa)	Tool speed (r/min)	Feed rate (mm/min)	Polishing times	Prior to polishing R_a (μm)	After polishing R_a (μm)
1	120[a]	5.1	1000	179.9	10	1.532	0.408
2	150[a]	5.7	1000	119.4	6	1.532	0.426

[a] Granularity number

(2) Retrieving

There are six cases up to the requirement in the casebase when the level of material processing performance is grade 3. The similarity between new example and every example retrieved was calculated, respectively. The number of more similar examples is four and the information about these examples is given in the Table 2.

(3) Reasoning and modifying

Using Eqs. (14) and (18), the retrieved examples were reasoned and modified, and the results are: $\rho(p_i, q)^2 = \{0.3433, 0.5553, 0, 0.0084, 0.0084\}$, $\alpha_i = \{0.6182, 1, 0, 0.0151, 0.0151\}$, among them $i = 1, 2, \ldots, 5$. It can be concluded that the pressure has the largest influence on the surface roughness in a given retrieval examples ranges. Using Eqs. (15)~(18), the reasoned cases were modified. Table 3 gives the revised examples. Contrasting by data between Tables 2 and 3, maximum adjustment range is pressure in parameter modification because the influence coefficient of the polishing pressure is the largest in all correlation coefficients.

3.2 Verification

In order to demonstrate the methodology proposed in this paper, some polishing experiments were carried out. Polishing force needed was calculated according to the polishing pressure and contact area. Workpiece was applied to polishing force by the abrasive tool installed in the spindle of machine tool. Polishing force was measured by using the electronic balance (type: ACS-30A) fixed under the workpiece. Tool speed and feed rate were provided by the machining tool. The surface roughness of workpiece was measured by using surface roughness tester (type: JB-4C). The first two sets of data in Table 3 were chosen to carry experiment and experimental results are given in Table 4. It can be seen from the table data that two sets of experimental results meet the requirement of surface roughness. It is feasible that using the method of the fuzzy comprehensive evaluation and case-based reasoning solves polishing process planning.

4 Conclusions

(1) The fuzzy comprehensive evaluation and case-based reasoning method used for selecting process parameters of mold polishing process is put forward. Primary case selection in casebase is firstly finished through the fuzzy comprehensive evaluation for material cutting. The similar cases can be automatically retrieved again through calculating the similarity between the two cases with the method of the k-NN. In case reasoning, the main influence parameters are obtained by calculating the correlation coefficient between every parameter and polishing quality. Process parameters, such as grit, polishing pressure, and tool speed, are adjusted and adapted. Linear extrapolation and parameter adjustment are adopted to modify the case reasoned.

(2) The proposed method has been validated using an example analysis. The polishing database consists of previous experiment data. Workpiece material is ZG310-570 and the surface roughness prior to polishing is 1.532 μm. The level of material processing performance is grade 3 according to fuzzy comprehensive evaluating, and the number of cases up to the requirement is six. The most similar cases are automatically retrieved by using k-NN method. In case inference, it is found that polishing pressure is the most important parameter. Some polishing experiments were finished by using first two sets of four cases modified. The experiment results by using these process parameters obtained from the model given in this paper are generally acceptable, which are 0.408 and 0.426 μm, respectively. It is feasible and effective way for solving polishing process planning.

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