Mining and Reuse on Design Knowledge of Non-standard Special Tool Based on Deep Learning

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Mining and Reuse on Design Knowledge of Non-standard Special Tool Based on Deep Learning

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Abstract

Aiming at the problems of design difficulty, low efficiency and unstable quality of non-standard special tools, facing the strong correlation between part machining features and tools, this article takes the two-dimensional engineering drawings of tools and parts as research objects, proposes the research on mining and reuse on design knowledge of non-standard special tool based on deep learning. Firstly, a dual-channel deep belief network is established to complete the feature modeling of machining features and tool features; secondly, the deep belief network is used to realize the association relationship mining between the machining features and tool features; thirdly, both the key local features of the tool and the overall similar design case of the tool are reused through association rule reasoning; finally, the non-standard special turning tool is used as an example to verify the effectiveness of the proposed method.

Keywords Non-standard special tool, Deep belief network, Association relationship mining, Design knowledge reuse

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1.Introduction

Non-standard special tool is a kind of tool that is specially customized by changing the material, blade shape and geometric Angle of the general tool, and it is used to process some special structure, size, material characteristics. As the complexity of aerospace parts increases, non-standard special tools are more and more widely used [1]. The structural complexity, diversified functions and high performance of the parts in the CNC machining tasks make the tool design develop in the direction of "specialization, high precision, high efficiency and reliability" [2]. However, the current non-standard special tool design mainly relies on the experience of engineers to complete, but the design process of non-standard special tools is closely related to the processing characteristics of parts to be processed, there is a very complex correlation between the structure shape, dimension precision, material properties of non-standard tools and the processing characteristics of the parts to be processed, this ambiguous correlation leads to the great difficulty in the design of non-standard special tools, The conventional empirical design method will be affected by subjective conditions, which will lead to problems such as long tool design cycle, low efficiency and unstable quality.

In view of this situation, considering the case of non-standard special tool design, not only can intuitively present the processing features of the part to be processed and the corresponding non-standard special tool features, but also contains the tool design rule knowledge, expert design experience knowledge, and the complex correlation between the processing features and tool features. Therefore, we believe that it is an important method and approach to solve the problem of non-standard tool design to excavate the hidden tool design knowledge and realize reuse in the

case of non-standard tool design.

Non-standard tool design knowledge is expressed through the interaction between the tool design result data and the machining feature data of the part to be machined, and this data is usually presented as images and text in tool design cases, so this kind of influence relation has the complex relation of geometry structure and semantic attribute. Therefore, how to mine the hidden correlation between the machining features and the corresponding non-standard tool features from the image and text data of tool design cases is the key to realize the reuse of tool design knowledge. The realization of this process has the following difficulties:

(1) Multimodality of associated content. The correlation between machining features and tool features is implicitly distributed in the data of different modalities, including graphical geometric structure information and textual attribute information. The content of a single modality is complete and intuitive, and the information of multi-modality is complementary. Therefore, how to ensure the synchronization and consistency of the multi-modal data feature modeling is the basis.

(2) Multidimensional uncertainty of association structure. The design of non-standard special tools is not only determined by the processing characteristics, but also related to the tool design factors. The interaction between multi-features and multi-factors and the difference in design experience constitute a complex multi-dimensional uncertain mapping between machining features and tool features. Therefore, discovering the multi-dimensional uncertain association is the key.

Above all, this paper proposes the mining and reuse of non-standard special tool design knowledge based on deep learning. Firstly, the features are decomposed according to the non-standard tool design process, then a feature modeling method based on image and text multimodal data is proposed, and then a deep learning-based association mining method between machining features and tool features is proposed, finally, the tool design case reuse is realized based on association rule reasoning. By rapidly pushing high-quality similar cases for designers, the design quality and efficiency of non-standard special tools are improved.

2.Related Works

The paper will first carry on the related research elaboration from the following four aspects: tool design method, the reuse of tool design knowledge, multi-modal feature modeling based on deep learning, and association relationship mining based on deep learning. Finally, a summary of related research is made.

(1) The method of tool design

Now, the methods of tool design are roughly divided into three categories: based on basic theory, relying on empirical knowledge and computer-aided [3]. Among them, tool design based on basic theory is mainly through complex mathematical calculation to complete the selection of important geometric parameters of tool and structural design. For example, Yuan Zhejun et al. [4] summarized the design principles and application specifications of important parameters of tool design, aiming at the design problems of universal tools, so as to provide theoretical basis for tool designers; Radzevich S P [5] proposed a curved surface production method from the perspective of design theory and basic calculation of gear tools, so as to realize the optimal design of gear tools. Tool design relying on empirical knowledge is to use the law and experience of tool wear damage and durability accumulated in the process of using the tool to achieve the tool parameter optimization design. For example, Tao Meng [6] summarized the basic rules of material, structure and selection of CNC machining tools based on actual processing and production experience, so as to provide empirical knowledge for tool design; Peter Monka et al. [7] conducted experimental research on the design of a special turning tool, and summarized the relationship between the shape and service life of the tool and the cutting parameters through the cutting test, so as to realize the optimization of the tool design parameters. Computer-aided tool design is to establish an expert system for tool design by means of a computer, and to complete tool design by means of automated modeling and simulation. For example, Wang Yujun et al. [8] developed a 3d design software for non-standard cutting tools for blade milling under UG secondary development platform, and improved the design quality and efficiency of non-standard cutting tools through parametric metered production. Chen Lulu [9] aiming at the design problem of integral end mills with unequal tooth spacing, deduced and established the mathematical model of cylindrical end mills, helices

and helical surfaces, and realized the computer-aided automatic modeling design of integral end mills.

(2) the reuse of tool design knowledge

The existing research on the reuse of tool design knowledge is mainly from the perspective of tool product, tool structure and geometric parameters, etc. Rajkumar Roy et al. [10] introduced the tool design knowledge and the factors to be considered in the design in detail, and elaborated the problems and challenges of tool design knowledge reuse. Duan Shaolin [11] classified the tool knowledge in the cloud environment according to the tool product classification method, and described the processes of tool knowledge perception and acquisition, tool knowledge ontology modeling, and product full life cycle application, etc., so as to realize the integration and reuse of tool product knowledge. Sun Yuwen et al. [12] discussed the key technologies of tool CAD system, such as frame structure, knowledge representation and working drawing, so as to realize the reuse of tool geometric structure in the process of tool design. Ji W et al. [13] developed a "Shape-Performance-Application" integrated design system to solve the design problem of special tools, and realized the reuse of tool design knowledge from the perspective of combining tools with application programs. Niu Zhanwen et al. [14] established the geometric model of chamfering machining, derived the geometric model and mathematical expression of the rotary surface of the cutting edge, and optimized the design of the cutting tool from the perspective of the reuse of structural design knowledge, aiming at the structural characteristics of the cutting tool design. Li Lingyan et al. [15] established a mathematical model of arc cutting edge, main rear knife surface and secondary rear knife surface according to the tool parameters, aiming at the complex new tool design problem, and realized tool design knowledge reuse from the perspective of geometric parameters.

(3) Multi-modal feature modeling based on deep learning

Multi-modal feature modeling includes two parts: feature extraction and feature fusion. The characteristics of ensuring the integrity of information and expressing specific and complex features abstractly bring new ideas for multi-modal feature modeling [16,17]. For example, Cheng M [18] designed a cross-domain deep belief network model to recognize images, which uses the shared model to capture low-level features and separates high-level neurons to capture high-level features of specific fields. Nitish Srivastava et al.[19] proposed a generative Boltzmann machine model for learning multi-modal data, combining features of different data to create a fusion representation of multi-modal data. Zheng Yu [20] described the multi-modal data fusion principles and cases from three aspects of stage, feature and semantics, and realized multiple projects of urban big data fusion by establishing different deep learning models. The above researches show that deep learning can realize the feature extraction and fusion of multi-modal data by establishing a network model, taking into account the original features of a single mode and the complementarity of multi-modal data.

(4) Association relation mining based on deep learning

The association mining methods based on deep learning can fit complex and fuzzy nonlinear association through unsupervised autonomous learning, and can update network parameters by continuously increasing samples to achieve a better knowledge mining effect [21,22]. For example, Wang Yixing [23] used deep learning algorithms to deeply mine valuable information from a large amount of heterogeneous, low value density, and fast processing power data to achieve grid fault prediction, fault diagnosis and load prediction. Zhou Chao [24] proposed a hybrid deep learning model combining a sparse autoencoder with a deep belief network, which uses to mine key information from a large amount of text data to achieve text classification. Pouyanfar S et al. [25] proposed a deep convolutional network that improves the performance of classification for various multimedia data sets including images, videos and semantics. The above researches show that the association mining algorithms based deep learning have advantages in multi-modal data mining tasks with multi-dimensional data and complicated association rules.

(5) Summary

Non-standard special tool is a tool for processing some special parts. The characteristics and functions of the machining features of the parts to be processed have a great influence on the design process of the tool. But most of the existing researches on the reuse of non-standard tool design knowledge realize the parameter optimization in the tool design results, and cannot make full use of the implicit experience and knowledge between the machining features of the part to be processed and the features of the tool. Therefore, it is very necessary to realize the reuse of tool design

knowledge by mining the deep relation between machining features and tool features by combining machining features, tool design principle and design experience. For multimodal and fuzzy nonlinear correlation of data for machining features and tool features, The deep learning method can realize the low-dimensional feature mapping of different modal data and model-level fusion of multi-modal data, integrate the feature extraction results of different modes into the unified network framework, and ensure the integrity and intuitiveness of single-modal data and the complementary correlation between multi-modal data. In addition, based on the advantages of unsupervised and semi-supervised autonomous learning in deep learning, the irregular implicit association between machining features and tool features can be mined from multi-modal multidimensional data such as images and texts.

3.Mining and Reuse on Design Knowledge of Non-standard Special Tool Based on Deep Learning

3.1 Selection of data sources

The reuse of tool design knowledge is finally reflected in the reuse of tool design cases, so the research object of this paper is a large number of non-standard special tool design cases. Tool design cases in enterprises have two data formats: 2D engineering drawings and 3D model drawings, both of which can truly reflect machining features and tool features. However, in order to improve the availability of data and reliability of mining results, data sources must meet the following requirements:

(1) The data can clearly and completely express all machining features and tool features;

(2) The data processing technology is relatively mature;

(3) This kind of data can complete the complex association relation mining task;

However, 3D model data as a data source has the following disadvantages:

(1) 3D data must be converted to a point cloud model or voxel model before it can be used as input to machine learning. However, the point cloud is sparse and the voxel model is gridded, so it is difficult for them to reflect the coherence of the line structure and the expression of complex parts is not very clear;

(2) The technology of 3D model data used in machine learning is relatively immature, so it is difficult to guarantee the implementation of complex association rules mining task;

In comparison, 2D engineering drawings are very mature in the fields of feature expression, data extraction and complex data mining. Therefore, 2D engineering drawings are selected as the data source.

3.2 Fundamental

Mining and reuse of non-standard special tool design knowledge is an example-based reuse problem essentially. Mining non-standard special tool design knowledge through the correlation between machining features and tool features to achieve case-based tool design knowledge reuse. Therefore, the problem can be described as follows:

Given machining features and corresponding tool features $S=\{(X,Y)_i | i=1,2,...,m\}$,there are m tool design cases in total. Input any machining feature X and its corresponding tool feature Y into the tool design knowledge mining and reuse model, hoping to obtain the mapping function $Y=\Phi(X)$ between X and Y through learning.

$$\begin{aligned} X &= \{X_{str}, X_{att}\} \\ Y &= \{Y^1 \cup Y^2 \cup ... \cup Y^n\} \quad (1) \\ Y^n &= \{Y^n_{str}, Y^n_{att}\} \end{aligned}$$

X --machining features (composed of the features of the workpiece to be processed and the relevant features of the parts in the part), represented by structural features X_{str} and attribute features X_{att};

Y --special tools for processed parts, jointly represented by multiple key local features Y^n of the tool, where each feature is represented by the structural feature Y^n_{str} and attribute feature Y^n_{att} of the corresponding part.

On this basis, this article studies non-standard tool design knowledge mining and reuse using deep learning, whose basic principles can be divided into the following three parts, as shown in Fig.1.

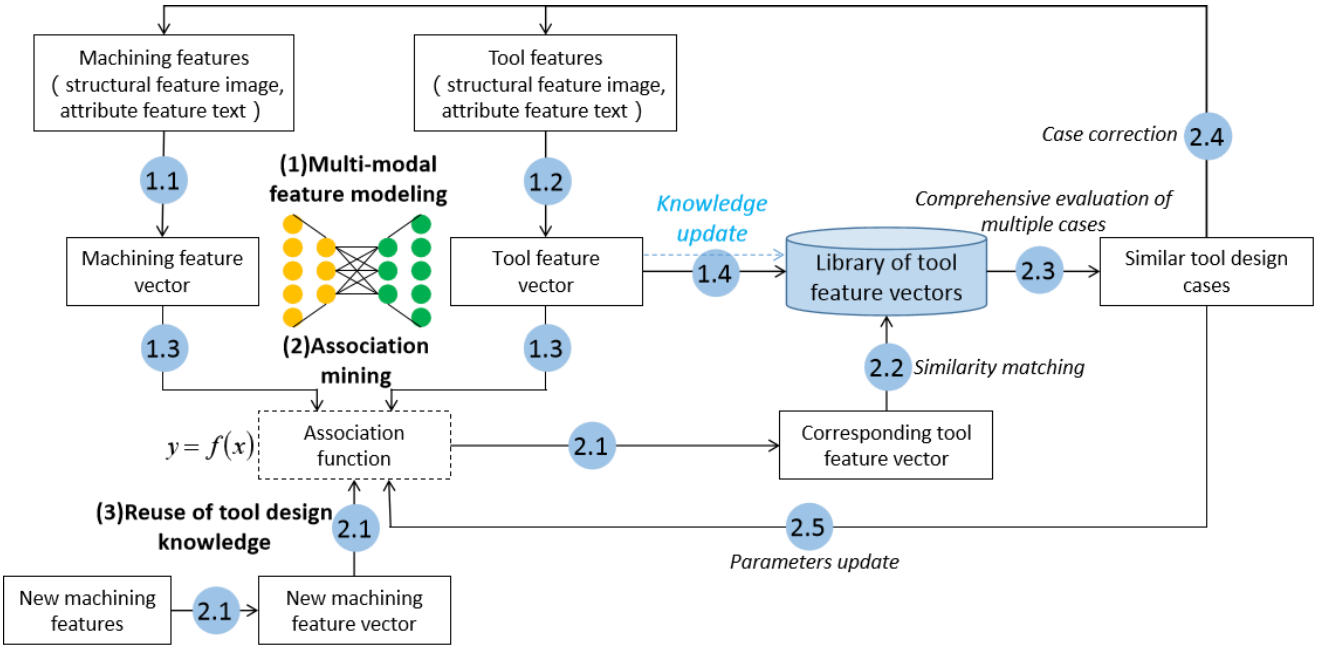


Fig.1 Basic principles of research on mining and reusing of non-standard tool design

(1) Multi-modal feature modeling: X and Y both represent the original feature information, which is composed of multi-channel pixel matrix map and multi-modal coupling data of text attributes. They are presented in a complex high-dimensional data, which requires dimensionality reduction, de-redundancy, and fusion processing to obtain a low-dimensional spatial map of high-dimensional features. So the objective function is as follows:

$$\begin{aligned} x &= g(X, \alpha) \\ y &= h(Y, \beta) \end{aligned} \quad (2)$$

x -- feature vector of machining feature, $x = g(*)$ -- modeling function of machining feature, X -- original multi-modal feature of machining feature, α -- parameters obtained by training;

y -- feature vector of tool feature, $y = h(*)$-- modeling function of tool feature, Y -- original multi-modal feature of tool feature, β -- parameters obtained by training;

(2) Association mining: The correlation between machining features and tool features is a carrier of complex and implicit non-standard tool design knowledge, which exists in visible features and cannot be described or expressed in simple linear relationships. So the objective function is as follows:

$$y = f(x, \theta) \quad (3)$$

$y = f(*)$ -- correlation function between machining feature vector x and tool feature vector y, θ -- parameters obtained by training.

(3) Reuse of tool design knowledge: The tool design cases are the integration of comprehensive tool design knowledge, and pushing similar tool design cases is an effective means to achieve reuse. So the objective function is as follows:

$$Y = \phi(y) \quad (4)$$

$Y = \phi(*)$-- function of the reuse, Y -- tool feature, y -- tool feature vector obtained by association function.

In summary, the objective function for mining and reuse of non-standard special tool design knowledge can be expressed as follows:

$$Y = \phi(f(g(X))) = \Phi(X) \quad (5)$$

3.3 Multi-modal feature modeling

The process of feature modeling is to extract and fuse the multi-modal coupled machining features and tool features. First, the original features are divided into machining features and multiple key local features of the tool according to the tool design theory and non-standard special tool design characteristics, which contain structural features and attribute features. Then, the vector of machining features and tool features are obtained by pretreatment, feature extraction and feature fusion of the multi-dimensional multi-modal and associatively coupled data. The process can be expressed as follows:

$$\begin{aligned} x &= g(X_{str}, X_{att}, \alpha) \\ y &= \sum_n h(Y_{str}, Y_{att}, \beta)^n \end{aligned} \quad (6)$$

The meaning of each parameter in the formula is the

same as that in section 3.1, and $\sum_{t}$ means combining the local features of the tool to obtain the overall feature vector of the tool.

In order to achieve the low-dimensional feature expression of the above multi-modal high-dimensional complex data, taking into account the integrity of the original data and the complementarity between the multi-modal data, this paper proposes a feature modeling method based on dual-channel deep belief network (2-DBN). The original data is pre-processed to obtain bimodal high-dimensional image and text data, and then the network model is used to extract and merge the processing features and tool features. The structure of the 2-DBN for multi-modal feature modeling is shown in the Fig.2.

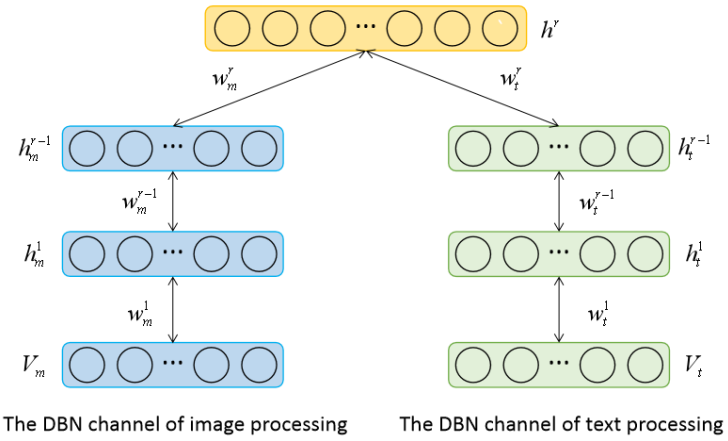


Fig.2 Dual-channel DBN model structure

As shown in the figure, the model is a dual-channel DBN structure made up of different layers of Boltzmann machines (RBM). The advantages of the DBN model in image processing and text extraction are used to extract the structural features and attribute features of the machining features and tool features, and then the different types of data are fused through the joint distribution layer of the two-channel structure. Thus, multi-modal feature modeling of machining features and tool features is realized. The specific application process of the model is as Table1:

Table1 The process of feature modeling

Input: Pixel map of structural feature V_m, data of attribute feature V_t, label Y_{lab}
Output: Feature vector h
Stage1: Extraction of structural feature
Step1.1: The pre-processed pixel map of structural feature V_m is used as the input of the structural feature extraction part of the 2-DBN model;
Step1.2: The structural feature vector h_m is obtained by calculating the RBM of each layer;
Stage2: Extraction of structural feature
Step2.1: The pre-processed data of attribute feature V_t is used as the input of the attribute feature extraction part of the 2-DBN model;
Step2.2: The attribute feature vector h_t is obtained by calculating the RBM of each layer;
Stage3: Fusion of the feature
Step3.1: Structural feature vector h_m and attribute feature vector h_t input into the connection distribution layer (RBM) simultaneously;
Step3.2: The fusion feature vector h_r is obtained by calculating the RBM of fusion layer;
Step3.3: Input the label vector y_{lab} and the fusion feature vector h_r to the top-level RBM to obtain the feature vector h.

The structural feature image is mapped from the high-dimensional original data to the low-dimensional

feature space, and the physical attribute information is mapped to the feature vector space, and then multi-modal feature fusion is realized using the fusion connection layer through the 2-DBN model. The model uses multi-layer RBM learning and training, and constantly updates the network parameters through unsupervised training and optimization of upper and lower algorithms, and finally obtains the feature vectors of machining features and tool features.

3.4 Association mining

Tool features are designed for machining features, and tool design knowledge is diverse and interrelated. Especially for non-standard tools, the design rules will undergo specific changes, and design experience is very important. However, most of the design knowledge is hidden in the tool design results. The machining features and tool features can only express the visible results, and cannot express the complex relationship between the knowledge. Therefore, the correlation between machining features and tool features has the following characteristics:

(1) Multimodality of associative content.

Both machining features and tool features include complementary associated image structure and text attributes, which exist in common can describe the complete features.

(2) Multi-dimensional nonlinearity of associative structure.

The multi-dimensional factors of the machining feature correspond to the multi-dimensional factors of the tool. These factors jointly affect the design result of the tool, and there is also a certain correlation between the various factors.

(3) Uncertainty of associative relationship.

A key feature of the tool is determined by multiple characteristics of the machining features, and the relationship between the factors of the specific machining task will change to some extent. Moreover, differences in designer experience will lead to different tool design results.

As shown in the Fig.3, Deep Belief Network (DBN), as a typical neural network model, combines the dual characteristics of unsupervised learning and supervised tuning, and can realize deep mining of multi-dimensional complex nonlinear association relationships, which has high applicability to the above deep hidden association rule mining task in complex data.

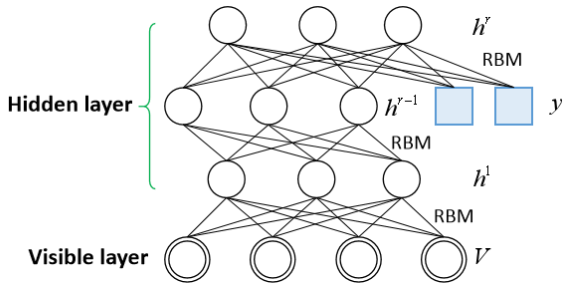


Fig.3 Structure of the Deep Belief

Therefore, this article uses the DBN model to mine the association between machining features and tool features, and its specific application process is shown in the Table2.

Table2 Process of the association mining

Input: Machining feature vector x
Output: Tool feature vector y
Step 1: The machining feature vector x obtained by the feature modeling network is used as the input of the association relationship mining network;
Step2: The feature vector of each layer is obtained by calculating the RBM;
Step3: The tool feature vector y is added as a label layer, which is used as the input of the top-level classification RBM with the feature vector output from the r-1 layer. Then the associated feature vector is obtained by calculation.
Step4: The trained model is developed into a deep perceptron: the input is the machining feature vector, the label layer is the output layer, and the feature vector obtained by the model is the tool feature vector.

In the process of association relationship mining, the conditional probability of RBM obtained in the

unsupervised learning stage is used to estimate the conditional probability of each layer of DBN, so as to obtain the associated feature vectors of machining features and tool features. The weights and offsets obtained from the unsupervised pre-training phase are used to initialize the weights and offsets of the deep perceptron during the supervised tuning, ,and the network parameters are adjusted and optimized through the back propagation algorithm. The tool feature vector is regarded as the label to adjust the mapping function of machining feature vector-associated feature vector-tool feature vector, so as to realize the association relationship mining between machining features and tool features.

3.5 Reuse of tool design knowledge

Because the tool design case is the carrier of tool design knowledge, pushing similar non-standard special tool design cases to tool designers is a good way to reuse tool design knowledge. Based on the association rules, the tool feature vector is obtained from the new processing feature through the machining features modeling network and the association mapping function of the machining features to the tool features. Then, a reuse method based on similarity matching and multi-case comprehensive evaluation is proposed to realize the similar cases reuse of multiple key local feature and the overall tool.

(1) Similar cases reuse of key local features based on similarity matching

Obtaining the similar cases of key local features needs to match feature vectors from the library, whose key is to find the similarity between the two. Therefore, this paper adopts the similarity matching method based on the cosine similarity measurement to obtain the similar cases of local key feature. And the steps are as follows:

Step1: Input the local tool feature vector y^n as a vector for similarity matching;

Step2: Take the vector $y^{n}{}'$ in the corresponding local tool feature vector library as another input, traverse all the vectors, calculate the cosine value $cos\left(y^n, y^{n}{}'\right)$ between the two vectors. Set threshold k:

If $cos\left(y^n, y^{n}{}'\right) > k$, save the cosine value, vector and its corresponding case name; otherwise, discard the vector and continue to calculate the similarity of the remaining vectors.

Step3: Sort all the saved tool local feature vectors according to the cosine value, and obtain the 3 with the highest similarity;

Step4: Get the tool design case corresponding to the local feature vector with the highest similarity in Step3, mark the local feature name, retain the similarity value and push it to the designer.

(2) Similar cases reuse of overall tool based on multi-case comprehensive evaluation

The reuse of similar case of overall tool is based on the reuse of the local features. Since the similarity values are filtered by setting thresholds, there will be certain assurance. Therefore, the greater the number of cases, the higher the matching of the cases. This paper proposes a multi-case comprehensive evaluation method, with case frequency as the main factor and similarity value as the auxiliary factor to evaluate the cases.

$$\begin{cases} wei(c_i) = sim(c_i) / \sum_{i=1}^{3} sim(c_i) \\ deg(c_i) = 10 \sum_{j=1}^{n} wei(c_i)_j \\ score(c_i) = freq(c_i) \times log \dfrac{deg(c_i)}{freq(c_i)} \end{cases} \tag{7}$$

$wei(c_i)$--the ratio of the similarity $sim(c_i)$ of a case i in a local feature to the sum of the similarity values of the top three cases in that local feature;

$deg(c_i)$ --word degree: 10 times of the sum of $wei(c_i)$ in all cases of the design task obtained by case i (the 10 times enlargement is to meet the requirement that the word degree and word frequency are in the same order of magnitude, and also prevent negative values from appearing in the calculation);

$freq(c_i)$-- word frequency: the number of case i.

In summary, the specific application process of this article is as Fig.4, and this includes the following steps:

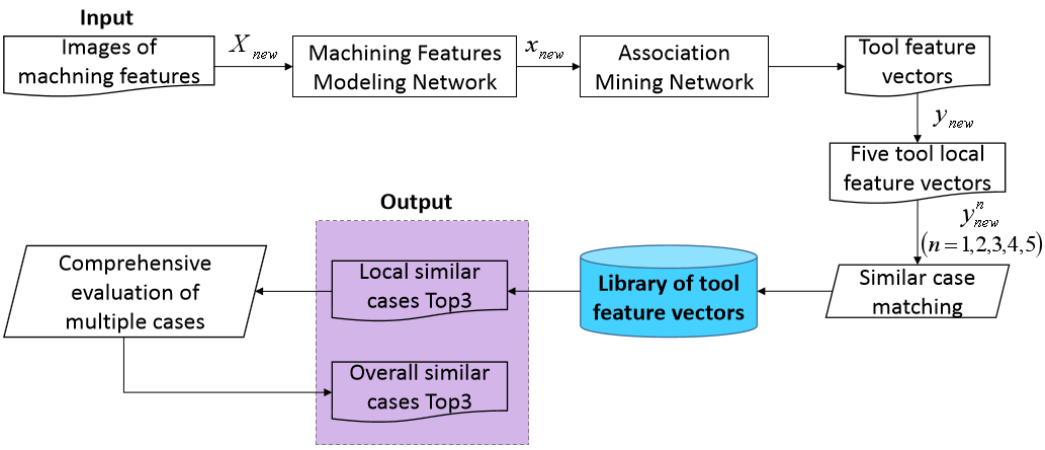


Fig.4 Process of tool design knowledge reuse

Step1: Processing of new machining features. The machining feature in new tool design task is preprocessed and feature modeled to obtain machining feature vector x_{new}.

Step2: Acquisition of tool feature vector. The machining feature vector in Step1 input to the association mining model, and then obtain the tool feature vector y_{new} corresponding to the machining feature using the trained network.

Step3: Match based Cosine similarity. Split the tool feature vectors and obtain each key local feature vectors of the tool separately according to the vector positioning rules. Then obtain the similar cases of each key local feature through vector matching based on cosine similarity, and take the first three and retain the similarity value.

Step4: Comprehensive evaluation of multiple cases. The top three cases of the local feature similarity value are comprehensively evaluated based on the improved Rake algorithm to obtain the top three tool design cases.

Step5: Cases push. Push the top three tool cases of local features and the comprehensive top three tool cases to the tool designer at the same time, as the design reference of key local feature detail and overall tool, respectively.

4. Case Study

4.1 Introduction to data set

The following is a non-standard special turning tool in CNC machining as a object to verify the effectiveness of the method proposed in this article. There are 923 non-standard special turning tools known, including 157 face groove-face groove cutters, 162 inner hole grooves-inner hole groove cutters, 159 outer circular grooves-outer circular groove cutters, 159 end face-end surface turning tools, 154 inner hole-inner hole turning tool, 143 outer circle-outer circle turning tool. In order to increase the amount of data, the original tool map is transformed by rotating and mirroring, and the number of samples is expanded to four times the original. For 3692 samples, 520 in each type of tool are randomly selected as training data, and 572 samples are left as test data. Some samples are as Fig.5 and Fig.6.

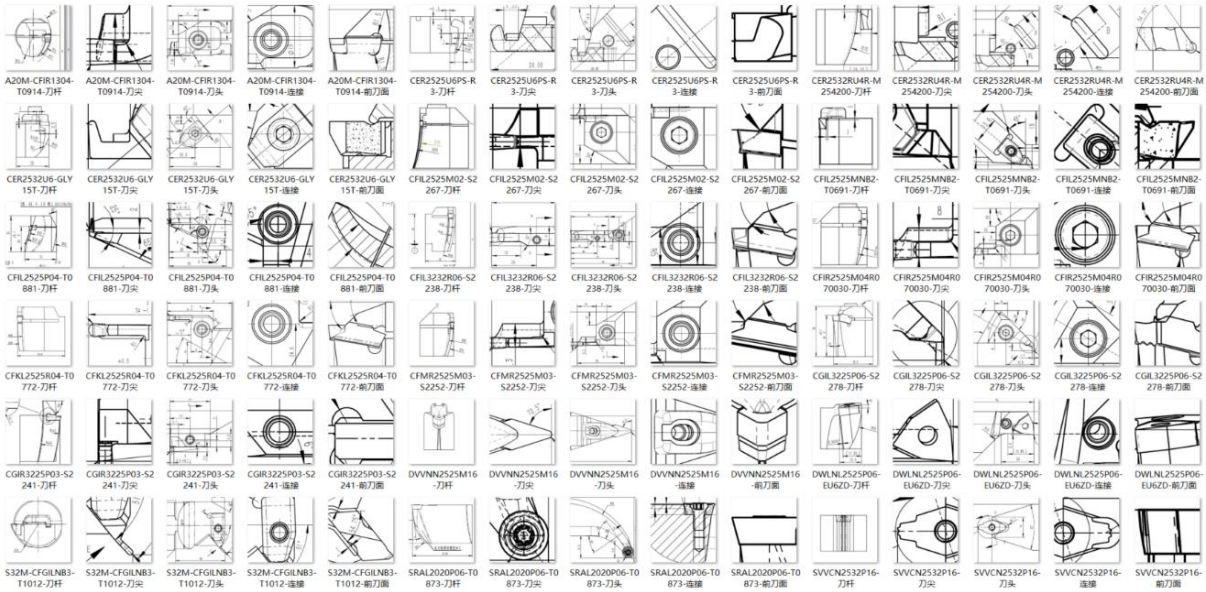


Fig.5 Part of tool features' engineering drawings

Fig.6 Part of machining features' engineering drawings

4.2 Modeling of machining features and tool features for non-standard special turning tools

The machining features and tool features are modeled according to the design features and sample features of non-standard turning tools. First determine the content of the feature modeling shown as follow:

$$X_{str} = [X_{str}]$$
$$X_{att} = [l, \theta, \varphi, Ra, IT, type, material, machine] \quad (8)$$

X_{str} -- structural features of machining features, consists of the pixel matrix of the machining features;

X_{att} --attribute features of machining features, consists of dimensional information of machining features (including length l , angle θ and diameter φ), processing surface roughness Ra , processing accuracy IT , type of machining feature $type$, material $material$ and processing equipment $machine$.

$$Y_{str}^{n} = \left[Y_{str}^{n} \right]$$
$$Y_{att}^{n} = \begin{bmatrix} l^{n}, \theta^{n}, \varphi^{n}, (\gamma_0, \alpha_0, \kappa_r, \lambda_s)^{n}, \\ coat^{n}, IT^{n}, type^{n}, material^{n} \end{bmatrix} \quad (9)$$

Y_{str}^{n} -- structural features of local features of tool , consists of pixel matrix of each local feature;

Y_{att}^{n} -- attribute features of local features of tool, consists of dimensional information of machining features (including length l , angle θ and diameter φ), min geometric angle $(\gamma_0, \alpha_0, \kappa_r, \lambda_s)$, processing accuracy IT , type of machining feature $type$, material $material$ and processing equipment $machine$ of each local feature.

$$Y^{n} = \{Y_{str}^{n}, Y_{att}^{n}\}, n = 1,2,3,4,5$$
$$Y = [[Y^{1}], [Y^{2}], [Y^{3}], [Y^{4}], [Y^{5}]] \quad (10)$$

Y^{n} -- local features of tool, consists of the structural features and attribute features of itself;

Y -- tool features, represented by five local features of the turning tool: blade connection, blade and blade tip, tool head structure, front tool surface structure and tool rod section.

Then, the 2-DBN model is established to model the machining features and tool features.

Create a 2-DBN model as shown in Fig.7 to model the machining features.

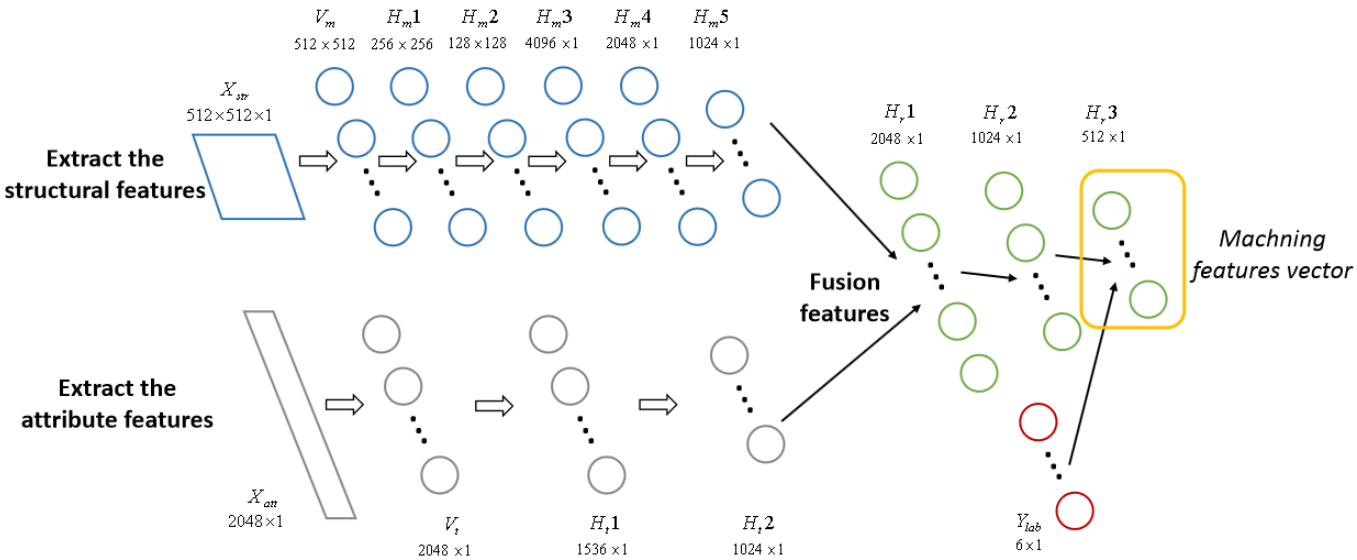
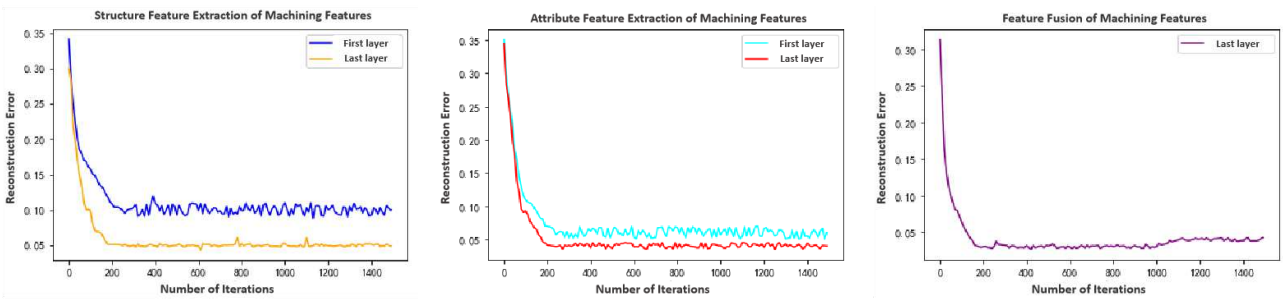


Fig.7 Network of machining features modeling based on 2-DBN

Input the training set that includes 3120 machining features into the above model, and complete the model training after 1000 iterations. The average reconstruction error of every 10 iterations is used as an output, and the reconstruction error curve of RBM is drawn to evaluate the effect of the model (take the first and last layer RBM as an example).



(a) (b) (c)

Fig.8 RBM reconstruction error curves of machining feature modeling network

From the results as Fig.8, it can be seen that the reconstruction error of the RBM of each layer of the machining features modeling network is stable at 0.05-0.1 between 200 and 300 steps. The convergence value

proves that the model can realize the mapping of the original machining features to low-dimensional feature vectors.

In the same way, the 2-DBN model is used to realize the tool feature modeling, and the curve of reconstruction error is drawn to evaluate the effectiveness of the model.

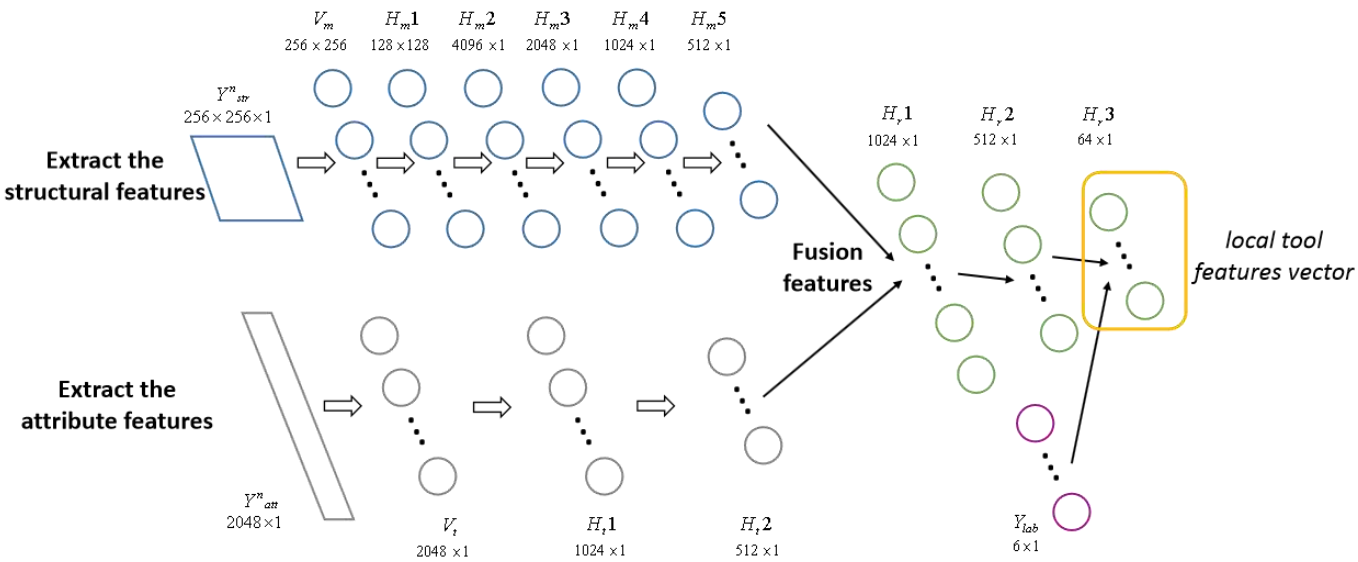
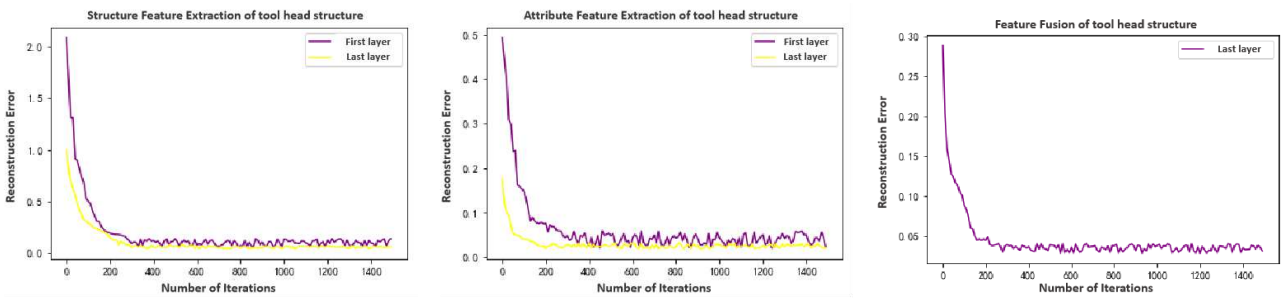


Fig.9 Network of tool features modeling based on 2-DBN

Take the structure of the tool head structure as an example to explain the model training results.



(a) (b) (c)

Fig.10 RBM reconstruction error curves of tool head structure feature modeling network

As shown in the Fig.10, the RBM reconstruction error of each layer is stable between 0.02-0.1 in about 200-300 steps, which proves that the modeling results are valid. Similarly, the remaining local feature modeling results have similar stability and convergence, which will not be repeated here.

Finally, after obtaining five key local feature vectors of the tool, namely blade connection y^1, blade and blade tip y^2, tool head structure y^3, front tool surface structure y^4 and tool rod section y^5, a complete tool feature vector is obtained by vector positioning combination in order to ensure the integrity of the tool. As shown in Fig.11:

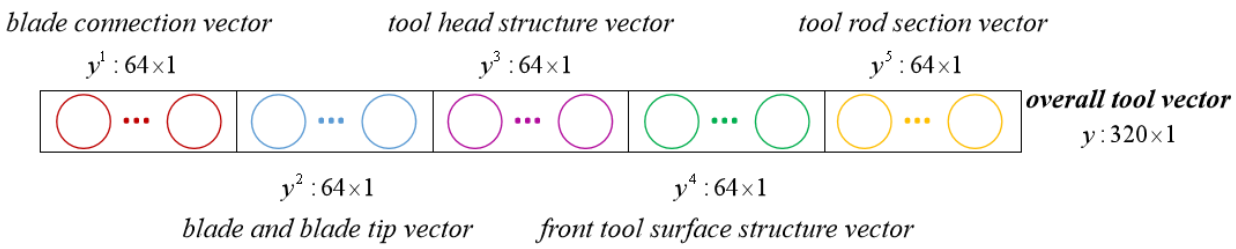
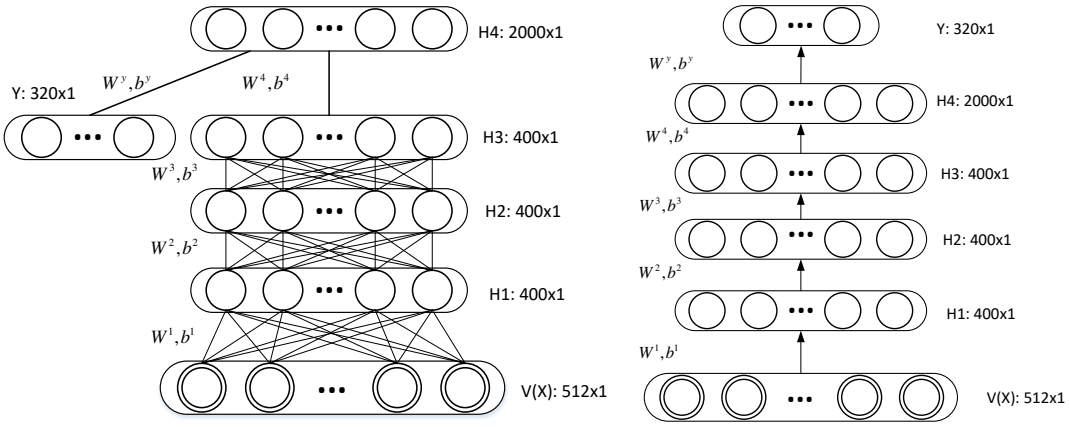


Fig.11 The process of obtaining the overall tool feature vector

4.2 Design of DBN model for association relationship mining

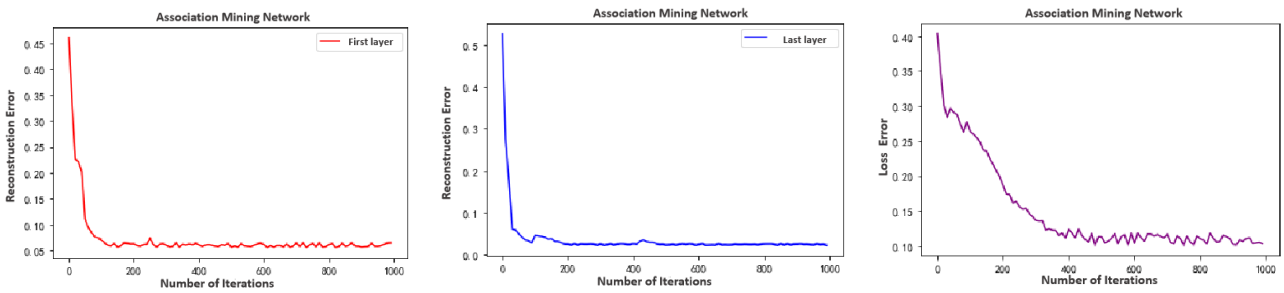
After feature modeling, the feature vectors of machining features and tool features are obtained, and then the DBN model is established to mining the association between the two. Fig.12 shows the association mining network under unsupervised training and supervised training, respectively.



(a) (b)

Fig.12 Association mining network based DBN (a: unsupervised training; b: supervision and tuning)

Input the 3120 training samples into the network model, and the reconstruction error curve of each layer is obtained after 1000 iterations (take the first and last layer RBM as an example). Since the supervised learning of the DBN model is to train a deep perceptron through the backpropagation algorithm, the tool feature vector as the label layer output from model and the label is used to judge the effect of model recognition. Therefore, the label layer error curve is introduced to evaluate the model's effect as shown in Fig.13.



(a) (b) (c)

Fig.13 Error curve of association mining network

The RBM reconstruction error of each layer in association mining model stabilizes between 0.02 and 0.06 at 150-200 steps, and the label layer loss error converges to about 0.12 at 400 steps. It is proved that the network can realize the mapping of machining feature vectors to tool feature vectors, that is, the association relationship between machining features and tool features is mined.

4.4 Reuse of tool design knowledge based association rule reasoning

Finally, the above models are verified through the reuse of test cases. The tool engineering drawings in the non-standard tool cases of the test group are modeled to tool feature vectors, which stored in the tool feature vector library (including the local feature vector libraries of each tool) with the corresponding tool engineering drawings. According to the reuse process of Section 4.3, the tool design case corresponding to the machining features were obtained. Then evaluate the reuse effect through the correct rate of tool case matching: if the tool case obtained is the tool design case corresponding to its machining feature, the reuse is successful; otherwise,

it fails. The results of reuses according to the different local features of tool are as Table 3:

Table 3 Results of tool case reuse

Local features	Number of test samples	Top1 number of samples passed test	Top3 number of samples passed test	Top1 accuracy%	Top3 accuracy%
blade connection	572	237	446	41.43	77.97
blade and blade tip	572	272	467	47.55	81.64
tool head structure	572	281	474	49.13	82.87
front tool surface structure	572	244	451	42.66	78.85
tool rod section	572	247	455	43.18	79.55
the whole tool	572	268	462	46.85	80.77
average	572	258.12	459.17	45.13	80.27

In the actual tool design process, due to the mutual reference between the tool features and the certain professional reserve of the tool designer, it is allowed to push multiple similar tool design cases. Therefore, the accuracy of top3 is used as the evaluation of the tool design knowledge reuse model in this paper. It can be seen from the table that the accuracy of test samples of each local feature is about 80%. Since the non-standard special tool is a kind of complex part, it is acceptable to have some similarities in the key local features during the design process. Therefore, the final accuracy of reuse in this paper is 80.27%, which can meet certain engineering requirements.

5.Conclusion

Aiming at the problems of design difficulty, low efficiency, and unstable quality that cannot meet the modern production in non-standard tool design, this paper proposes the research on mining and reuse of non-standard special tool design knowledge based on deep learning. Reuse the tool design knowledge through the extraction-fusion of machining features and non-standard tool features and the mining of the association between them. Taking the design knowledge mining and reuse of the non-standard special turning tools as an example, it is verified that the method proposed in this paper can realize the reuse of tool design cases, thereby speeding up the tool design efficiency.

Availability of data and materials

The data used in this article will not be shared, because the data comes from a tool design company in Xi'an, Shaanxi Province, China. The sharing of these data will cause great losses to the company.

Competing interests

I have no competing interests with my co-authors.

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Authors' contributions

Mingwei Wang and Jingtao Zhou proposed the problem to be solved in this article and the idea of solving the problem; Xiaoying Chen and Zeyu Li implemented the problem solving process and wrote the paper.

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Figures

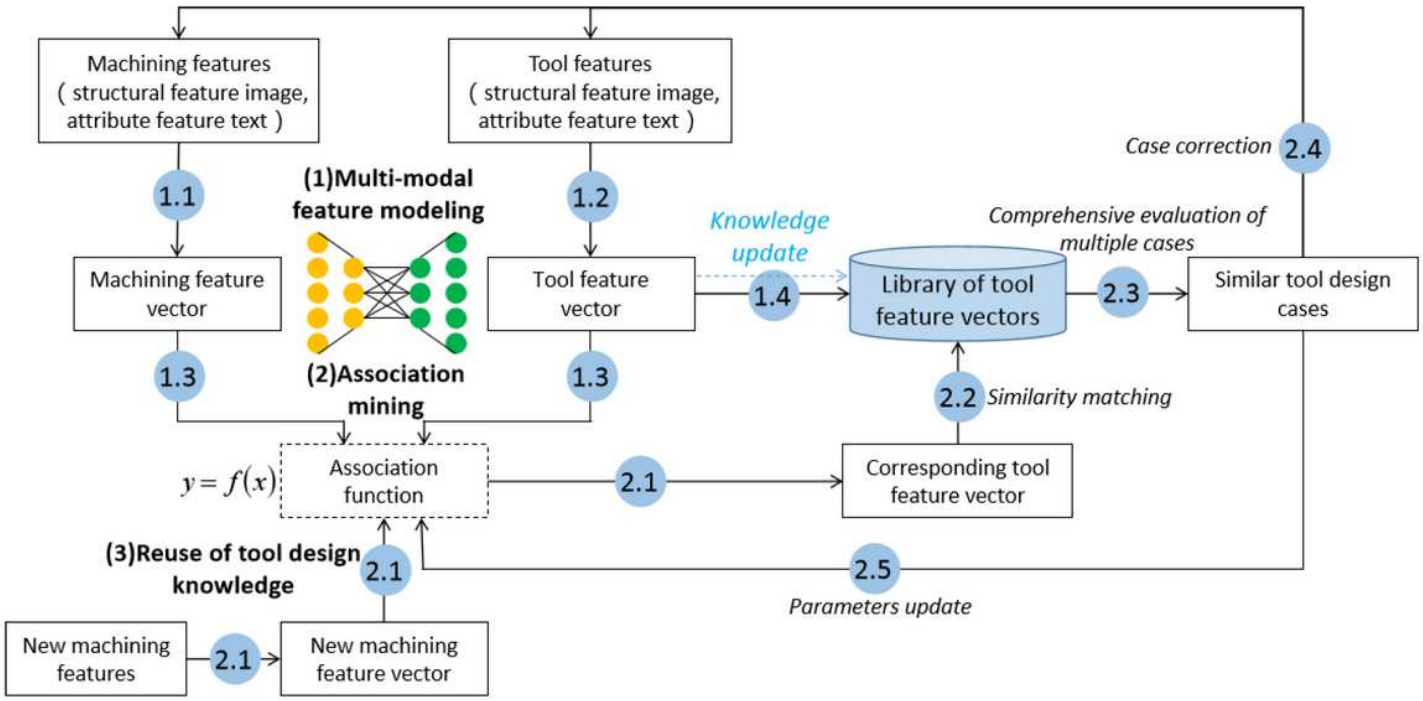


Figure 1

Basic principles of research on mining and reusing of non-standard tool design

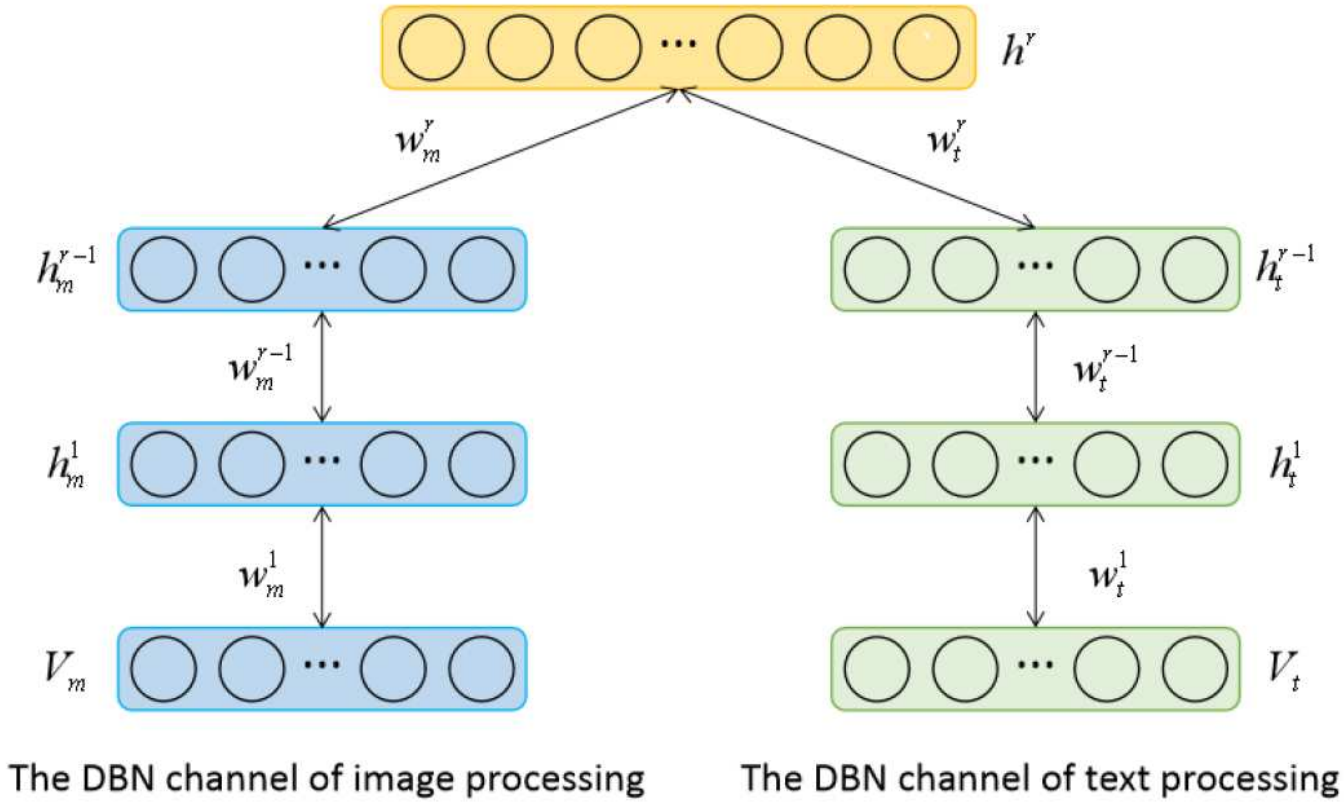


Figure 2

Dual-channel DBN model structure

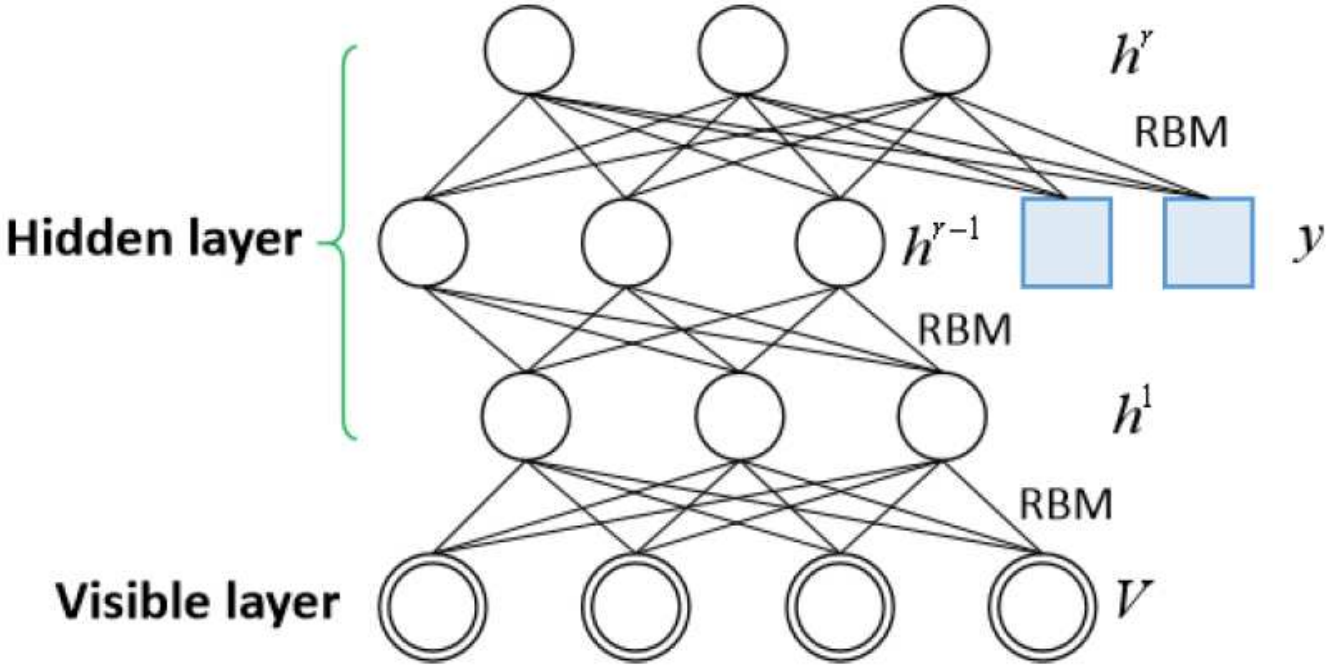


Figure 3

Structure of the Deep Belief

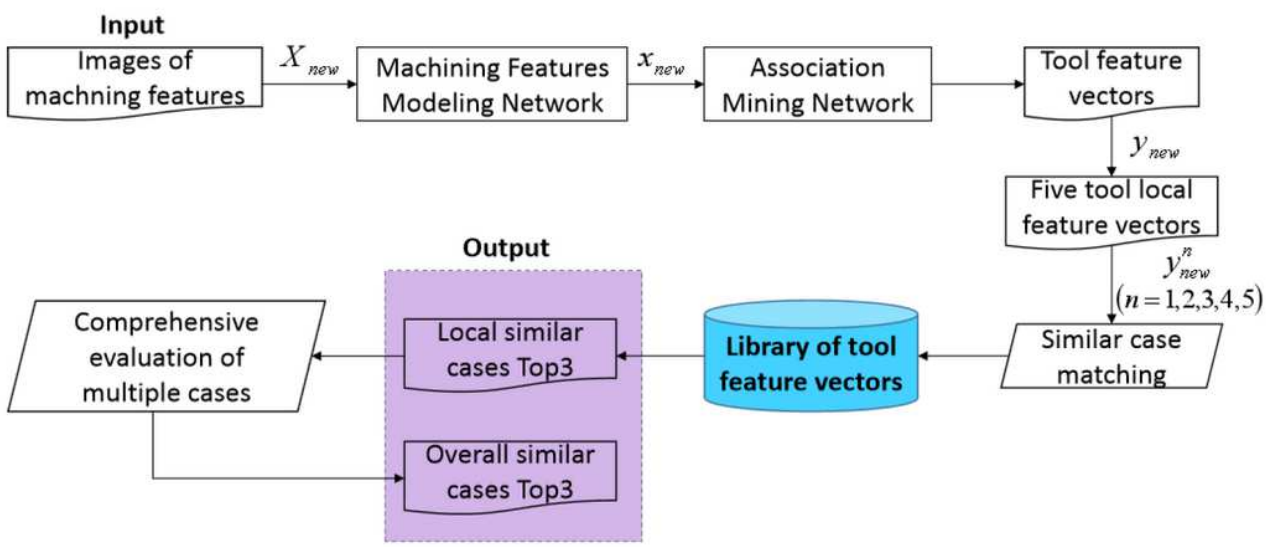


Figure 4

Process of tool design knowledge reuse

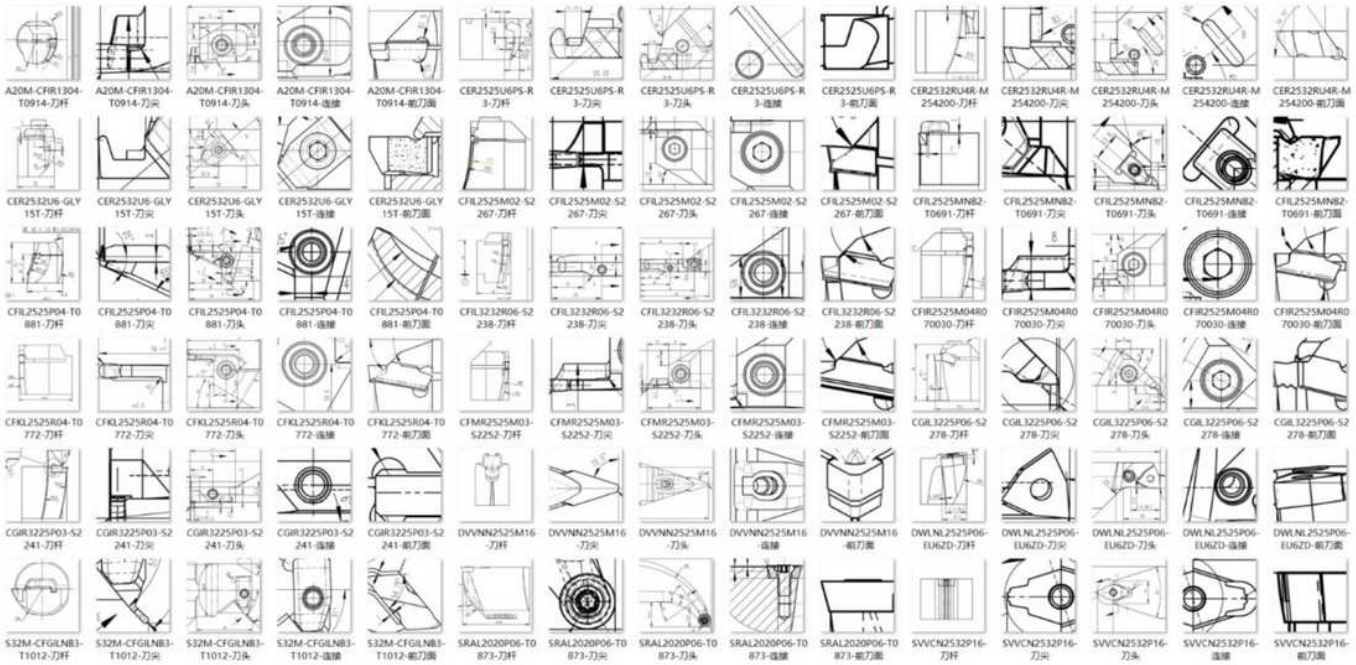


Figure 5

Part of tool features' engineering drawings

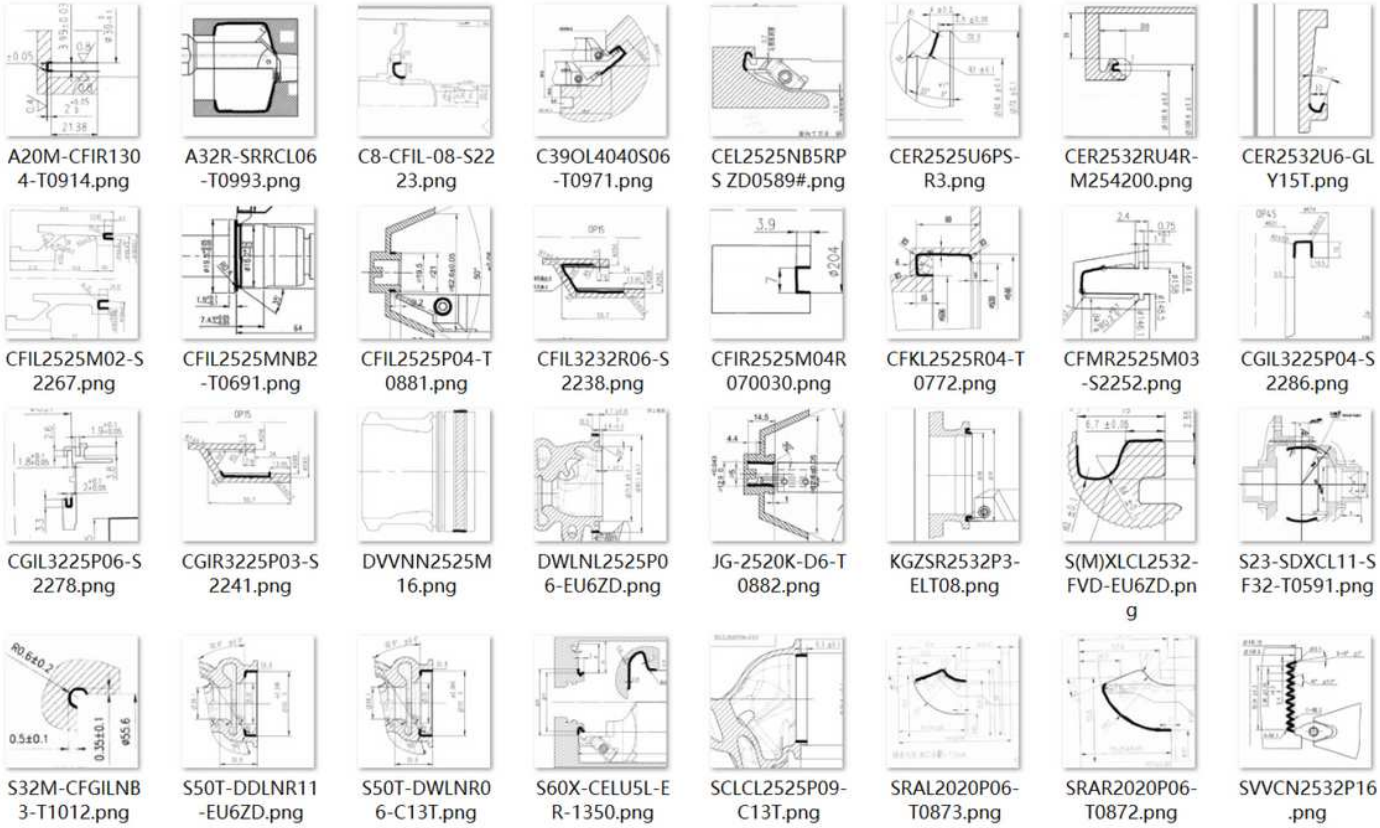


Figure 6

Part of machining features' engineering drawings

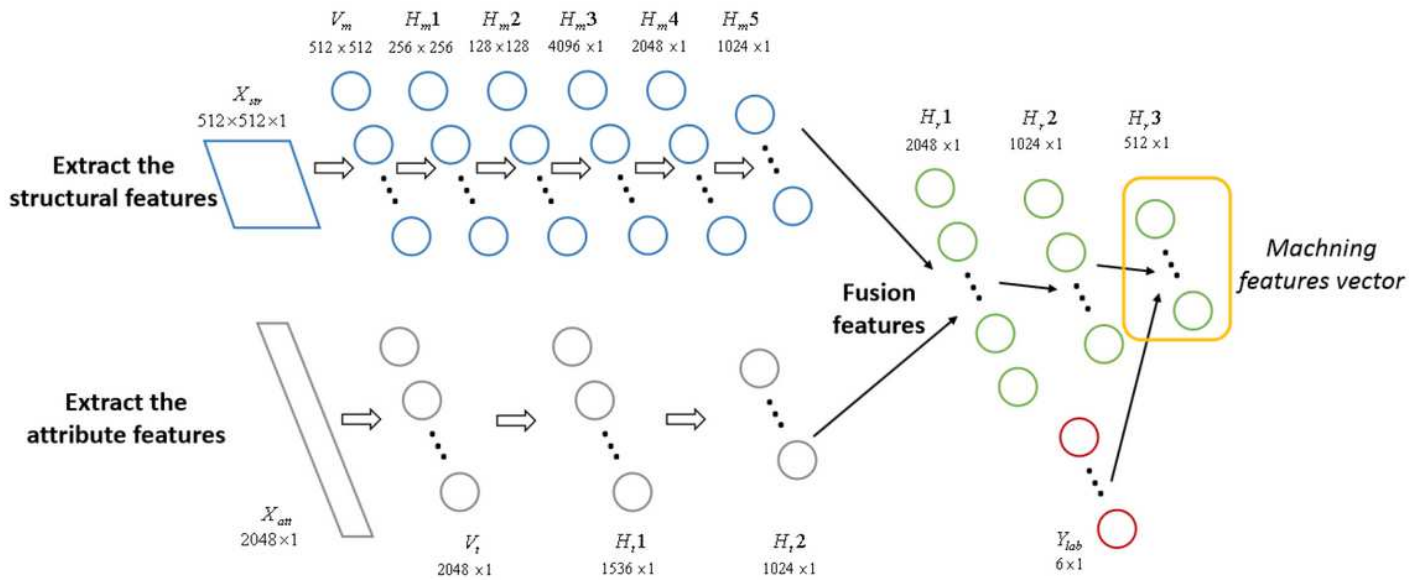
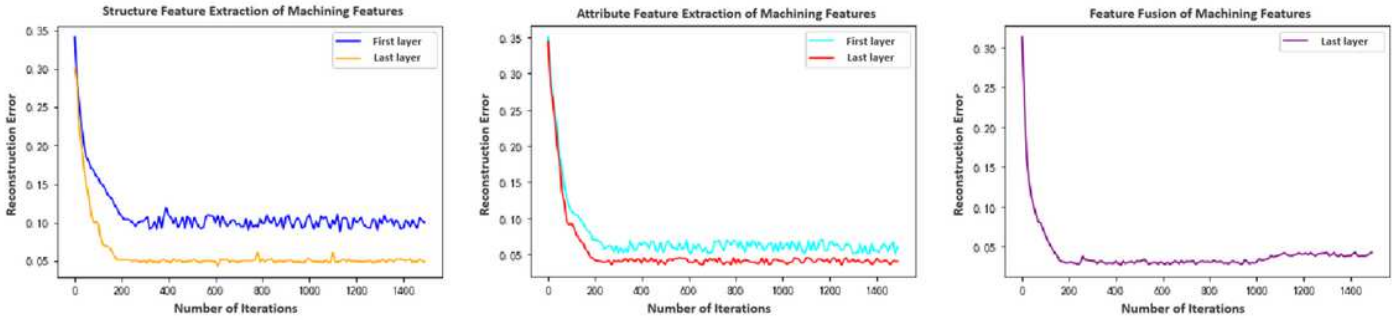


Figure 7

Network of machining features modeling based on 2-DBN



(a) (b) (c)

Figure 8

RBM reconstruction error curves of machining feature modeling network

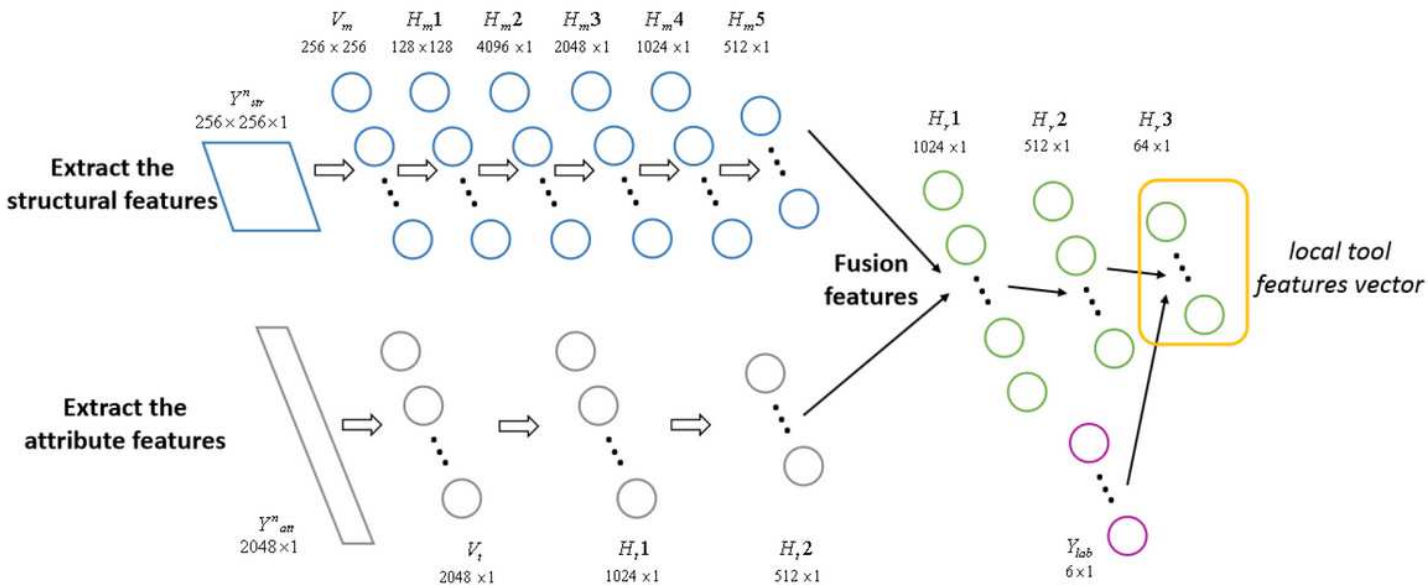


Figure 9

Network of tool features modeling based on 2-DBN

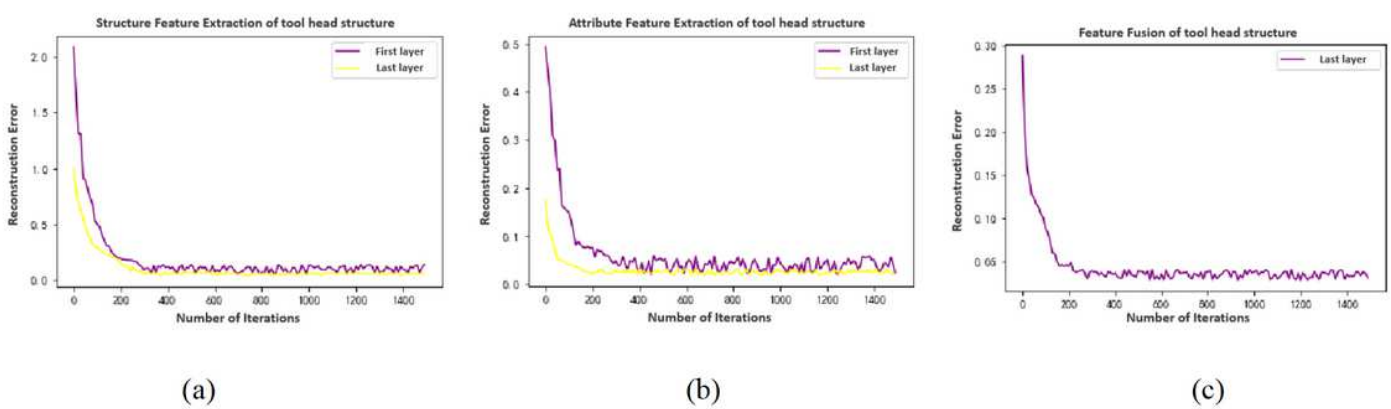


Figure 10

RBM reconstruction error curves of tool head structure feature modeling network

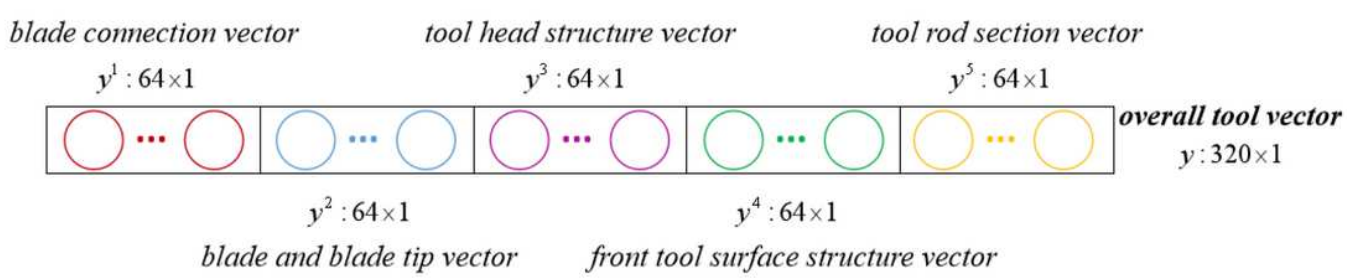


Figure 11

The process of obtaining the overall tool feature vector

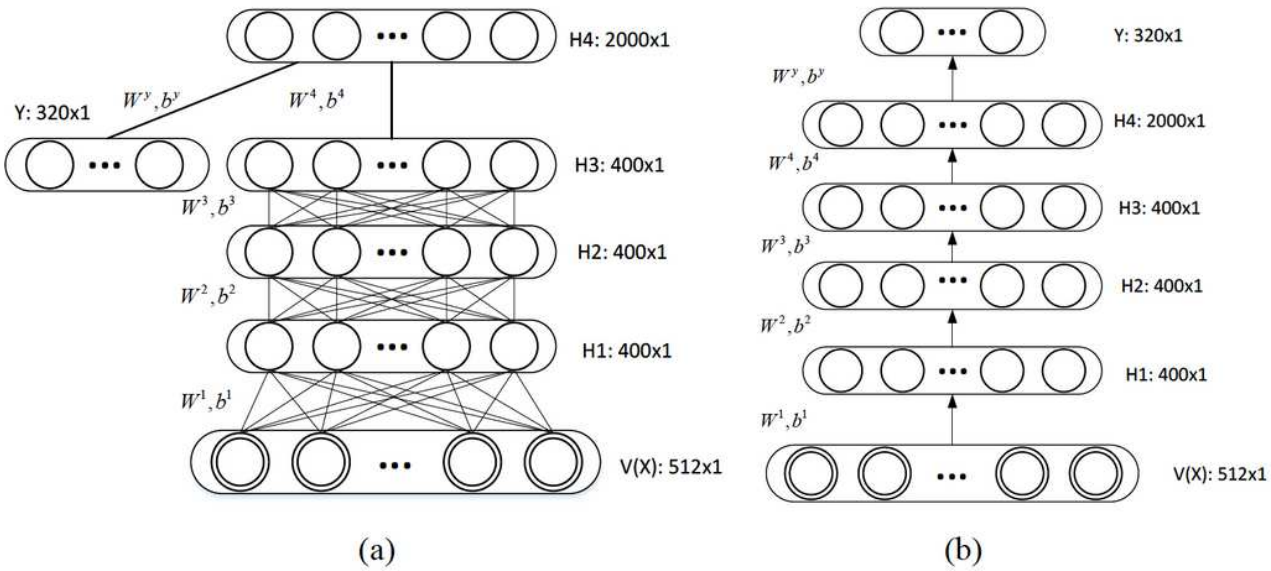


Figure 12

Association mining network based DBN (a: unsupervised training; b: supervision and tuning)

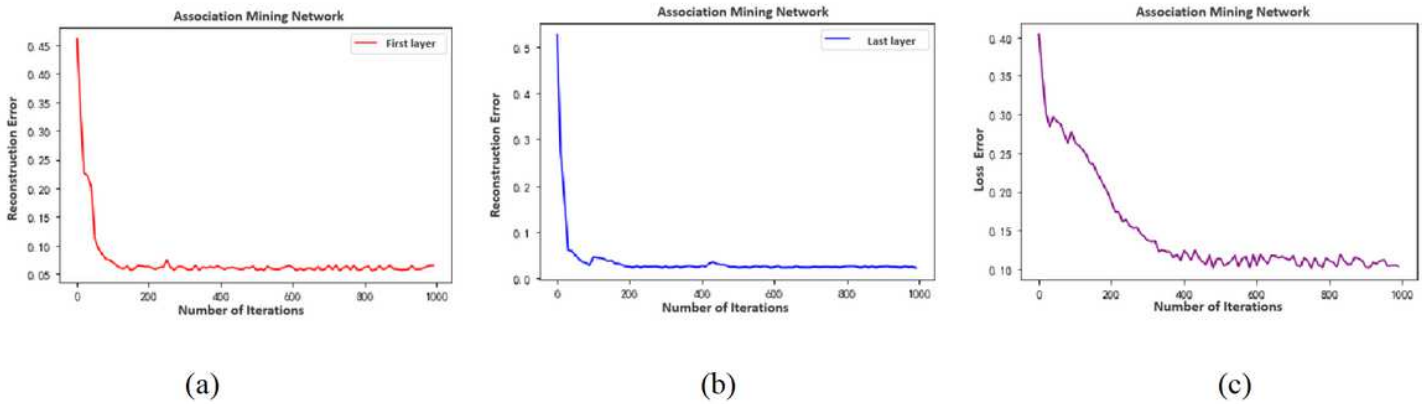


Figure 13

Error curve of association mining network