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Research Article

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Tool Wear Recognition and Signals Labeling with Small Cross Labeled Samples in Impeller Machining

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Abstract

Data driven deep learning method is the main way to study the condition monitoring of mechanical equipment, in which sufficient labeled signals to train the model parameters is a typical problem. The existing methods to obtain the labeled signals mainly focus on manual marking. For the non-batch impeller processing with variable working conditions, manually marking signals is not the wisest move. To solve this problem, this manuscript puts forward a deep conditional random field neural network (CRFNN) method. This framework fully utilizes the sensitivity of the conditional probability model to adjacent data marker information, and small cross labeled samples are used to predict the labels of unknown signals. At the same time, the variational autoencoder is used to convert the one-dimensional time series signal into three-dimensional image, which solves the problem that the empty tool signals have a great impact on the tool wear condition monitoring in the process of impeller blade machining. Experimental results on a CNC machining center demonstrate the effectiveness and feasibility of the proposed method, and outperforms the existing works under industrial small labeled samples.

Keyword: Deep conditional random field neural network, signals labeling, small cross labeled samples, tool wear recognition.

1. Introduction

With the development of science and technology, intelligent operation and maintenance of key components of major equipment has become an important part of industrial innovation [1,2]. Intelligent diagnosis is an important research topic in the field of mechanical manufacturing [3,4]. Data-driven intelligent monitoring method is

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the most widely used and effective means for equipment performance degradation detection. The main idea is that large number of samples are measured by diverse sensors, and the signal characteristics are automatically learned and recognized [5-7]. Most of the existing data-driven methods rely on a large amount of labeled data to establish diagnosis models. In the process of signals acquisition in the laboratory, it can be stopped at any time to check the status, and the amount of data is small, so the labeled data is easy to obtain. However, in engineering applications, it is impossible to outages in real time [8,9]. In the face of massive engineering data, it is difficult to obtain marked and intercepted information [10,11]. Therefore, developing an automatic data labeling and interception method or reducing the dependence of the model on the labeled signals has important practical significance for the intelligent diagnosis of key components.

Existing methods have been initiated to conduct the research on signals label prediction, including traditional marking methods and deep learning methods. Liu et al. [12] used the nonlinear threshold with the characteristics of simple structure, added noise components to neurons to smooth threshold response and adaptively adjusted parameters in the learning process for handwritten numeral recognition. Aiming at the time series classification problem with insufficient information of small samples, Wang et al. [13] adopt the dynamic Bayesian classification architecture and multivariate Gaussian kernel function to construct a dynamic full Bayesian classifier. Chen et al. [14] proposed a modified random forest method based on graph semi-supervised learning and decision tree to solve the problem of gearbox fault diagnosis under insufficient sample labeling. Mao et al. [15] present a semi-random subspace method to further generate a classifier with sparse structure and fully integrate features for bearing fault type recognition.

With the development of deep learning, many scholars extend the neural network model to the fields of image marking, speech recognition, fault diagnosis, and so on. Zhong et al. [16] proposed a joint framework based on generative adversarial network and conditional random field (GAN-CRF) for hyperspectral image classification task, realized the framework training with a limited number of labeled samples to learn the

feature classification of the remaining samples. Ma et al. [17] extended the traditional vector-based support vector machine to tensor space and proposed a multi-mode tensor machine model suitable for high-dimensional heterogeneous data for multi classification of industrial big data. Zhang et al. [18] proposed a multi label classification model based on backpropagation neural network and huff model, which marked each digital sign with different labels to study the audience classification. Cheng et al. [19] presented a weighted integrated neural network, which combines random image clipping with integrated learning, comprehensively considers the uncertainty of class probability and solves the problem of image labeling with overlapping parts.

From the above research, it can be concluded that the current research on label prediction is still limited to the condition that the cutting parameters change little, or even exists only under a single laboratory condition. Fewer studies have been conducted on time-varying cross conditions such as rotating speed, feed rate and other cutting parameters. For the method that can adapt to label prediction under multi-factor conditions, it is only applied to handwritten font recognition or image processing, and rarely applied to mechanical equipment condition monitoring.

However, for the signals labeling in the impeller machining process, the issues that must be taken into account are: (1) In the process of impeller passage machining, empty tool segment and cutting segment appear alternately, which will cause the collected signals contain a large number of empty tool segment signals and directly affects the accuracy of tool wear prediction. It is difficult and time-consuming to manually remove the empty tool segment signals thus suitable empty tool signals processing method must be taken seriously. (2) Impeller machining in engineering applications is single-piece, small batch production. Generally, the impeller with a specific size is processed according to the production requirements of the manufacturer. That is, the cutting parameters, workpiece materials and dimensions, and impeller passages number among different impellers vary greatly. Therefore, the method under research should fully consider the applicability and generalization to complex conditions.

Facing the above problems, the deep conditional random field neural network (CRFNN) method is proposed in this paper to intercept and mark the signals in the process of impeller milling. For the first time, probability constraints are introduced in neural networks and applied to impeller processing to actively learn the correlation between adjacent signals, while small cross labeled samples are used to train model parameters for label prediction. For the problem of empty tool section, variational autoencoder (VAE) is used to transform the time series data into three-dimensional images to eliminate the effect of empty tool section through multiple iterations.

The remaining structure of this paper is: the proposed method is described in detail in Section 2. Section 3 introduce the experimental procedure. Section 4 shows the experiment results. The main contribution and further work are given in Section 5.

2. Proposed method

In this paper, we propose to introduce probabilistic constraints into the neural network to line into CRFNN model, which is inspired by the idea of recognition on freehand sketches. The model parameters are trained with small cross marked samples to adapt to the complex and variable machining conditions of the impeller, and achieve tool wear recognition, where the dependence of the existing model on a large number of labeled signals has been overcome. The main research processes are list in **Fig.1**.

2.1 Processing of empty cutting signals

The milling of the impeller is an intermittent cutting process, and the collected signals often contain empty tool signals. Empty tool signals have a great impact on tool condition monitoring. Therefore, studying how to remove the empty cutting signal from the collected information or eliminate the influence of the empty cutting signal on the machining signal plays a great role in tool wear recognition [20]. In this paper, variational auto-encoder (VAE) method is used to convert the time-domain signals into three-dimensional images. The empty cutting segment signals and processing signals are all transformed into images. Meanwhile, the deep feature information of the images is automatically extracted, which can well eliminate the influence of empty cutting signals.

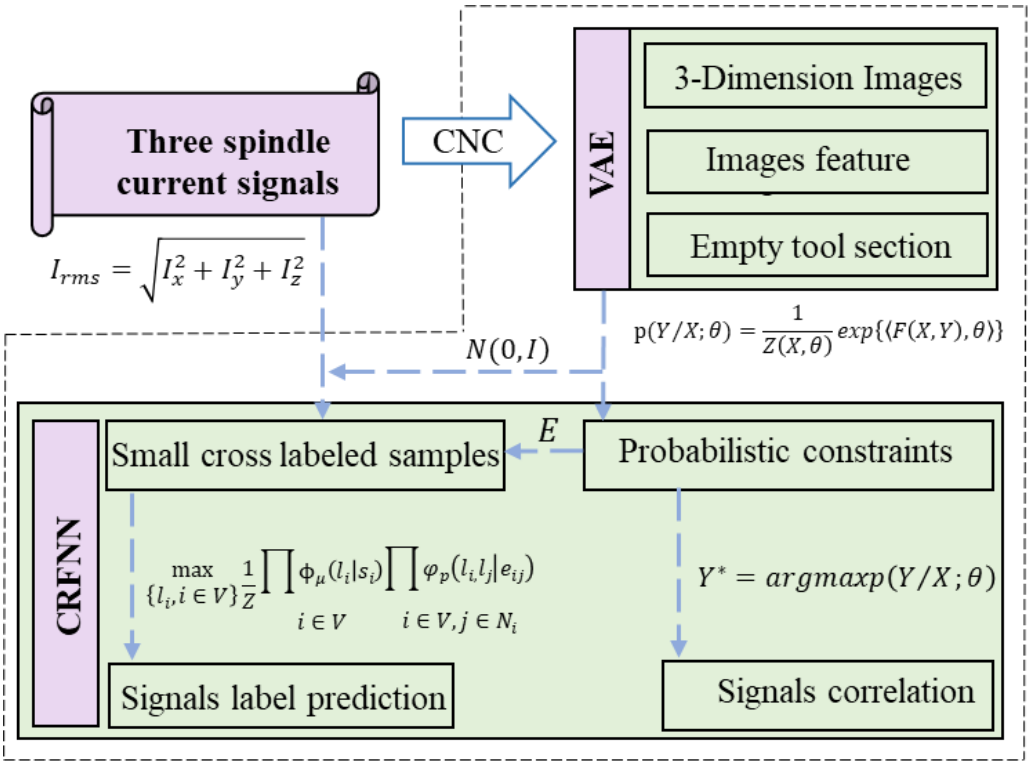


Fig.1. Process of the proposed method.

The purpose of VAE model is to build a model to generate target data X from implicit variable Z. It is hoped to train a model $x = g(z)$, which can map the original probability distribution to the probability distribution of the training set, that is, their purpose is to transform between distributions [21]. For any given sample x, there is a corresponding independent and multivariate normal distribution $P(z|x)$, so that

$$p(Z) = \sum p(Z|X)P(X) = \sum N(0,I)p(X) = N(0,I)\sum p(X) = n(0,I) \tag{6}$$

Therefore, in order to make the model generative, a hypothesis exists that $p(Z)$ conforms to a normal distribution. All $p(Z|X)$ are expected to align with $N(0,I)$, then an additional loss function needs to be added into the reconstruction error:

$$L_\mu = \|f_1(X_k)\|^2, L_{\sigma^2} = \|f_2(X_k)\|^2 \tag{7}$$

It represents the mean μ Log of K, and variance σ^ 2. To reach n (0, I) is to hope that they are as close to 0 as possible. However, this will face the problem of how to select the proportion of these two losses. If it is not selected well, the generated image will be blurred. Therefore, the KL divergence $KL(N(\mu,\sigma\text{^}2)\|N(0,I))$ of normal

distribution. The loss function with standard normal distribution can be written as:

$$L_{\mu,\sigma^2} = \frac{1}{2}\sum_{i=1}^{d}\left(\mu_{(i)}^2 + \sigma_{(i)}^2 - \log\sigma_{(i)}^2 - 1\right) \tag{8}$$

Where d is the dimension of the implicit variable Z, μ (i) and σ_{(i)}^{2} represents the ith component of the mean vector and variance vector of the general normal distribution respectively.

VAE model calculates the mean and variance in the coding process. The key to realization is to add noise signals into cutting data during encoder process, so that the results of decoder is more robust. The extra KL function (to make the average value 0 and the variance 1) is equivalent to the conventional term of the encoder, and it is expected that all contents of the encoder have a zero average value [22]. The VAE model reconstructs the one-dimensional time series signals into three-dimensional images, the empty tool segment signal and milling signal are included in the image, which weakens the impression of the empty tool segment signal on the machining signal.

2.2 Conditional random fields neural network label prediction model

Random field is a graph model, which contains the set of nodes and edges. Nodes represent a random variable, and edges represent the dependence between random variables [23]. Conditional random field (CRF) is a special Markov random field, which is used to construct the conditional probability distribution model between a set of output random variables and a group of given input random variables. It has been extensive used in sequence labeling or data analysis. CRF combines the given features of the whole sequence to obtain the best label. It fully considers the correlation between adjacent data.

For a given input sequence $\mathrm{X} = [x_1, x_2, \cdots, x_t]$, the conditional probability of predicting the output sequence is $\mathrm{Y} = [y_1, y_2, \cdots, y_t]$ [18]:

$$\mathrm{p}(Y/X;\theta) = \frac{1}{Z(X,\theta)} exp\{\langle F(X,Y),\theta\rangle\} \tag{9}$$

$$Z(X,\theta) = \sum exp\langle F(X,Y),\theta\rangle \tag{10}$$

where $F(X,Y)$ represents the vector of characteristic function and θ represents the

model parameters to be learned. $Z(X,\theta)$ is the normalization factor obtained by summing all possible tag sequences, $<\cdot>$ represents the inner product between two vectors.

The feature function vector can be further written as:

$$F(X,Y) = \sum_{t=1}^{T}\sum_{j=1}^{J} F_j(X,Y_t) \tag{11}$$

Considering the interaction between two adjacent labels, $Z(X,\theta)$ can be considered as the sum of continuous labels, therefore, formula 1 can be redefined as:

$$\mathrm{p}(Y/X;\theta) = \frac{1}{Z(X,\theta)} exp\{\langle F_j(X,y_{t-1},y_t),\theta_j\rangle\} \tag{12}$$

where J is the sum of all characteristic functions.

Conditional random fields (CRF) also have three basic problems [24]: (1) Evaluation problem, the characteristic function and weight of conditional random field CRF are known, and the input sequence x and output sequence y are given. The conditional probabilities $P\ (y_i|x)$ and $P\ (y_i-1,y_i|x)$ are calculated. (2) Learning problem, given the characteristic function and training data set (that is, including multiple input sequences X and corresponding output sequences Y, the weight value of each characteristic function is solved. (3) Decoding problem, the characteristic function and weight of CRF are known to calculate the output sequence y that maximizes the conditional probability.

$$Y^* = argmaxp(Y/X;\theta) \tag{13}$$

The CRFNN model designed in this paper has four hidden layers, an input layer and an output regression layer. The size of the input layer is dual-channel 300 × 300 × 2, which is a three-dimensional image obtained by transforming and extracting time series data by VAE. The design of hidden layer refers to the architecture of convolution neural network, and the four hidden layers are four convolution blocks, each convolution block is composed of a convolution layer, a correction linear unit and a maximum pool layer. Next, two fully connected layers are attached to the fourth convolution block. Attenuation regularization is adopted to the first fully connected layer to reduce overfitting. The last layer has n-label output units corresponding to n-labels. The loss

function is softmax. The framework of CRFNN is present in **Fig. 2.**

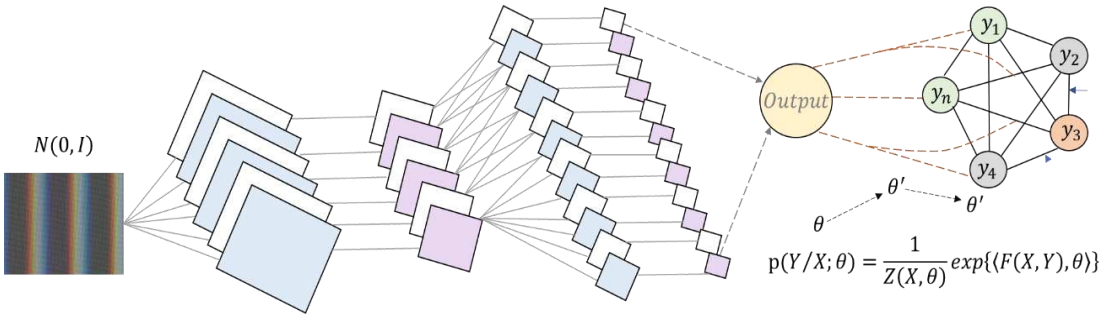


Fig.2. CRFNN framework for signals labeling

The information provided by a single data is relatively limited. The label of the data has a great correlation with the global data. The milling tool is usually a two-edge or four-edge ball end milling cutter. Considering that the impeller blade is a complex curved surface machining process, the cutting edge will not participate in cutting at the same time, and one cutting edge may be the main cutting edge and the other cutting edges may participate in cutting. Therefore, the degree of cutting flank wear is inconsistent, which greatly increases the difficulty of data label prediction.

The above designed deep neural network model can predict the data label, but the relationship between the data is ignored [25]. It is necessary to optimize these relationships, which is helpful to find the best configuration of the global optimal solution. We choose a CRF model to optimize the deep neural network model, and the deep CRF neural network (CRFNN) is formed. The proposed model comprehensively considers the relationship between data and actual processing conditions, and realizes the accurate prediction of data labels. CRF model has been proved to be an effective chart probability description structure.

In order to use CRF for data marking, we need to define a connected set $G = (V, E)$, where V is all data sets and E is the relationship set between data. Suppose i represents a data point in the image, S_i is a feature related to the description of tool wear state, N_i is the adjacent data in the data set, and e_{ij} is the description feature related to the data points i and j [26]. By solving the objective function, the label $\{l_i \mid i \in V\}$ of these data points can be optimized according to the following formula:

$$\max_{\{l_i, i \in V\}} \frac{1}{Z} \prod_{i \in V} \phi_\mu(l_i|s_i) \prod_{i \in V, j \in N_i} \varphi_p(l_i, l_j|e_{ij}) \tag{14}$$

where ϕ_μ is unary node potential function, φ_p is pairwise edge potential function between two connected nodes, and Z is a normalization factor to ensure that the probabilities range from 0 to 1 [27].

3. Experimental Verification

3.1 Experimental setup

The experiment was carried out in the impeller machining center of three-axis CNC machine tool of turbine machinery Co., Ltd. Due to the limitations of the production process and machining requirements of the impeller complex surface, it is impossible to stop the machine in real time to check the tool wear states. In the case of continuous operation of numerically controlled machine tool, signals of the whole process from the beginning of cutting with a new tool to the end of machining to replace the tool are collected. The machining method of impeller is cycloid milling. The machining system is gmc1020l three-axis horizontal milling CNC system made in ZOJE Machine Tool Co., Ltd., and the control system is a siemens system. The milling current signals are collected by the Hall current sensor produced by LEM company in Switzerland. The spindle speed during machining is about 1800 rpm (the variation range is about 100 rpm). The tool used is a FA520B-20mm diameter Lin's four edge cemented carbide flat end milling cutter, and the material is alloy steel. The sampling frequency is set to 10 kHz. The experimental machine tool, and the impeller machining process are shown in **Fig. 3**. The parameter settings of the experiment are shown in **Table 1**.

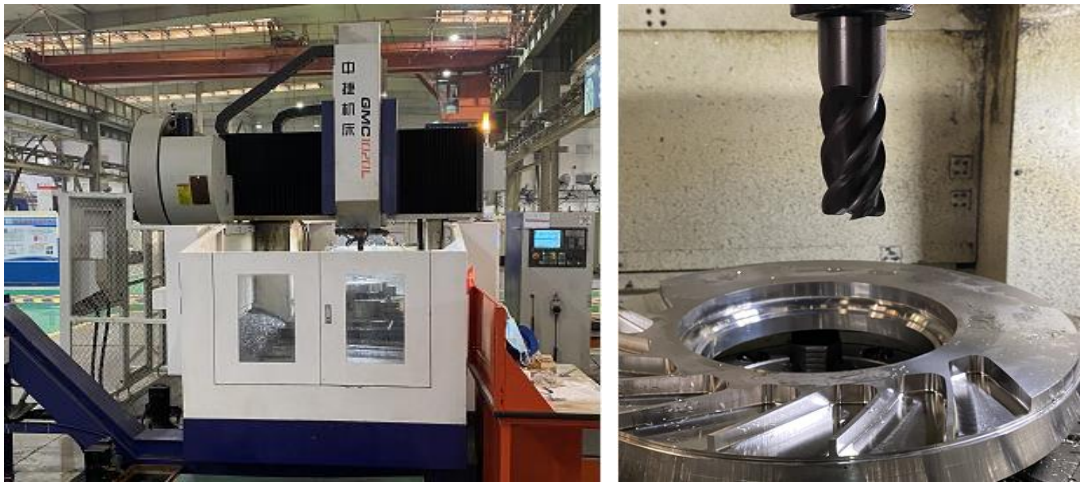


Fig.3. Experimental equipment and impeller

The collected signals are the full cycle current signal of impeller machining, including both machining section signal and empty tool section signal. **Fig. 4** shows the time-domain diagram of the current signals of one working procedure. Through the local enlarged drawing, the peak is the signal of the processing section and the trough is the signal of the empty tool signals.

Table 1. Experimental parameters list

Experimental parameters	Symbol	Value
Spindle speed	rpm	1800±100
Sampling frequency	Hz	10240
Processing time	h	4.25
Sensors number	-	3
Tool cutting edges number	-	4
Impeller passage	-	16

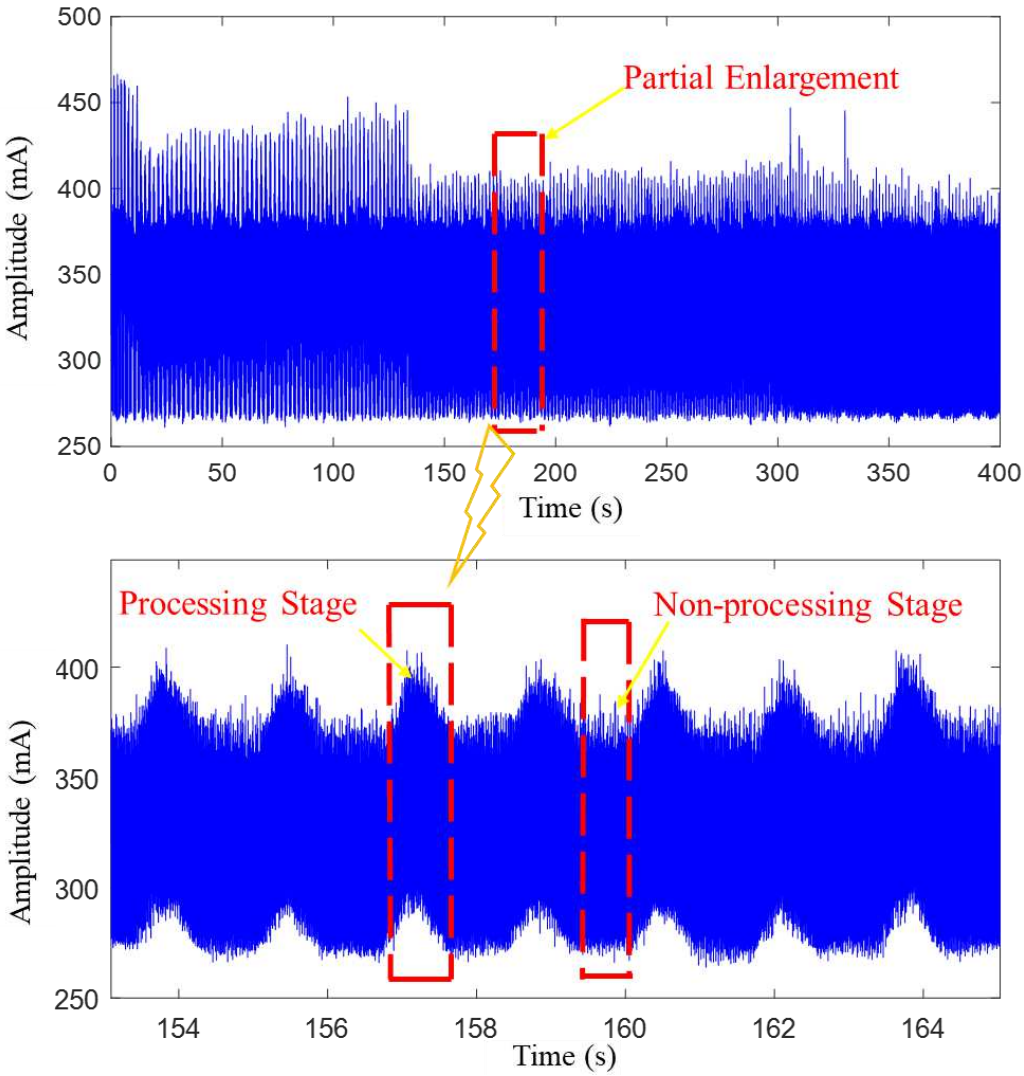


Fig.4. Processing signal acquisition.

3.2 Small cross labeled samples

Considering the machining conditions of impellers, this paper presents cross samples. Cross samples are defined as signal samples of cutting conditions with large differences, including cutting parameters, tool model, impeller hardness, impeller diameter, number of impeller passage, etc. Generally, the tool wear is divided into three life cycle stages on the wear degree of the flank: initial wear stage, normal wear stage and severe wear stage. In the actual cutting process, the tool is in the normal wear stage most of the time. Once the severe wear stage is reached, continued processing will cause scratches on the workpiece, which will seriously restrict the processing quality of the workpiece. Therefore, the tool life cycle in this paper is divided into four stages: initial wear, early normal wear, late normal wear and severe wear. The normal wear stage is

divided into the early normal wear, and late normal wear. When the tool reaches the late normal wear, it can remind the staff to pay close attention to the tool state, and replace the tool in time.

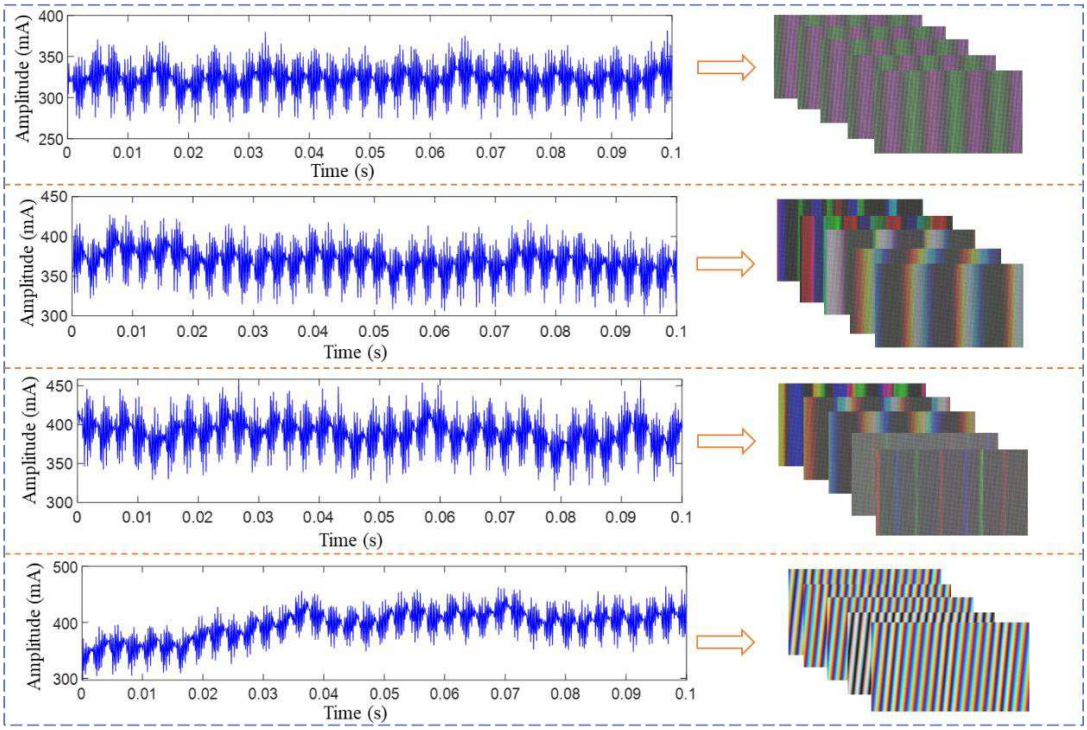


Fig. 5. Signal image sample making

The collected spindle motor current signals are converted into 3D images sized 180 × 320 ×3. Each image contains 172800 signal points. Calculated according to the sampling frequency of 10K, each picture contains a 16 second processing signal, including enough cutting segment signals and empty tool segment signals. The time domain signals and corresponding pictures of the four tool wear states are shown in **Fig. 5**. Small cross labeled samples are made to train the parameters of neural network. The whole parameters used are shown in **Table 2.**

Table 2. The detailed parameters of the whole model.

Part	Parameter	Weights	Value
VAE	Input-layer	-	180*320*3
	Hidden-layer 1	3*3*3	[2 2]
	Hidden-layer1 2	3*3*3	[2 2]
	Hidden-layer1 3	3*3*3	[2 2]
	Decoder 1	7*7*3	[3 4]
	Decoder 2	-	16

	Input samples	-	300*300*2
	Block 1	38*38*32	[15 15]
	Block 2	16*16*64	[5 5]
CRFNN	Block 3	6*6*128	[3 3]
	Block 4	3*3*128	[3 3]
	Softmax	1	-
	Output	-	[0 1 2 3]

4. Results Analysis

4.1 Signal processing of empty tool section

Because the collected signal is a whole continuous machining process, the cutting section and the empty tool section are both included in the signals. In the past, the cutting section signal was intercepted manually section by section. For a large amount of engineering data, there are many empty tool segment signals, almost every three seconds, the machining signals contain a section of empty tool signals. it is very time-consuming to intercept the cutting section signals manually, which is unrealistic work in engineering applications. However, if the influence of an empty tool section signal is not eliminated, it will seriously interfere with the making of signal samples and further affect the signals analysis results.

In this manuscript, VAE method is applied to handle the signal images. Considering the accuracy and speed of image processing by neural network, the collected signals are made into three-dimensional images with a 180 × 320 ×3 size. The image features are deeply studied through multiple iterative processing of neural network, the cutting section signals are strengthened and the empty tool section signals are weakened, so as to reduce the influence of the empty tool section signal on the cutting section signal. **Fig.6** shows the image processing result with 320 iterations and the display step is 40. It can be seen from the experimental results that when the number of iterations is 320, the cutting section signal in the original picture can be restored better. VAE network not only reduces the influence of empty tool segment signals on signal feature learning but also further decreases the amount of calculation. Thus, the workload of engineering signals processing is alleviated.

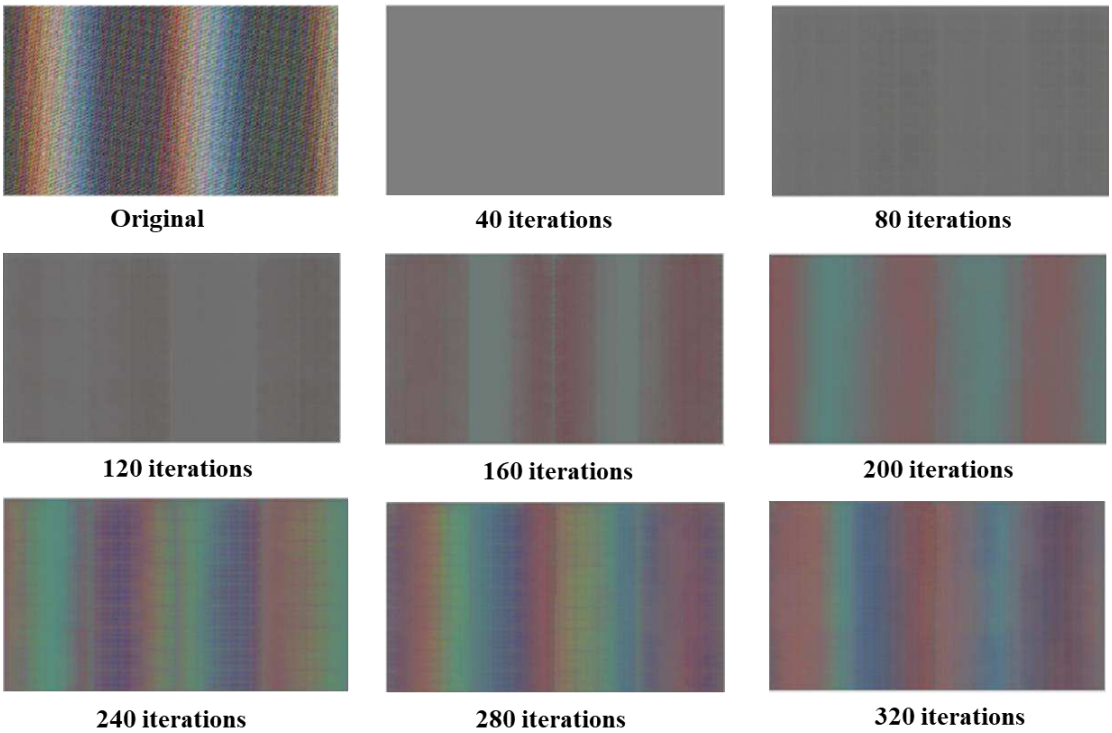


Fig.6. Image feature recognition results.

4.2 Signal label prediction accuracy

In this paper, a deep CRFNN model is used to predict the current signals label in milling. Without any manual signal processing, CRFNN directly learns the relevant information of images processed by the form VAE model, memorizes and extracts the feature relationship between the images. The tool wear state is divided into four states, and the number 0 1 2 3 is used to distinguish different tool wear state. The signal belonging to initial wear stage is marked with 0, the signal belonging to the early stage of normal wear is marked with 1, the signal belonging to the late stage of normal wear is marked with 2, and the signal belonging to the severe wear stage is marked with 3. The prediction results of labels in different wear states are shown in **Fig. 7**. Through the clustering results, the data have better prediction for different wear state categories.

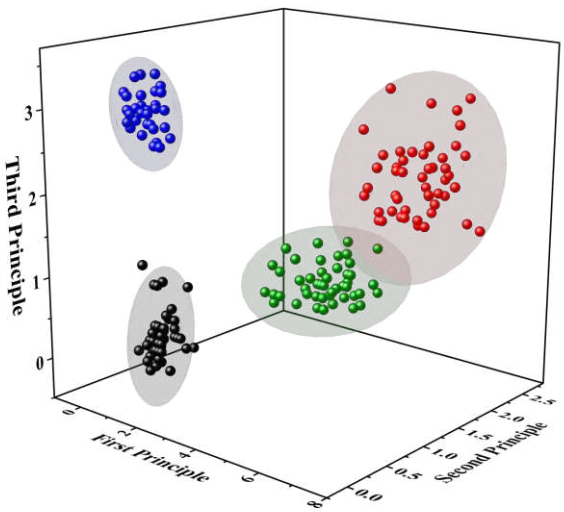


Fig.7. Sample label prediction clustering results

The deep CRFNN model learns the relationship and characteristics between images through multiple iterations to find the optimal solution of the whole network. The number of iterations has a great impact on the performance of a neural network. If the number of iterations is not enough, the learning ability of neural network will be insufficient and the deep characteristics of signals cannot be fully learned. The excessive number of iterations will lead to a long running time of the network and affect the practicability of the neural network. Therefore, the influence of the iterations number on the performance of neural network is explored. The influence of the iterations number on the neural network error is shown in **Fig. 8**.

From Fig.8, with the increase of the iterations number, the error of the neural network gradually decreases. When the number of iterations reaches 750, the performance of the neural network is beginning to stabilize and the error is the smallest.

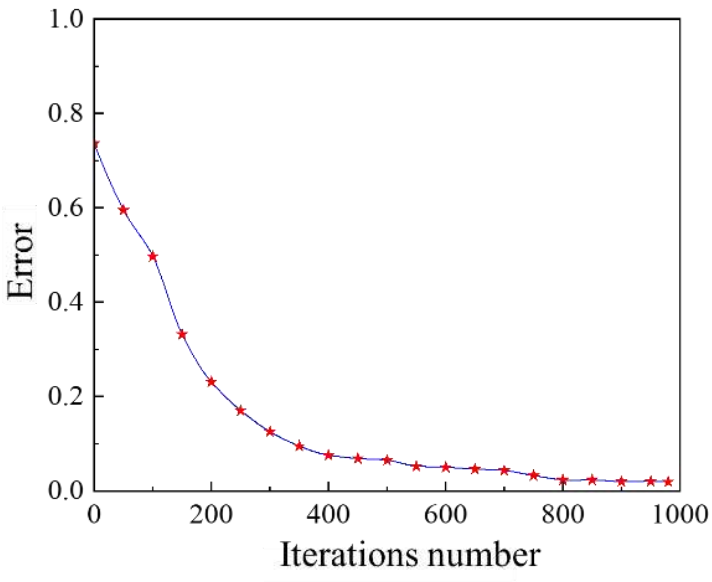


Fig.8. Relationship between iteration number and error

When the neural network model structure is built, there are many unknown parameters such as weights, kernel size. Therefore, some labeled signals are needed to train the neural network to determine the unknown parameters information. The purpose of CRFNN model designed is to predict the labels of a large number of unknown data with a small amount of labeled data. The principle is to train the designed network model through a few of labeled data, determine the unknown parameters of the model, and then use the trained network to predict the label of unlabeled data Therefore, the performance of neural network is also related to the number of labeled data. Exploring the number of labeled samples can directly display the performance of the network. The exploration results are shown in **Fig 9**. As can be seen from Fig. 9, with the increase of the number of labeled samples, the accuracy of network prediction labels gradually increases. When the number of labeled samples is 35%-37% of the total samples, the accuracy of sample prediction tends to be stable. Therefore, the constructed CRFNN model can predict the labels with only 35% of the data samples.

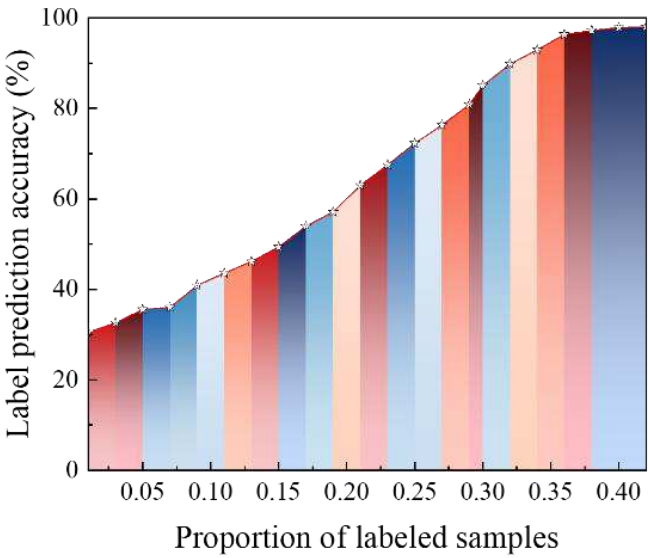


Fig.9. Effect of the labeled samples number on accuracy

4.3 Comparative experimental verification

In this paper, CRFNN model is used to predict the label of VAE processed images. To test the availability of the proposed method, comparative experiments are used. The comparative test is designed as follow: The CNN model is directly used to learn the original time-series signals without any processing, and to identify the two-dimensional original signals. It should be noted that in order to ensure the reliability of the comparative experiments, all the methods are to identify the collected original signals, and no manual elimination of empty tool section signals is required. The neural network adopted has a similar structure with four hidden layers. The comparative results are shown in **Fig. 10.**

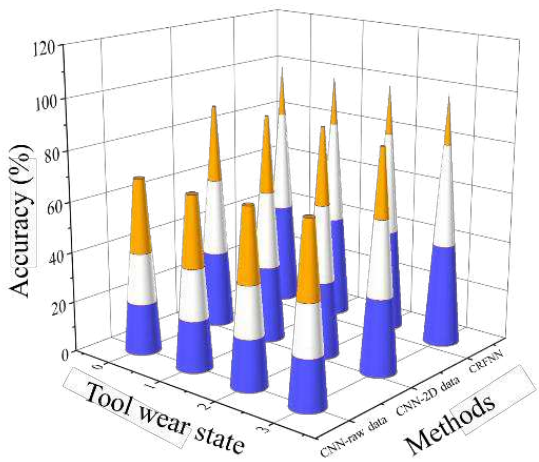
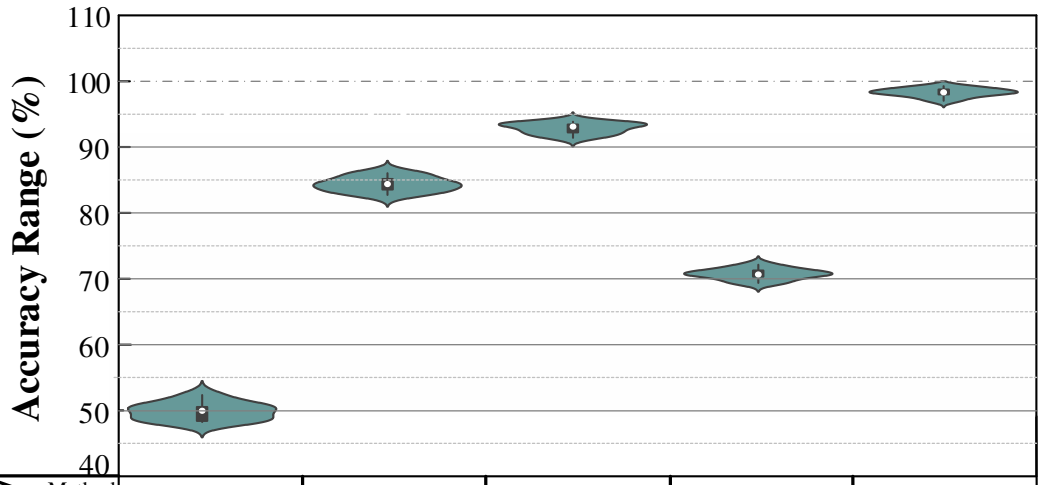


Fig.10. Comparison with the original CNN method.

From Fig. 10, the accuracy of label prediction directly using CNN model for the original one-dimensional signal is the lowest. This is because the original time series signals contain a lot of empty tool segment signals without any manual processing. The sample learned by the neural network are likely to be mixed with samples made of empty tool segment signals, which has a great impact on the recognition accuracy. Compared with one-dimensional original signals, after converting the signals into two-dimensional signals, the proportion of cutting segment signals in the sample is increased to a certain extent, so the accuracy is improved. When the original signals are made into three-dimensional images, since the largest proportion of cutting section signals in the whole sample, the influence of empty tool section signals on the sample is weakened. At the same time, the probability constraints are added into the neural network to fully learn the information between adjacent samples, the accuracy of label prediction is gradually improved**.**



Method / Acc	NB	CNN	SAE	RF	**CRFNN**
1	48.32	84.54	92.14	70.35	**98.24**
2	50.01	83.27	93.38	71.52	**98.73**
3	49.13	84.18	91.41	70.58	**98.01**
4	48.24	82.75	93.25	69.36	**98.21**
5	49.41	83.61	92.84	70.74	**97.29**
6	48.32	83.02	92.71	70.53	**98.14**
7	50.47	85.14	92.43	71.23	**98.41**
8	48.32	86.02	91.78	72.14	**97.10**
9	51.27	84.24	93.41	71.02	**97.04**
10	48.32	85.96	93.84	69.56	**98.52**

Fig. 11. Comparison with the original CNN method.

In order to further verify the accuracy of the proposed method in sample labels prediction, a comparative experiment with other models is carried out. The comparison method used is naive Bayes (NB), random forest (RF), convolutional neural network (CNN), and sparse auto-coding (SAE), including traditional classification methods and neural network methods. The data processed by the comparison method are the collected original current signals. In order to avoid the contingency of a single result, ten repeated tests are carried out in this paper, and the test results are shown in **Fig. 11** Through the comparison results, the following conclusions can be drawn. The traditional methods are insufficient in dealing with the problem of classification and recognition for massive engineering data, and the accuracy is usually 50% ~ 60%. As the representative neural network of deep learning methods, CNN and SAE models face the original data containing large number of empty tool segment signals, the accuracy of samples label prediction can reach 80% ~ 90%. However, the accuracy of the proposed method for samples label prediction is more than 98%, which has greater significance and value for guiding the actual processing.

5. Conclusion

The acquisition of massive labeled signals is a great challenge for tool wear condition monitoring. This paper proposes a CRFNN model to accurately predict the signals label with small cross labeled samples. It breaks the limitation that the existing deep learning methods need to mark signals manually, and more suitable for impeller machining with different size and machining parameters in engineering application. In addition, the basic idea of this paper has broad application prospects in parts quality assurance, factory job scheduling and production automation. The main contributions of this paper are summarized as follows:

1) A novel CRFNN model is proposed to learn the relevant information between signals, where the probability constraint is introduced into the neural network to predict the label of massive engineering signals with small cross labeled samples, which solves the problem that the neural network parameter training depends on manually labeled signals. It takes up the research on tool wear monitoring in the process of variable

condition impeller machining.

2) Variational autoencoder is applied to transform one-dimensional time series signals into three-dimensional images. Through learning and processing the images, the problem that empty tool segment signals have a great impact on the cutting segment signals during the impeller machining process is solved. The accuracy of tool wear state recognition is significantly improved, which provides a solution for equipment condition monitoring under intermittent machining.

3) The contribution of this manuscript is expected to help direct the research on variable condition equipment monitoring with small cross labeled samples not limited to impeller blade machining but job-shop production.

Future research will focus on optimizing the performance of the network and exploring the function of a smaller number of labeled samples to predict the labels of unknown signals. The labeled signals obtained will be extended to the equipment fault diagnosis and early warning to promote the research on key components intelligent operation and maintenance of major equipment.

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