



Tool selection method based on transfer learning for CNC machines

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Abstract. Owing to the changes in product requirements and development of new tool technology, traditional tool selection approach based on the human experience is leading to time-consuming and low efficiency. Under the cooperation of historical data resource accumulated by manufacturing enterprises, with human expert resource, a new tool selection mechanism can be established. In this paper, we apply transfer learning to tool selection issue. Starting from the foundation of migration, we showed a unified expression of expert experience and process case in a multi-source heterogeneous environment. Then, we propose a transfer learning algorithm (TLrAdaBoost) based on AdaBoost, which uses a small amount of target domain data (expert experience sample) and a large number of source domain low-quality data (process case sample), to build a high-quality classification model. Experimental results show the effectiveness of the proposed algorithm.

1 Introduction

Tool is the executive part of CNC machine, which directly affects the machined surface. It needs to realize the function of CNC machine tool on the upper layer, and determines the processing quality of products on the lower layer. Tool selection is reasonable or not, not only related to the machine tool processing efficiency, workpiece size accuracy and surface roughness or other related indicators, but also plays an important role in production costs and enterprise efficiency. In the traditional tool selection process, due to the level of experience and knowledge of the process personnel uneven, there is a great difference in the cutting performance of tools selected by different process personnel. In other words, there is uncertainty in the selection results, resulting in time-consuming and low efficiency. In recent years, traditional tool selection based on the human experience is increasingly unable to adapt to the development needs of manufacturing enterprises, mainly for the following reasons: (1) The growing demand for personalized products, which leads to an increasingly diversified product type and product structure of manufacturing enterprises, and the product cycle changes rapidly (Car et al., 2009); (2) New tool materials

and structures continue to emerge, the general process personnel lack experience of tool selection, and need more help from human experts. Therefore, for the celerity and accuracy of tool selection, it is desirable to have a new tool selection mechanism to make up for deficiencies above.

Manufacturing enterprises have accumulated a large amount of historical data on the selection of tool, tool selection knowledge exists in these massive data and information, at the same time, machine learning and knowledge discovery technology development makes using these data and information possible. For example, Ahmad et al. (2010) propose a new system approach to optimize tool sequences using genetic algorithms. Oral and Cakir (2004) define computer-aided optimum operation and tool sequencing to be used in the generative process planning system developed for rotational parts. These literatures are mainly focused on tool sequence optimization. In addition, Geng et al. (2013) present a new method for selecting the optimal multi-cutter set for five-axis finish machining. Meng et al. (2014) present a new method of the optimal barrel cutter selection for the flank milling of blisk. These literatures are focused on tool geometry selection or path generation. In this paper, we focus on

identifying and extracting features from tool selection data and information to learn a more intelligent selection method.

In order to identify and extract features, firstly, we need to understand what kind of composition the data and information has. They mainly come from the following two types of resources: (1) Expert experience resources: the domain professional knowledge and technical level is high, but domain experts have the characteristics of scarcity, so the quality of resources is high, but the number is less. (2) Process cases resources: manufacturing enterprises have a large quantity of process cases, so these resources are numerous but with lower quality. It can be seen that these two types of resources and the sample sets extracted from them will be unbalanced in quantity and quality. Besides, within the same type of resources, there is almost no guarantee that the number of samples collected for each tool is equivalent. Therefore, due to the imbalance in the data source, our method for tool selection is to solve an unbalanced problem. If we only use a small number of high-quality expert experience resources as training samples, it is not enough to learn a reliable classifier. Meanwhile, only using lots of low-quality process resources as training samples can't guarantee that the learned classifier has a low error rate. Owing to the unbalanced nature of the data sources, we try to apply transfer learning to the knowledge balance and integration of expert experience and process cases in tool selection.

The remaining sections are organized as follows: In the next section, we present the literature review on tool selection and transfer learning. After that, in Sect. 3, we generalize our approach, explain its principles, and decompose it into two main parts. In Sect. 4, we give a unified expression of multi-source heterogeneous knowledge, establishing the basis of transfer learning. In Sect. 5, we define some notations we will use later and give our algorithm. Section 6 briefly introduces the scene vector similarity calculation method. In Sect. 7, we give examples to verify the validity of the method. Finally, concluding remarks are given in Sect. 8.

2 Related work

Over the years, there has been some reported work on transfer learning. At first, it is a key point to establish the basis of transfer learning, which means we must get the unified representation of the knowledge. It is difficult and laborious to extract empirical knowledge from human experts and formalize the knowledge into decision rules that can characterize the expert performance (Leake et al., 1996). But under certain circumstances, it works well. According to the characteristics that human experts diagnose the fault of transformer, Shi et al. (2009) analyze and discuss the system structure, knowledge representation and reasoning mechanism to build fault diagnosis expert system of transformer. Besides, the structured characteristics of the case-based process system and the large amount of process cases can help us to model well.

Therefore, we extract features from multi-source heterogeneous knowledge resource of tools, which contains expert experience and process cases, and unify them to establish the basis of transfer learning.

Secondly, transfer learning theory resolves the problem of unbalanced learning and sample migration between different domains, which is mainly used for internet applications, like, text classification, clustering problem, collaborative filtering, image recognition, emotion classification, etc. Currently, transfer learning has well resolved unbalanced problem (Pan and Yang, 2009). Transfer learning first appeared in the field of human learning, mankind is able to quickly learn new knowledge largely due to the ability of knowledge transfer. For example, the knowledge transfer will occur between cycling and riding motorcycles. It focuses on the knowledge transfer between different but similar areas, tasks and distributions. When the task from one new domain comes, new domain samples are relabeled costly, and it would be a waste to discard all the old domain data (Li et al., 2015). Wang et al. (2014) propose a transfer learning method for collaborative filtering, called Feature Subspace Transfer (FST) to overcome the sparsity problem in collaborative filtering. Kuhlmann and Stone (2007) proposed a graph-based method for identifying previously encountered games, and applied this technique to automate domain mapping for value function transfer and speed up reinforcement learning on variants of previously played games. Wu and Dietterich (2004) integrated the source domain data in Support Vector Machine (SVM) framework for improving the classification performance. Argyriou et al. (2008) proposed a transfer learning algorithm in heterogeneous environment, and presented methods for learning and expressing the heterogeneous environment structure. In this paper, the data source characteristics of transfer learning are similar to those of the AdaBoost algorithm, then we ameliorate the AdaBoost algorithm with continuous confidence output to make it have the ability of sample migration, and improve the classification performance, so that it is successfully applied to the tool selection in the field of industrial manufacturing.

3 Principle explanation

The new tool selection method we proposed is based on transfer learning, we first identify and extract features from multi-source heterogeneous knowledge resources of tools and unify them to establish the basis of transfer learning. And then, we ameliorate the traditional AdaBoost algorithm, and propose our transfer learning algorithm TLRAdaBoost to solve the problem of imbalance within and between domains in the sample sets. Finally, we use the scene similarity matching method to select the tool model or name. Based on this, a new tool selection mechanism is established. The schematic diagram is shown in Fig. 1.

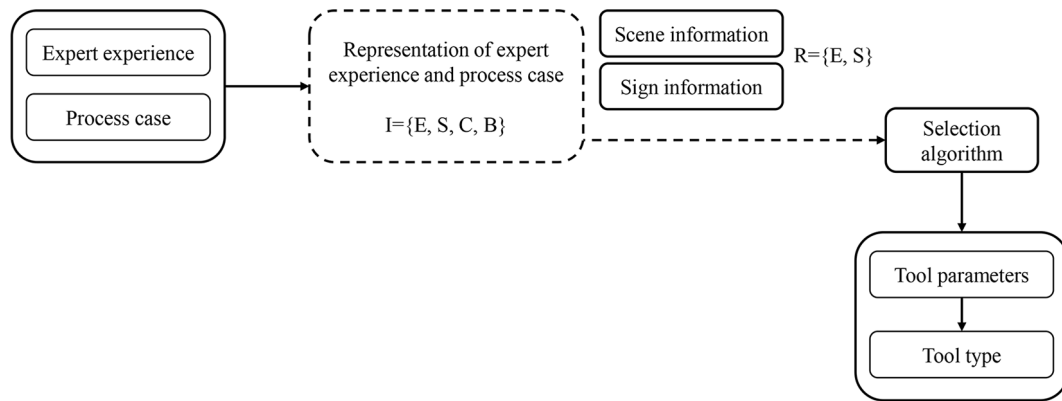


Figure 1. The selection principle of tools.

There are two key points in our approach: we establish the unified expression of expert experience and process case. Nevertheless, these two parts are multi-source heterogeneous and require a uniform representation of knowledge from different resources. By doing so, a large number of high-quality training samples can be provided for selected algorithm model. Secondly, TLRAdaBoost algorithm, using the ideology of transfer learning, is proposed to deal with the problem of unbalanced learning and sample migration between different domains. For learning an effective classifier for tool selection problem, a sufficient number of high quality training samples are required. AdaBoost algorithm has a solid theoretical basis and efficient computing performance, its advantage is that after several iterations, it can easily provide such high-quality training samples, and thus improve the classification performance of weak classifier, which has made a great success in face recognition, such as Freund and Schapire (1995), Schapire et al. (1998) and Schapire and Singer (1999). However, it has two shortcomings when dealing with the problem of tool selection: (1) AdaBoost is based on the assumption that the distribution of the class within the domain is roughly balanced, but the tool selection problem is an unbalanced classification problem in one field. It will lead to a decline in classifier performance. (2) AdaBoost requires samples of training classifiers and test classifiers from the same domain, which does not have the ability to migrate samples from other areas and can't solve the problem of imbalance between domains. To resolve the existing problems of AdaBoost algorithm, our TLRAdaBoost algorithm makes a use of transfer learning theory, so that it has the ability to deal with unbalanced classification learning and data migration. At the same time, we introduce the similarity matching of scene vectors, and finally realize the selection of tools.

To sum up, we will introduce the core content of our algorithm.

4 The unified representation of expert experience and process case

Based on the above analysis, we firstly extract empirical knowledge from human experts and formalize the knowledge into clear representation. Empirical knowledge in broad sense refers to people with the ability to identify and handle problems, which contains cognitive elements and skill elements (Von Krogh and Roos, 1996). Cognitive elements of problem identification are referred to as the “mental model” by Johnson Laird (Polanyi, 1966), who believes that it is a reflection of reasoning capability achieved in the practice of dealing with the similar problems in brain. Skill elements of solving problems mainly include specific knack, craft and skill in a certain context. Empirical knowledge exists in the various forms of “cases” in everyday life, which is generally more obscure. The knowledge embedded in these “cases” has three characteristics: operational, contextual, specific (Zhou et al., 2010). We use these characteristics to describe “cases”, which means that we use a scenario – “scene information” to define general feature knowledge, and define specific knowledge in the “cases” with the “sign information”. Then, we further establish the knowledge expression model, so as to solve the problem.

Tool selection expert experience refers to knowledge and skills about tool selection of the experts from tool manufacturer and manufacturing enterprises, which exists in the brain of these experts or their related discourses. According to the method above, a tool selection expert experience can be represented as a “case” using the logical process of “scene information + sign information → tool parameters → tool type”. The specific representation, which contains four elements, is as follows.

$$I = \{E, S, C, B\}$$

I – indicates a case; E – is a finite set which represents scene information; S – is a finite nonempty set that represents sign information; C – is a finite nonempty set that represents the

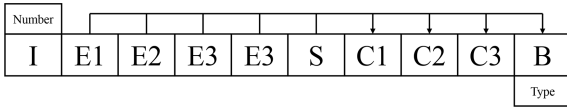


Figure 2. Data structure of expert experience and process cases.

information of tool parameters; B – is a nonempty set that represents the name or type of the cutting tool.

Scene information: it refers to the information about machine tool, workpiece, process, etc, related to a specific processing work step.

Sign information: it refers to a detailed description of the main signs of different processing problem under a certain scene information. The basic form of processing will be the sign information here.

Cutting tool parameter information: it refers to the attribute features of the selected tool under requirements of actual processing work step, including toolbar information, the clamping way of blade, blade information.

Name or type of cutting tool: it refers to the experts select the cutting tool parameter information according to the specific scene and sign information, and then determines the tool type for the actual machining. Such as cylindrical turning tool (CTG NR2020K12).

For example, in the selection of CNC turning tool, the instances of expert experience can be expressed in four member groups which mainly include the characteristic items in Table 1.

Process case is referred to the results of cutting tool selection by the technicians according to the specific production requirements. It exists in a large number of CNC machining process cards and cutter specification cards. It is not hard to find those two parts including all the information of the above four-member group. Therefore, the representation of a process case can be referred to the representation of expert experience. Tool selection of expert experience and process cases can be expressed by a data structure as shown in Fig. 2. The arrow reflects the internal logical relationship of the structure.

Through the above data structure, the sample set of expert experience and process cases can be expressed by vector $I = \{E, S, C, B\}$. In the two groups of samples, sign information S only has one characteristic attribute. Taking the selection of CNC lathe tool as an example, characteristic attribute S refers to the basic processing form that has 5 attribute values. Most of the models of the CNC lathe tool can be divided into these 5 categories based on the basic processing form, so the sign information S can be used as the label information of samples.

5 TLRAdaBoost algorithm

5.1 Relevant definition

In order to make the algorithm more clearly, we give the definitions related to the problem. This algorithm is concerned with the migration of instances between the similar domains, sharing the same classification objectives between domains.

5.1.1 Basic symbols

- X_a is Target Sample Space, X_b is Source Sample Space.
- $Y = \{1, 2, \dots, C\}$ is Class Space.
- *Function* $c: X \rightarrow Y$, Samples $x \in X$ are mapped to real class labels $c(x) \in Y$.

5.1.2 Test data set

- $S = \{x_1, \dots, x_m\}$, $S \in X_a$, m is the number of elements in the collection.

5.1.3 Training data set

- $T_T = \{x_i^a c(x_i^a)\}$, $x_i^a \in X_a$, $i = 1, 2, \dots, d$
 - $T_S = \{x_j^b c(x_j^b)\}$, $x_j^b \in X_b$, $j = 1, 2, \dots, q$
- $c(x)$ is true label of x , T_T is target training data set, T_S is source training data set and including $T_{S1} T_{S2}, \dots, T_{SK}$.

5.2 Description

The description of the TLRAdaBoost algorithm is as follows:

Input: Tagged data set: $T_T, T_{S1} T_{S2}, \dots, T_{SK}$; Test data set S ; Basic classification algorithm “Learner”; Iteration number N .

- Step 1. Merge all source domain training set and target domain training set.

$$T = T_{S1} \cup T_{S2} \cup \dots \cup T_{SK} \cup T_T$$

- Step 2. Initialization:

$$w_i^1(x_i) = 1/|T|, (x_i, y_i) \in T$$

- Step 3. Do For $t = 1, 2, \dots, N$

1. Based on the weights w_i^t of the training set, call the basic classification algorithm “Learner”, training weak classifier.

Table 1. The characteristic items contained in expert experience (CNC turning tool).

Primary characteristics	Secondary characteristics	characteristic item
<i>E</i>	The machine information Workpiece information Processing information	Machine type, clamping way, spindle power, tool accessories. Blank type, workpiece material, workpiece geometry, size. Machining accuracy, surface quality, cutting depth, cutting feed.
<i>S</i>	Processing type	Cylindrical/Surface processing, hole processing, thread machining, spherical surface machining, groove machining.
<i>C</i>	Cutter bar type Clamping system	Section of cutter bar, cutter bar width, cutter bar length, cutting groove type. Lever type, upper-clamping, hole clamping, sunk screw clamping, pull clamping, hook pin clamping.
<i>B</i>	Blade information Tool model	Blade material, blade shape, cutting edge shape, cutter head shape, back angle of blade, cutting direction, height of tool nose, blade length, blade accuracy. Such as: cylindrical turning tool (CTGNR2020K12).

- a. Class distribution: $p_l = \sum_{i:y_i=l} w_i^t, l = 1, 2, \dots, C$;
- b. To redivide T : $T = T_1^t \cup T_2^t \cup \dots \cup T_{n_t}^t$, and compute the sum $p_i^{j,l} = \sum_{i:(x_i \in T_j^t, y_i=l)} w_i^t$ of the weights of $l \in \{1, \dots, C\}$ class samples in T_j^t ;
- c. $h_t(x)$: $x \in T_j^t, h_t(x, l) = \ln(p_i^{j,l} / p_l), j = 1, \dots, n_t$;
- d. To select $h_t(x)$ and make $Z_t = \sum_{j=1}^{n_t} \prod_{l=1}^C (p_i^{j,l} / p_l)^{p_l}$ the minimum;
- e. To computer the Transfer Efficiency of each source training data set and the target training data set: $a_t^k, k = 1, \dots, K$.

2. To adjust sample weight:

$$w_i^{t+1} = \begin{cases} w_i^t \exp(-h_t(x_i, y_i) + \sum_{l=1}^C p_l h_t(x_i, l) + \alpha_k^t) / Z_t, (x_i, y_i) \in S_i \\ w_i^t \exp(-h_t(x_i, y_i) + \sum_{l=1}^C p_l h_t(x_i, l)) / Z_t, (x_i, y_i) \in T_T \end{cases}$$

– Output: Strong Classifier: $H(x) = \operatorname{argmax}_l \{f(x, l)\}$

In the formula, $f(x, l) = \sum_{t=1}^T h_t(x, l)$.

5.3 Analysis

TlAdaBoost, based on real-AdaBoost that has continuous confidence output, is proposed, which is able to deal

with data migration and sample imbalance among different classes.

The training sample set collected from the whole sample space is $S = \{(x_1, y_1), \dots, (x_m, y_m)\}$, for multi-classification problem $y_i \in \{1, 2, \dots, C\}$, the confidence level of label l is $h_t(x, l)$ that is the output of weak classifier $h_t(x)$. The strong classifier that has better classification performance consists of $T(t = 1, \dots, T)$ weak classifiers $h_t(x)$ in some way. Linear combination is the most commonly used combination so we use combination function $f(x, l) = \sum_{t=1}^T h_t(x, l)$ and the strong classifier $H(x) = \operatorname{argmax}_l \{f(x, l)\}$. The strong classification algorithm always hopes that the training error rate Eq. (1) is the least:

$$\varepsilon = \sum_{i=1}^m w_i^1 \llbracket H(x_i) \neq y_i \rrbracket \tag{1}$$

In the formula, $w_i^1 = 1/m$, the value of $\llbracket H(x_i) \neq y_i \rrbracket$ is 1 if the conditions meet, otherwise is 0.

When the class distribution is unbalanced, assuming that the prior probability of different labels is $p_l = Pr_{x \in S} [y = l]$, a reasonable approach is to change the average confidence value to $f(x) = \sum_{l=1}^C p_l f(x, l)$. It is proved that when T is very large, $h_t(x)$ is independent of each other and $h_t(x, l)$ is uniformly bounded, so the error rate of the training error rate expressed by the symbolic function can be transformed into the extreme value problem of the exponential function. In other word, Eq. (1) can be approximated as Eq. (2).

$$\varepsilon = \sum_{i=1}^m w_i^1 \llbracket H(x_i) \neq y_i \rrbracket \leq \sum_{i=1}^m w_i^1 \prod_{t=1}^T \exp(-h_t(x, y_i)) + \sum_{l=1}^C p_l h_t(x_i, l) \tag{2}$$

By training $h_t(x)$ to make Eq. (1) minimum is transformed into making Eq. (2) minimum. The extremum of Eq. (2) can be done by training $h_t(x)$ one by one in a recursive way, specifically by selecting $h_t(x)$ such that $Z_t = \sum_{j=1}^{n_t} \prod_{l=1}^L (p_t^{j,l} / p_l)^{p_l}$ is minimized. Z_t is called as the normalization factor. Therefore, the training error rate can be estimated as Eq. (3).

$$\varepsilon \leq \prod_{t=1}^T \left(\sum_{j=1}^{n_t} \left(\prod_{l=1}^L (p_t^{j,l} / p_l)^{p_l} \right) \right) \quad (3)$$

Transfer Efficiency is a measure of the performance of the target task before and after the migration. In the T iteration process, the algorithm first will be trained on the target field training set for weak classifier $h_t(x)$ that obeys the distribution of $w(T_T) / \|w(T_T)\|$, while $\|v\|$ is the L1 norm of feature vector. Then, each source training set is combined with the target training set in turn to generate a new training set $T_{S_{ii}} \cup T_T$ that obeys the distribution of $w(T_{S_{ii}} \cup T_T) / \|w(T_{S_{ii}} \cup T_T)\|$. On the basis of this, the new classifier $h_t^*(x)$ is trained. Weight error of the training set can be calculated by Eq. (4).

$$\varepsilon = \sum_{(x_i, y_i) \in T_T} w_t(x_i) |h(x_i) - y_i| / \|w_T(T_T)\| \quad (4)$$

Calculated by the formula, ε_t is the weight error of $h_t(x)$, and ε_t^{*i} is the weight error of $h_t^*(x)$. The transfer efficiency is defined as the difference of the weight error that is $\alpha_t^i = \varepsilon_t - \varepsilon_t^{*i}$. If $T_{S_{ii}}$ is the positive migration, there is $\exp(\alpha_t^i) \in (1, e]$, or $\exp(\alpha_t^i) \in (1/e, 1]$ when it is the negative migration, otherwise $\exp(\alpha_t^i) = 1$.

6 Scene information vector similarity calculation

The ultimate goal of tool selection is to select a tool that can meet the requirements of machining according to the scene information of a practical application of the CNC cutter. TLrAdaBoost algorithm only achieves the preliminary classification of tools, it is necessary to select a specific tool name or model by measuring the similarity between the scene information vector of all the sample samples in the class space and the actual application scene vector. Vector similarity refers to the degree of similarity between two equal dimension vector objects. There are two kinds of measurement methods: distance measure method and similarity function method (Zhang et al., 2009). In this paper, the angle cosine method (Eq. 5) is used to measure the degree of similarity between two vectors.

$$\begin{aligned} \text{sim}(x, y) &= \cos(x, y) = (x, y) / (\|x\| \cdot \|y\|) \\ &= \sum_{i=1}^n x_i \cdot y_i / \left(\sum_{i=1}^n x_i^2 \cdot \sum_{i=1}^n y_i^2 \right)^{1/2} \end{aligned} \quad (5)$$

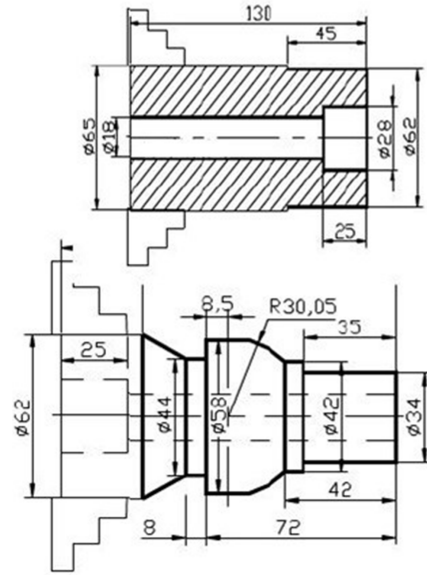


Figure 3. Shaft parts process diagram.

The geometric significance of the cosine angle is the cosine value of two vectors in N -dimensional space consisting of N elements. Each element in a vector needs to be dimensionless before using it, so that the elements are positive and the range of cosine value is $[0, 1]$. The larger the value is, the smaller the angle between two vectors is and the more similar the two vectors are. When two vectors are exactly the same, the value is 1 (Tian and Xie, 2006).

7 Instance verification

Our method based on transfer learning, which is different from the traditional one, automatically selects tools through the computer, ensuring the rapid and accurate selection of tools. The method is verified by an example as follows.

A process diagram of shaft parts is shown in Fig. 3. Machining inner holes of $\varnothing 28 \times 25$ is a step in the processes. Requirements: turning, rough machining, the workpiece material is cast steel. For the sake of convenient calculation, we give parametric representation and construct the training sample set only for machine type, workpiece material, machining accuracy, basic processing form, blade shape and tool number. The results are shown in Tables 2, 3.

We use the sample set of target domain and the sample set of source domain as the input data, and the basic processing form as the class label. Meanwhile, the TLrAdaBoost algorithm is used to study the training samples, the training results are 6 kinds of samples: inner hole turning, end surface turning, spherical turning, threading, groove turning, end milling, groove milling. And inner hole turning is in line with the requirements of instances. Its parametric matrix is A:

Table 2. Target domain sample set (Expert experience sample set).

Number	Characteristics	Representation
1	Lathe + cast steel + rough turning + turning inner hole + T-blade + 2#	(1, 2, 1, 2, 1, 2)
2	Lathe + cast steel + rough turning + turning the end + S-blade + 4#	(1, 2, 1, 1, 2, 4)
3	Lathe + cast steel + rough turning + turning spherical + T-blade + 5#	(1, 2, 1, 5, 1, 5)
4	Lathe + cast iron + finish turning + threading + A-blade + 3#	(1, 1, 2, 6, 3, 3)

Table 3. Source domain sample set (Process case sample set).

Number	Characteristics	Representation
1	Lathe + cast iron + rough turning + turning groove + S-blade + 4#	(1, 1, 1, 5, 4, 4)
2	Miller + cast steel + finish milling + milling the end + face milling cutter + 10#	(2, 2, 1, 1, 1, 10)
3	Lathe + cast steel + finish turning + turning inner hole + T-blade + 2#	(1, 2, 1, 3, 1, 2)
4	Lathe + cast steel + rough turning + threading + A-blade + 3#	(1, 2, 1, 6, 3, 3)
5	Miller + cast steel + finish milling + milling groove + face milling cutter + 10#	(2, 2, 1, 5, 1, 10)
6	Lathe + cast iron + rough turning + turning inner hole + S-blade + 4#	(1, 1, 1, 2, 2, 4)

$$A = \begin{bmatrix} 1 & 2 & 1 & 2 & 1 & 2 \\ 1 & 2 & 1 & 3 & 1 & 2 \\ 1 & 1 & 1 & 2 & 2 & 4 \end{bmatrix}$$

The first 4 columns of the matrix are the scene information matrix

$$B = \begin{bmatrix} 1 & 2 & 1 & 2 \\ 1 & 2 & 1 & 3 \\ 1 & 1 & 1 & 2 \end{bmatrix}.$$

The parameterized representation of the scene information vector is $C = [1 \ 2 \ 1 \ 2]$. According to Eq. (5), the angle cosine of each row vector in matrix B and vector C is calculated separately. And the final result shows that the scene “number 1” in the target domain sample set is exactly the same as instance scene. Therefore, the “T-blade + 2#” is the final selection of CNC tool. The results proved to be correct.

We also choose groove processing tool selection as an experimental validation. The dataset comes from Xi’an Winway Tools Co. Ltd., including tool design drawings, process files, and expert experience data. For the sake of data representation and experiment convenience, 12 properties of tool selection knowledge representation were selected as the sample shared attribute space, covering the machine tool factors, process factors and workpiece factors, as shown in Table 4.

A total of 50 sets of samples are used in the experiment, of which 35 groups are in the form of turning and the rest are in the form of milling. During training, samples A0001–A0049 are randomly input to the classifier and the number A0050 is used as a test sample to verify the feasibility of the algorithm. Sample data set as shown in Appendix A. Table A1 shows tool selection scene information and tool model of the sample dataset, Table A2 shows tool design drawings corresponding to the tool model.

In order to ensure the unity of presentation of tool selection scene information, data pre-processing is required before tool selection. Discrete attributes X_1 – X_5 , X_9 – X_{11} need to be binarized. Table 5 uses the clamping method X_2 as an example. Other discrete attributes are handled in the same way. Continuous attributes X_6 – X_8 uses K -means clustering to divide continuous attribute space into six intervals, and then uses different integer values to represent the data falling in each sub-interval. The representation of scene information is shown in Appendix B. In Table B1, the clustering center values represents the continuous attributes X_6 – X_8 .

The scene information selected for test sample A0050 is: turning, screw fastening form, A03550, bar, cutting performance 2.5, diameter 21.00 mm, groove deep 0.75 mm, groove width 2.40 mm, finishing, Ra1.6. The size of the part slot is shown in Fig. 4. Continuous attributes diameter, groove depth and groove width are divided into appropriate clustering intervals according to the value of the distance from the clustering center. Therefore, the scene information of No. A0050 can be expressed as a vector:

$$PV = [000001011]$$

The basic processing form X_{11} is as a class label space, scene vector PV 's class label of test sample A0050 is predicted with the learned classifier. Then, we get its class label is cylindrical groove machining. Finally, the sample data set under the same class label is extracted, including A0002, A0003, A0012, A0014, A0016, A0026, A0027, A0031 and A0040. These samples are pre-processed to form a tool scene information matrix KV , expressed here as integer values.

Table 4. Dataset properties.

Machine type X_1	Tool clamping method X_2	Workpiece material X_3	Blank shape X_4	Cutting performance X_5	Diameter X_6/mm
Groove deep X_7/mm	Groove width X_8/mm	Processing accuracy X_9	Surface roughness $X_{10}/\mu m$	Basic processing form X_{11}	Tool model X_{12}

Table 5. Discrete attribute clamping method X_2 .

	Screw fastening form	Press plate form	Lever fastening form	Integrated form	Wedge block fastening form	Compound fastening form
Integer value	0	1	2	3	4	5
Binary value	000	001	010	011	100	101

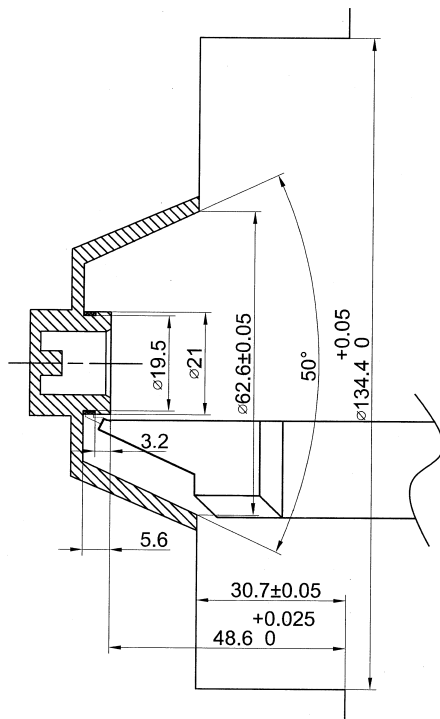


Figure 4. Test sample A0050 part slot size.

$$\mathbf{KV} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 1 & 2 & 0 & 1 & 1 \\ 0 & 0 & 4 & 0 & 2 & 5 & 4 & 2 & 1 & 1 \\ 0 & 1 & 3 & 0 & 2 & 5 & 4 & 1 & 0 & 3 \\ 0 & 1 & 4 & 0 & 2 & 5 & 3 & 0 & 1 & 0 \\ 0 & 0 & 4 & 0 & 2 & 4 & 3 & 1 & 1 & 1 \\ 0 & 1 & 2 & 0 & 1 & 5 & 5 & 1 & 0 & 3 \\ 0 & 0 & 4 & 0 & 2 & 3 & 5 & 1 & 0 & 3 \\ 0 & 0 & 5 & 0 & 3 & 4 & 2 & 2 & 1 & 1 \\ 1 & 0 & 4 & 0 & 2 & 3 & 1 & 0 & 0 & 3 \end{bmatrix}$$

According to Eq. (5), the angle cosine value M_i between each row vector in the matrix \mathbf{KV} and vector \mathbf{PV} , where \mathbf{KV} and

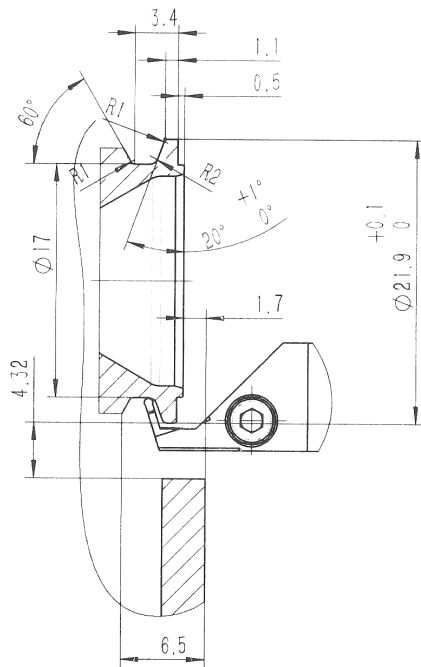


Figure 5. Sample A0002 part slot size.

\mathbf{PV} are converted to binary, is calculated respectively, and the result is shown in Table 6.

Among them, the similarity between the scene of sample A0002 and the experimental scene is greater than 85 %, that is, the selection results of No. A0002 may conform to the test sample scene, and the tool scheme drawing is shown in Appendix A, Fig. A1. After inquiry from the technical department of Xi'an Winway Tools Co. Ltd, the tool of No. A0002 can process the slot of test sample A0050. The corresponding tool type is Winway CFIL2525P1902-GK-20XD. The actual selection result of the test sample A0050 is Winway CFIL2525P04-T0881, as shown in Appendix A, Fig. A2. Comparing the two processing scenarios (Figs. 4 and 5), it can be found that the two tools have some interchangeability

Table 6. Similarity calculation results.

$M_1 = 0.8660$	$M_2 = 0.6124$	$M_3 = 0.3651$	$M_4 = 0.4082$	$M_5 = 0.4082$
$M_6 = 0.3651$	$M_7 = 0.3849$	$M_8 = 0.3849$	$M_9 = 0.4082$	

due to the similar processing factors and the non-conflicting spatial position constraints.

Data availability. Data are not publicly available.

8 Conclusion

We apply transfer learning to tool selection issue in the field of industrial manufacturing in this paper. Starting from the foundation of migration, we showed a unified expression of expert experience and process case in a multi-source heterogeneous environment. In addition, we proposed a transfer learning algorithm (TLrAdaBoost) based on AdaBoost, which uses a small amount of target domain data (expert experience sample) and a large number of source domain low-quality data (process case sample), to build a high-quality classification model. In this process, the imbalance data problem that AdaBoost can't solve is resolved. Finally, we use the scene similarity matching method to select the tool model or name. The results show that the proposed method using TLrAdaBoost can effectively classify samples by learning cross-domain knowledge.

Appendix A

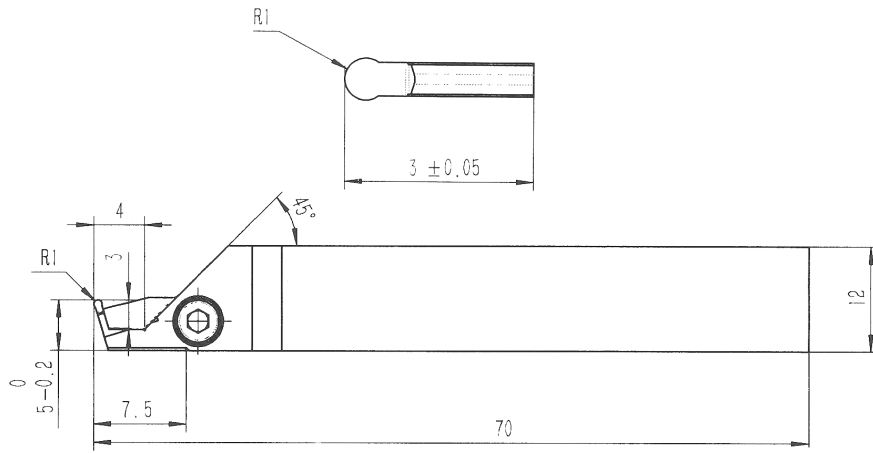


Figure A1. Sample No. A0002 cutting tool scheme.

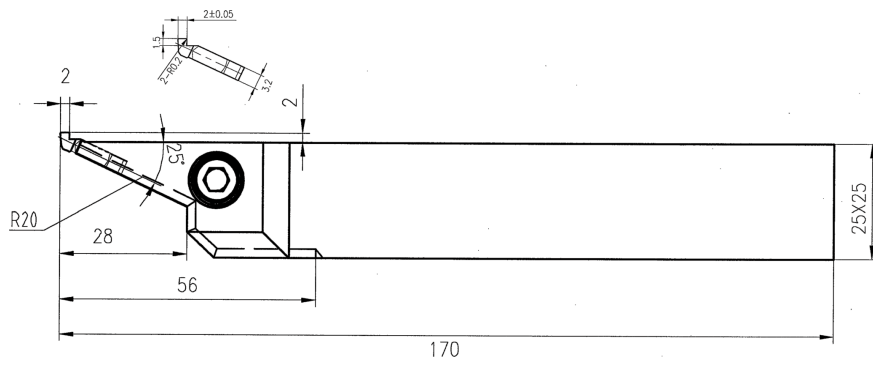


Figure A2. Sample No. A0050 cutting tool scheme.

Table A1. Sample data set.

Number	X ₁	X ₂	X ₃	X ₄	X ₅	X ₆	X ₇	X ₈	X ₉	X ₁₀	X ₁₁	X ₁₂
A0001	Turning	Press plate form	G41400	Bar	3	100.60	3.67	4.50	Finishing	3.2	End groove machining	CER2532RU4R-M254200
A0002	Turning	Screw fastening form	A03550	Bar	2.5	21.90	2.45	2.30	Finishing	1.6	Cylindrical groove machining	CFIL2525P1902-CK-20XD
A0003	Turning	Screw fastening form	G41400(HRC41-45)	Bar	3.5	109.3	5.80	9.00	Finishing	1.6	Cylindrical groove machining	CGIR2020M03-T0505
A0004	Turning	Screw fastening form	G41400(HRC41-45)	Bar	3.5	76.03	4.80	11.97	Roughing	12.5	End groove machining	CFIR2525P06-WW-C20
A0005	Turning	Screw fastening form	Incoloy901	Bar	4	46.28	1.14	29.01	Finishing	1.6	End groove machining	C6-CFIR-45065-03080035
A0006	Turning	Integrated form	G41400	Bar	3	9.40	2.80	2.03	Finishing	3.2	Internal groove machining	HW-2D162-615
A0007	Turning	Integrated form	G10450	Bar	3	6.00	0.95	8.00	Finishing	1.6	Thread machining	MR6-ISO1.0-048-6R1
A0008	Turning	Screw fastening form	G41400	Bar	3	37.40	4.05	28.00	Finishing	3.2	Internal groove machining	A32R-CGIR4004-T0920
A0009	Turning	Lever fastening form	G41400(HRC41-45)	Bar	3.5	11.51	1.78	2.16	Finishing	3.2	End groove machining	CFIR1212H03-T0870
A0010	Turning	Integrated form	G41400(HRC41-45)	Bar	3.5	5.60	0.80	8.05	Finishing	3.2	Thread machining	E05E-1.25ISO-10-NR-S9354
A0011	Turning	Integrated form	G41400(HRC41-45)	Bar	3.5	5.60	0.80	12.05	Finishing	3.2	Thread machining	E05E-1.0ISO-15-NR-S9354
A0012	Turning	Press plate form	GradeF5	Bar	3.5	109.20	6.60	4.57	Roughing	6.3	Cylindrical groove machining	CGIR2525P1604-WWWYL
A0013	Turning	Integrated form	G41400	Bar	3	12.00	2.00	2.50	Finishing	1.6	Internal groove machining	ZY15R04-62758
A0014	Turning	Press plate form	G41400(HRC41-45)	Bar	3.5	112.49	4.70	3.05	Finishing	0.8	Cylindrical groove machining	CFIL2525KNB3-T0904
A0015	Turning	Press plate form	G41400	Bar	3	14.00	3.90	3.00	Finishing	3.2	End groove machining	NB3R-2.5-T0449

Table A1. Continued.

Number	X ₁	X ₂	X ₃	X ₄	X ₅	X ₆	X ₇	X ₈	X ₉	X ₁₀	X ₁₁	X ₁₂
A0016	Turning	Screw fastening	G41400(HRC41-45)	Bar	3.5	92.00	4.35	4.78	Finishing	1.6	Cylindrical groove	CFIR3225M03-T0359
A0017	Turning	Press form plate form	G10450	Bar	3	38.00	2.73	4.30	Finishing	3.2	Internal groove	S32S-NB4L-4.3-250L-T0857
A0018	Turning	Screw fastening	GradeF5	Bar	3.5	96.00	6.10	9.65	Finishing	1.6	End groove machining	CFIR3232P08-T0910
A0019	Turning	Press form plate form	G41400(HRC41-45)	Bar	3.5	54.00	1.35	36.00	Finishing	1.6	Thread machining	CNR0050U16AHD
A0020	Turning	Screw fastening	A03550	Bar	2.5	58.00	6.50	6.00	Finishing	3.2	Internal groove	A40T-CGGJL06-WW
A0021	Turning	Screw fastening	G41400(HRC41-45)	Bar	3.5	16.50	4.00	2.00	Finishing	3.2	Internal groove	SNGR12Q08SC-T0572
A0022	Turning	Screw fastening	Incoloy901	Bar	4	108.20	4.50	7.10	Finishing	1.6	End groove machining	CGJL2525M03-T0984
A0023	Turning	Screw fastening	Incoloy901	Bar	4	109.20	4.80	13.50	Finishing	1.6	End groove machining	CGJL2525M03-T0986
A0024	Turning	Press plate form	G41400(HRC41-45)	Bar	3.5	42.06	3.02	30.24	Finishing	0.8	Thread machining	CNR0050U16AHD-T0056
A0025	Turning	Integrated form	A03550	Bar	2.5	11.20	2.56	2.60	Finishing	1.6	Internal groove	SCD2.6-10-65-0002
A0026	Turning	Press plate form	G41400	Bar	3	117.80	9.40	5.40	Roughing	6.3	machining	S(C)VJBL2532P22-FVD-PRSH992
A0027	Turning	Screw fastening	G41400(HRC41-45)	Bar	3.5	67.62	10.60	6.00	Roughing	6.3	Cylindrical groove	CGHR2525P06-T1052
A0028	Turning	Screw fastening	GradeF5	Bar	3.5	85.38	3.70	5.15	Finishing	1.6	End groove machining	CFIR2525M02L-T0215
A0029	Turning	Screw fastening	G41400(HRC41-45)	Bar	3.5	56.20	1.60	2.40	Finishing	3.2	End groove machining	NB3R-1.0M0
A0030	Turning	Press form plate form	A03550	Bar	2.5	55.60	1.00	0.80	Finishing	3.2	Internal groove machining	S40T-MVUNR16

Table A1. Continued.

Number	X ₁	X ₂	X ₃	X ₄	X ₅	X ₆	X ₇	X ₈	X ₉	X ₁₀	X ₁₁	X ₁₂
A0031	Turning	Screw fastening form	Incoloy901	Bar	4	86.60	2.65	8.50	Finishing	1.6	Cylindrical groove machining	CFIR3225P08-T0994
A0032	Turning	Screw fastening form	A03550	Bar	2.5	95.48	2.85	4.95	Finishing	0.8	End groove machining	CFIR2525M04-T0911
A0033	Turning	Screw fastening form	A03550	Bar	2.5	17.00	1.75	17.70	Finishing	0.8	Internal groove machining	S12U-SDRCP07-D
A0034	Turning	Screw fastening form	G41400	Bar	3	77.00	7.00	3.50	Roughing	25	End groove machining	CGIL3225P02R650700-QW
A0035	Milling	Screw fastening form	G41400(HRC41-45)	Square	3.5	42.93	2.11	0.90	Finishing	1.6	Internal groove machining	WWM254150-DJ-X32R-4
A0036	Milling	Compound fastening form	G41400(HRC41-45)	Square	3.5	34.10	0.50	4.22	Finishing	0.8	Internal groove machining	BF-D34D34.1-CC06-CF50
A0037	Milling	Integrated form	Incoloy901	Square	4	11.00	1.08	18.00	Finishing	0.8	Thread machining	TM-MJ11X1.25-10R1-SP-E0560
A0038	Milling	Integrated form	G41400(HRC41-45)	Square	3.5	6.00	0.79	14.00	Finishing	0.8	Thread machining	I/4-28UNJF-3B-8876
A0039	Milling	Compound fastening form	G41400	Square	3	50.10	1.00	3.00	Roughing	12.5	Internal groove machining	BR-D44.6D45.1-CC09-B50
A0040	Milling	Screw fastening form	G41400(HRC41-45)	Bar	3.5	60.00	1.40	3.20	Roughing	6.3	Cylindrical groove machining	SMT-40-125-25SF
A0041	Milling	Screw fastening form	A03550	Bar	2.5	66.60	3.09	26.00	Finishing	0.8	Thread machining	CNL0040H22Q-12-20SF
A0042	Milling	Wedge block fastening form	G41400(HRC41-45)	Square	3.5	45.00	2.50	25.00	Roughing	12.5	Internal groove machining	WWGMC3597-DJ-X28R40D
A0043	Milling	Integrated form	G41400	Bar	3	26.50	3.75	4.20	Finishing	3.2	Internal groove machining	MST-D18.5-4.2-90-SF20-E0392
A0044	Milling	Screw fastening form	G41400	Square	3	20.20	1.50	2.60	Finishing	3.2	End groove machining	SM20.2-15-80-SF20
A0045	Milling	Integrated form	G41400(HRC41-45)	Square	3.5	6.00	0.79	14.00	Finishing	1.6	Thread machining	M5-10-3F-60-D6

Table A1. Continued.

Number	X ₁	X ₂	X ₃	X ₄	X ₅	X ₆	X ₇	X ₈	X ₉	X ₁₀	X ₁₁	X ₁₂
A0046	Milling	Screw fastening form	G41400(HRC41-45)	Bar	3.5	45.10	0.55	22.00	Roughing	6.3	Internal groove	WWDBLHP-DJ-T45.1C
A0047	Milling	Integrated form	Incoloy901	Square	4	6.00	1.04	16.00	Finishing	0.8	Thread machining	1/4-28UNJF-L16-SP
A0048	Milling	Wedge block fastening form	G10450	Square	3	20.60	0.78	2.22	Finishing	3.2	Internal groove machining	WW/GLX15T-DJ-T15.75A15
A0049	Milling	Screw fastening form	G10450	Square	3	25.00	4.80	5.00	Roughing	6.3	Internal groove machining	MCA-16-C45-SP05-SF20
A0050	Turning	Screw fastening form	A03550	Bar	2.5	21.00	0.75	2.40	Finishing	1.6	Cylindrical groove machining	CFIL2525P04-T0881

Table A2. Sample tool data set.

Tool model X_{12}	Tool schematic
CER2532RU4R-M254200	
CFIL2525P1902-GK-20XD	
CGIR2020M03-T0505	
CFIR2525P06-WW-C20	
C6-CFIR-45065-03080035	
HW-2D162-615	

Table A2. Continued.

Tool model X_{12}	Tool schematic
MR6-ISO1.0-048-6R1	
A32R-CGIR4004-T0920	
CFIR1212H03-T0870	
E05E-1.25ISO-10-NR-S9354	
E05E-1.0ISO-15-NR-S9354	
CGIR2525P1604-WWWYL	

Table A2. Continued.

Tool model X_{12}	Tool schematic
ZY15R04-62758	
CFIL2525KNB3-T0904	
NB3R-2.5-T0449	
CFIR3225M03-T0359	
S32S-NB4L-4.3-250L-T0857	
CFIR3232P08-T0910	
CNR0050U16AHD	

Table A2. Continued.

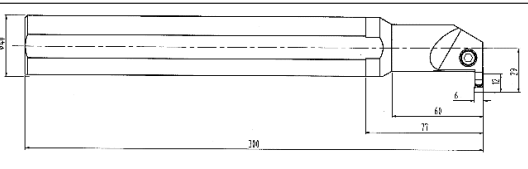
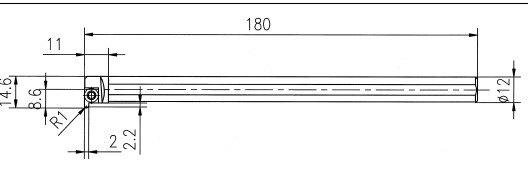
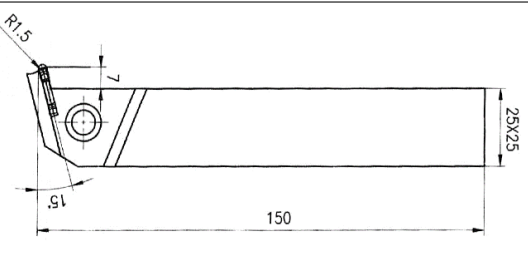
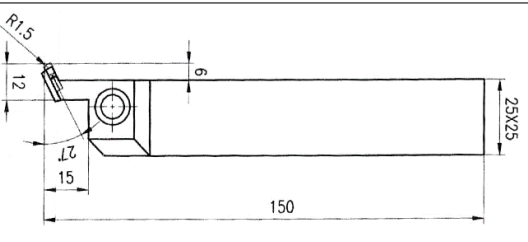
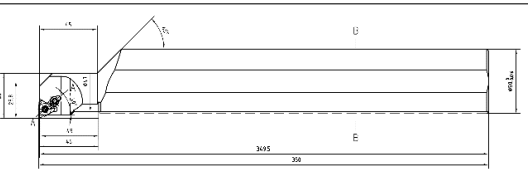
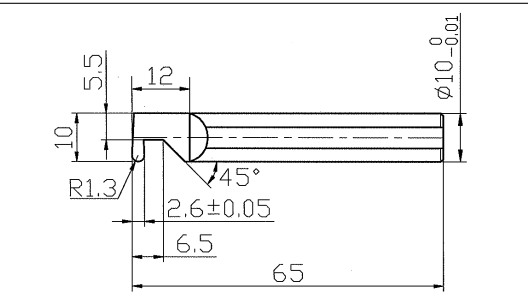
Tool model X_{12}	Tool schematic
A40T-CGGL06-WW	
SNGR12Q08SC-T0572	
CGIL2525M03-T0984	
CGIL2525M03-T0986	
CNR0050U16AHD-T0056	
SCD2.6-10-65-0002	

Table A2. Continued.

Tool model X_{12}	Tool schematic
S(C)VJBL2532P22-FVD-PRSH992	
CGHR2525P06-T1052	
CFIR2525M02L-T0215	
NB3R-1.0M0	
S40T-MVUNR16	
CFIR3225P08-T0994	
CFIR2525M04-T0911	

Table A2. Continued.

Tool model X_{12}	Tool schematic
S12U-SDRCP07-D	
CGIL3225P02R650700-QW	
WWM254150-DJ-X32R.4	
BF-D34D34.1-CC06-CF50	
TM-MJ11X1.25-10R1-SP-E0560	
1/4-28UNJF-3B-8876	

Table A2. Continued.

Tool model X_{12}	Tool schematic
BR-D44.6D45.1-CC09-B50	
SMT-40-125-25SF	
CNL0040H22Q-12-20SF	
WWGMC3597-DJ-X28R40D	
MST-D18.5-4.2-90-SF20-E0392	
SM20.2-15-80-SF20	

Table A2. Continued.

Tool model X_{12}	Tool schematic
M5-10-3F-60-D6	
WWDBLHP-DJ-T45.1C	
1/4-28UNJF-L16-SP	
WWGLY15T-DJ-T15.75A15	
MCA-16-C45-SP05-SF20	
CFIL2525P04-T0881	

Appendix B

Table B1. Representation of scene information.

	Attributes: Integer value						
Machine type X_1	Turning: 0	Milling: 1					
Tool clamping method X_2	Screw fastening form: 0	Press form: 1	plate	Lever fastening form: 2	Integrated form: 3	Wedge block fastening form: 4	Compound fastening form: 5
Workpiece material X_3	Aluminum alloy: 0	Medium carbon steel: 1	Alloy steel: 2	Titanium alloy: 3	Heat treated alloy steel: 4	High-temperature alloy: 5	
Blank shape X_4	Bar: 0	Square: 1					
Cutting performance X_5	2.5: 0	3: 1	3.5: 2	4: 3			
Diameter X_6 /mm	8.70: 0	21.10: 1	42.33: 2	59.72: 3	86.93: 4	109.54: 5	
Groove deep X_7 /mm	0.86: 0	1.69: 1	2.74: 2	4.25: 3	6.40: 4	10.00: 5	
Groove width X_8 /mm	2.39: 0	4.92: 1	8.38: 2	14.65: 3	26.71: 4	36.00: 5	
Processing accuracy X_9	Roughing: 0	Finishing: 1					
Surface roughness X_{10} /μm	0.8: 0	1.6: 1	3.2: 2	6.3: 3	12.5: 4	25: 5	
Basic processing form X_{11}	Cylindrical groove machining: 0	End groove machining: 1	Internal groove machining: 2	Thread machining: 3			

Competing interests. The authors declare that they have no conflict of interest.

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