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APPLICATION OF BIG DATA ANALYSIS BASED ON IMPROVED APRIORI ALGORITHM AND ARTIFICIAL INTELLIGENCE IN IMPROVING THE STABILITY OF CNC MACHINE TOOLS

Jun Guo,* Lei Xiang,* and Ying Wang*

Abstract

To compensate the machining accuracy of the CNC machine tool is influenced by machine tool parts, the external environment and other factors. Therefore, it is necessary to add appropriate compensation parameters to ensure the stability of machining accuracy. In addition, the compensation parameters of different lathes change at different times in real time. Therefore, an improved Apriori algorithm and an intelligent error compensation model which based on artificial intelligence proposed to establish an intelligent and accurate real-time parameter compensation scheme for the running lathe. The factors that affect the machining accuracy, such as the condition of components and the external environment, form several eigenvalues. Each eigenvalue corresponds to several compensation parameters. A data set consists of several eigenvalues, compensation parameters and a precision value. Several data form a data set. The result of the simulation tests show that the stability of the lathe is improved by 0.695 and 0.713 for the data of the training set and the test set, respectively. The measurement results show that 30 products are carved with the above method, and the accuracy meets the requirements. Therefore, the intelligent error compensation model can improve the stability of turning processing and product qualification rate.

Key Words

Improve Apriori algorithm, artificial intelligence, big data, CNC, intelligent error compensation model

* School of Information Engineering, Hunan Automotive Engineering Vocational College, Zhuzhou 412001, China; e-mail: m15797627637@163.com; simonleo810@126.com; csuftwy@163.com
Corresponding author: Lei Xiang

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1. Introduction

Quality and efficiency are the eternal themes of industrial production. In the intelligent metal cutting production line the CNC machine tool is the most important device that affects quality and efficiency. CNC machine tools belong to the precision manufacturing equipment, although their technical indicators can reach the appropriate level when they leave the factory, when there are used in the actual production line, their machining accuracy will be affected by factors, such as fixtures, tools, ambient temperature, vibration, component aging, and workpiece material characteristics [1]. In addition, with the continuous use of mechanical devices, their stability and accuracy will gradually reduce, which will inevitably affect the processing errors, and affect the subsequent process [2]–[4].

At present, many scholars have proposed various methods for error compensation, for example, Liu *et al.* [5] compensated the CNC machine tool by utilising the thermal error of the rotary feed axes. Bai *et al.* [6] analysed the research on compensating the error of the touch trigger probe in the testing of variable speed CNC machine tools. Zhao *et al.* [7] presented a geometric error model for CNC machine tools based on the Abbe principle, derives a model for compensating the geometric HTM error applicable to three-axis XYFZ machine tools, and states the prerequisites for the correct application of the model. Tan *et al.* [8] proposed a thermal error prediction method for CNC machine tools based on a cyclic LSTM neural network, and uses a clustering algorithm to build a neural network model. Patel [9] proposed a new optimum interval type-2 fuzzy fractional-order controller for a class of nonlinear systems. Patel and Shah [10] proposed type-2 fuzzy logic is used to design fuzzy inference system for dynamic parameter adaptation in metaheuristics, which can help in eliminating uncertainty and hence offers an attractive improvement in dynamic parameter adaption in metaheuristic method. Most of the above methods only focus on error compensation for an indicator of a specific device, with limited compensation effect and low reusability.

However, the Apriori algorithm can quickly find the correlation in a huge data set, and the artificial intelligence algorithm has its unique advantages for processing a large number of unstructured industrial big data, which can effectively compensate for the errors generated in the actual processing of products, and greatly improve the stability and accuracy of products [11]–[13]. For example, Amit and Rajneesh [14] proposed neural reinforcement learning classifier for elbow, finger, and hand movements. Kumar *et al.* [15] proposed recurrent neural network and reinforcement learning model for COVID-19 prediction. Vishnu *et al.* [16] proposed reinforcement learning-based energy management system for hybrid electric vehicles.

Therefore, based on the processing accuracy of CNC machine tools is affected by environmental factors and other factors. To compensate the processing accuracy of workpiece, the production data set provided by enterprises is used. Apriori algorithm is first used to analyse the correlation between data sets, and intelligent error compensation algorithm is used. Effectively compensate the error generated in the actual processing of the product, greatly improve the stability and accuracy of the product. Provide real-time, intelligent and accurate parameter compensation strategies for running lathes to ensure the stability of CNC machine tools.

2. Correlation Analysis

2.1 Association Rule Analysis

Association rules reflect the relevance between things [17], and can find the correlation between two or more data from the data set, that is, find the item set with high frequency from the data set, also known as frequent item sets. Association rules are widely used in data mining, and the specific concepts are as follows:

Definition 1. Known set $F = \{f_1, f_2, \ldots, f_k\}$. Each element in the set is called a data item, set F is called an item set, the data length in set F is called an item set length, and the item set containing k lengths is called a k-item set. The transaction database set is represented by D, and each sub transaction set is represented by T. Let D be the set of transaction T, $T \subseteq F$. Let M be the set of transaction F, if $M \subseteq T$, scale T contains M.

Definition 2. For $M{\subseteq}F$, $N{\subseteq}F$, and $M{\subseteq}F$, $N{\subseteq}F$, it means that there is an association rule between M and N. $M{\Rightarrow}N$, means M, N will appear in the same thing. M represents the first item set of association rules, N represents the next item set, and association rules represent that a transaction may contain M and N at the same time. Association rules have two important metrics, support and confidence.

Support is the percentage of transactions containing both M and N in D and all transactions. The formula is shown in (1):

$$\text{support}(M \Rightarrow N) = \frac{|\{T \ : \ M \cup N \subseteq T, T \in D\}|}{|D|} \tag{1}$$

Confidence is the ratio of the number of transactions containing M, N to the number of transactions containing M. The formula is shown in (2):

$$\text{confidence}(M \Rightarrow N) = \frac{|\{T \ : \ M \cup N, \ T \in D\}|}{|\{T \ : \ M \subseteq T, \ T \in D\}|} \tag{2}$$

Definition 3. To quantify and evaluate association rules, set min_sup and min_conf values, for item set M, if the support is not less than min_sup value, and the confidence is not less than min_conf value, then item set M is the frequent item set.

2.2 Analysis of Improved Apriori Algorithm

Apriori algorithm is the most classical algorithm for implementing association rules [18]. The principle is to search iteratively layer by layer. First, scan the data set to get a one-dimensional candidate set. Then, use the set minimum support to prune the one-dimensional candidate set to get a new frequent item set. After that, connect the frequent item set to a new two-dimensional candidate set. The Apriori algorithm searches for the k-item set through the $k{-}1$ item set, and repeats the pruning step and the connecting step until the maximum frequent item set is empty, ending the iteration process. The principles of the pruning step and the connecting step are as follows:

Connection step: the frequent item set C_k is obtained by connecting the $k{-}1$ item set L_{k-1} with itself. Record L_1 and L_2 as the first two item sets of L_{k-1}. Let $Li_{[j]}$ be the j the term of any subset. If the first k-2 terms of the two subsets are the same, that is, ($L1_{[1]} = L2_{[1]} \wedge L1_{[2]} = L2_{[2]} \wedge \ldots \wedge L1_{[k\text{-}2]} = L2_{[k\text{-}2]} \wedge \ L1_{[k\text{-}1]} < L2_{[k\text{-}1]}$), the result item set $\{L1_{[1]}, L2_{[2]}, \ldots, L1_{[k\text{-}1]}, L2_{[k\text{-}1]}\}$ is generated.

Pruning step: The superset C_k of the Apriori algorithm may or may not be frequent, but all frequent k-item sets must be in C_k. Therefore, prune all $(k{-}1)$ items in the k-item set C_k, delete all non-frequent $(k{-}1)$ item sets, and obtain L_k from the support.

The improved Apriori algorithm generates the k-item candidate set C_k from the $k{-}1$ frequent item set L_{k-1} through self-connection. When pruning, it judges whether the $k{-}1$ subset of a certain item set c in C_k is in L_{k-1}, and every item set in C_k is scanned once.

Finally, judge the count size of c. If the number of $k{-}1$ subsets containing c in L_{k-1} is greater than or equal to k, then delete item set c from C_k.

2.3 Analysis of Artificial Intelligence Algorithm

The artificial neural network model mainly considers the topological structure of network connection, characteristics of neurons, learning rules, *etc.* The neural network model

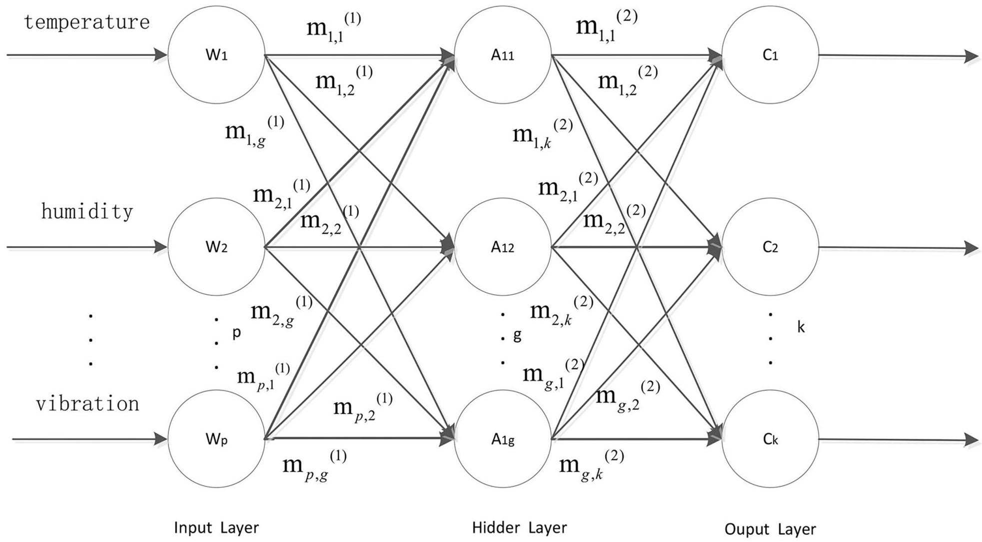

Figure 1. Fully connected neural network model.

consists of an input layer, a hidden layer, and an output layer. It contains different neurons [19], [20], each of which is also called a node. The input of each neuron can be the output of other neurons or the input of the whole neural network. For example, A_{11} in Fig. 1 is the output of W_1 and the input of C_1. The input of the neural network is the feature vector extracted from the entity. For example, if there are p inputs in Fig. 1, there are p feature vectors. In this paper, 18 feature vectors are used, including temperature, humidity, vibration, *etc.* Each neuron has its own parameters. In Fig. 1, the superscript of m represents the number of neural network layers, $m^{(1)}$ represents the parameters of nodes in the first layer, and $m^{(2)}$ represents the parameters of nodes in the second layer. The subscript of m represents the number of connecting nodes. For example, $m_{1,1}^{(1)}$ represents the weight on the edge connecting nodes W_1 and A_{11}.

The training of neural network is to adjust the number of hidden layers and the weight of each layer. The value of output layer node is the weighted sum of each layer. For example, A_{11} and C_1 values in Fig. 1 are shown in (3) and (4), respectively:

$$A_{11} = W_1 \times {m_{1,1}}^{(1)} + W_2 \times {m_{2,1}}^{(1)} + \cdots + W_p \times {m_{p,1}}^{(1)} \tag{3}$$

$$C_1 = A_{11} \times {m_{1,1}}^{(2)} + A_{12} \times {m_{2,1}}^{(2)} + \cdots + A_{1,g} \times {m_{g,1}}^{(2)} \tag{4}$$

Similarly, the values of $A_{12} \ldots A_{1g}$ and $C_{2.} \ldots C_k$ can be calculated, as shown in (5) and (6):

$$\begin{aligned}&[A_{11}, A_{12} \cdots A_{1,g}] \\ &= [W_1, W_2 \cdots W_p] \begin{bmatrix} {m_{1,1}}^{(1)} & {m_{1,2}}^{(1)} & \cdots & {m_{1,g}}^{(1)} \\ {m_{2,1}}^{(1)} & {m_{2,2}}^{(1)} & \cdots & {m_{2,g}}^{(1)} \\ \vdots & \vdots & \vdots & \vdots \\ {m_{p,1}}^{(1)} & {m_{p,2}}^{(1)} & \cdots & {m_{p,g}}^{(1)} \end{bmatrix}\end{aligned} \tag{5}$$

$$\begin{aligned}&[C_1, C_2 \cdots C_k] \\ &= [A_{11}, A_{12} \cdots A_{1g}] \begin{bmatrix} {m_{1,1}}^{(2)} & {m_{1,2}}^{(2)} & \cdots & {m_{1,k}}^{(2)} \\ {m_{2,1}}^{(2)} & {m_{2,2}}^{(2)} & \cdots & {m_{2,k}}^{(2)} \\ \vdots & \vdots & \vdots & \vdots \\ {m_{g,1}}^{(2)} & {m_{g,2}}^{(2)} & \cdots & {m_{g,k}}^{(2)} \end{bmatrix}\end{aligned} \tag{6}$$

3. Error Compensation Model

This error compensation model can be divided into two parts. The first part is the intelligent error compensation module. Due to the large difference between the eigenvalues in the data set, the data set is first normalised form 0-1 it falls within a specific range, to eliminate the deviation of the mining effect caused by the different values, so as to improve the speed of data convergence and find the global optimal solution. Then, the data provided by the manufacturer is filtered using the Apriori algorithm to obtain a more targeted data set. After that, the parameters are adjusted by the neural network method, and the corresponding intelligent error compensation model is built by constantly updating the parameters of the neural network model; finally, the trained error compensation algorithm model is deployed to the cloud platform for processing error accuracy compensation, thus reducing machine tool processing error.

The second part is the visual recognition module. First upload the qualified and unqualified sample images to the cloud platform as training data; then scale the image to the appropriate size to obtain high-quality image data; then use the neural network method to train the selected images, so that the computer masters the ability to distinguish whether the workpiece is qualified or not; finally, deploy the trained model to the cloud platform to check whether the artefacts are qualified.

The workpieces generated by the error compensation model are identified as qualified or unqualified workpieces

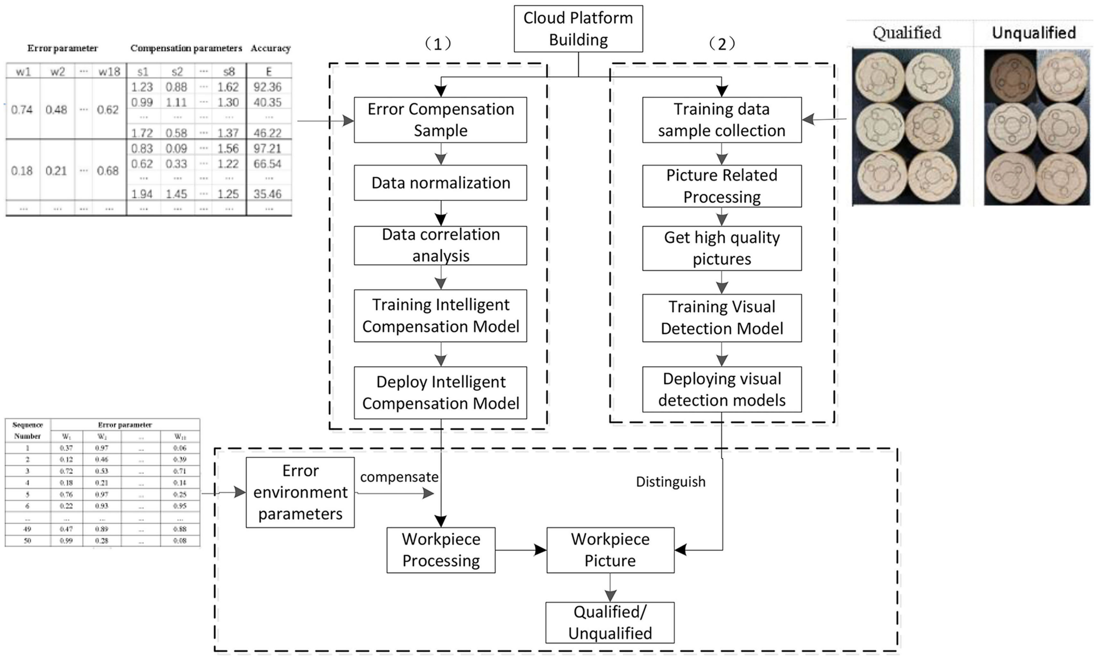

Figure 2. Overall system design.

by the visual inspection module. If there are too many unqualified workpieces, the error compensation algorithm will be readjusted.

The overall design of the system is shown in Fig. 2.

4. Algorithm Implementation

4.1 Implementation of Association Rules Based on Improved Apriori Algorithm

In the adjustment file provided by an enterprise, the same w_1, $w_2 ... w_{18}$ characteristic values will correspond to different c_1, $c_2 ... c_8$ compensation parameters, as shown in Fig. 3.

In addition, the number of occurrences of each compensation parameter value in c_1, c_2, and c_8 is different. For example, 1.842 occurs in c_1, c_2, and c_8 for 13, 3, 2, 1, 1, 0, 11, and 6 times, respectively. When 1.842 occurs 13 and 11 times, the score value is greater than or equal to 90. When 1.842 occurs less than 11 times, the score value is less than 90.

Therefore, using the association rules in 2.1 and the Apriori algorithm in 2.2, by setting the minimum support, for 1.842 as the c_1, $c_2 ... c_8$ compensation parameters, the c_1 and c_7 columns are relevant. These two columns are reserved for 1.842, and the remaining columns are deleted for 1.842. In the same way, the association rules and Apriori algorithm are used to find out the correlation between the rest of the compensation data in c_1, $c_2 ... c_8$, so as to obtain a more targeted data set.

The core code of the improved Apriori algorithm is as follows:

Input: DataBase of an enterprise's workpiece production transaction database. Minimum support threshold min_sup.

Output: Maximum frequent item set L in DataBase.

(1) $L_1 = \text{find\_frequent\_1} - \text{itemsets(DataBase)}$
(2) $\text{for}(k = 2; L_{k-1} \neq f; k++)$
(3) $C_k = \text{apriori\_gen}(L_{k-1}, min\_sup)$
(4) for each transaction $\text{t} \in \text{DataBase}$ do{
(5) $C_t = \text{subset}(C_k, t)$;
(6) for each candidate $\text{c} \in C_t$
(7) c.count $++$; }
(8) $L_k = \{c \in C_k | c.\text{count} >= \text{min\_sup}\}$
(9) $\text{return} L = U_k L_k$;

L is the frequent item set, C is the candidate item set, Apriori_gen is the process of generating candidate set C_k from frequent item set L_{k-1}.

4.2 Implementation of Error Compensation Algorithm Based on Artificial Intelligence

According to the relevant file adjust ment.csv provided by an enterprise, the error compensation algorithm is trained and deployed using the Section 2.3 neural network algorithm, so that the NC system has the automatic error compensation function, which can effectively improve the production qualification rate of the workpiece in the actual processing. There are 9,999 pieces of data in the adjustment.csv file, some of which are shown in Fig. 4.

In the Fig. 4, $w1$, $w2 \ldots w18$, respectively, represent external influence factors, such as tool wear, temperature, humidity, *etc.*, $c1$, $c2 \ldots c8$ are external compensation parameters, and the score value is the qualification criteria of the workpiece. If the score is greater than or equal to 90 points, the workpiece is qualified; if the score is less than 90 points, the workpiece is unqualified.

The specific implementation steps of intelligent error compensation algorithm are as follows:

Step 1: Data cleaning. Numerically controlled machine tool processing will produce many problematic

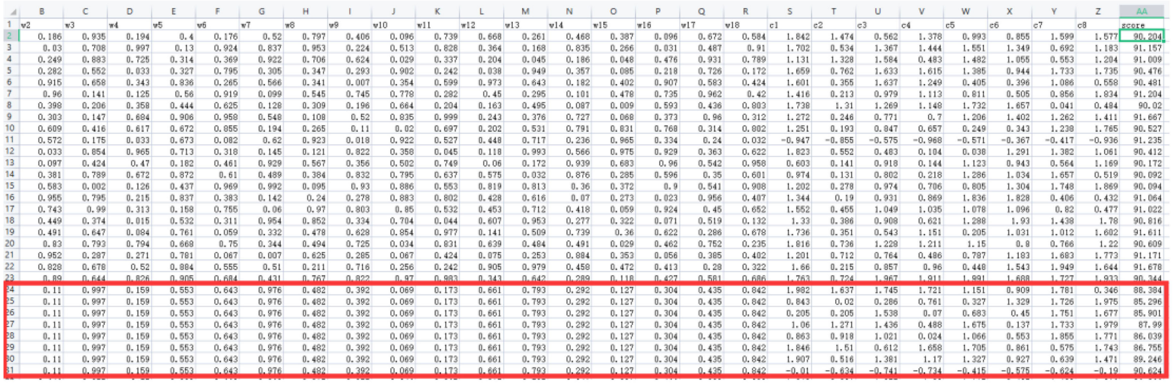

Figure 3. Different compensation parameters with the same characteristic value result in different results.

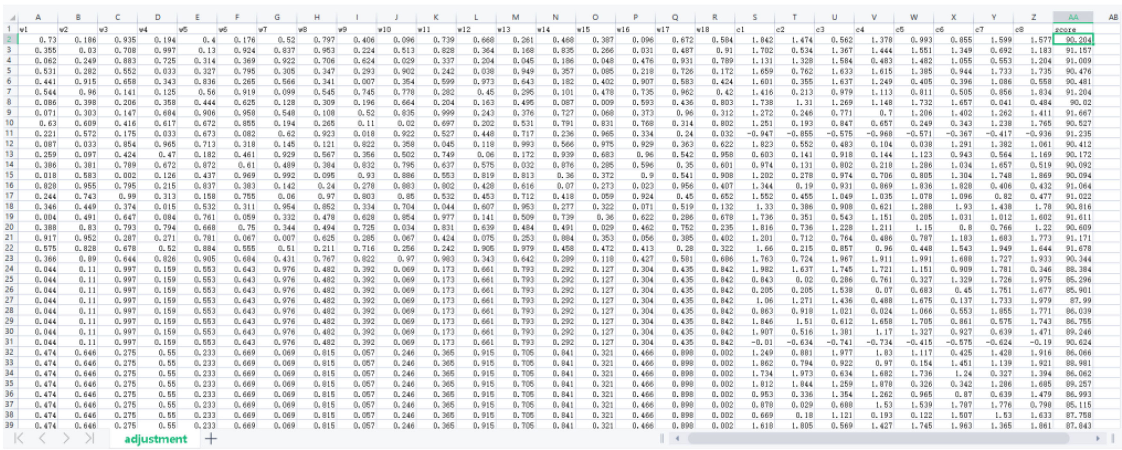

Figure 4. Some data in the adjustment file.

data, such as incomplete data, noise data, and redundant data. These dirty data will have a great impact on data analysis. The data set used in this paper, w_1, $w_2 \ldots w_{18}$ has many null values, that is, null values. Therefore, for these incomplete values, the mean value is used instead, and the mean value is expressed as average, as shown in (7):

$$\text{average} = (w_1 + w_2 + w_3 \ldots + w_{18})/18 \tag{7}$$

Step 2: Data normalisation. Data in neural networks often have different dimensions. To eliminate the impact of different dimensions of data, it is necessary to normalise the data to settle it in a specific interval. Data normalisation can improve the convergence speed and help to find the global optimal solution. Common data normalisation methods include maximum–minimum standardisation, 0-1 standardisation, and zero-mean standardisation. Since the first step uses the mean value to fill in the null value, this paper uses 0-1 standardisation, where s_2 represents the variance, s represents the standard deviation, and x^* represents the normalised data, as shown in (8) and (9):

$$s^{\,2} = [(w_1 - \text{average})^2 + (w_2 - \text{average})^2 + \ldots + (w_{18} - \text{average})^2]/18 \tag{8}$$

$$x* = [(w_1 + w_2 + w_3 \ldots + w_{18}) - \text{average}]/s \tag{9}$$

Step 3: Error compensation algorithm model training. The Section 2.3 neural network model is used to construct the neural network error compensation algorithm model. There are 18 nodes in the model input layer, which are the eigenvalues w_1, $w_2 \ldots w_{18}$; there are eight nodes in the output layer, which correspond to c_1, $c_2 \ldots c_8$, respectively. The optimal model is obtained by continuously updating the network parameters using the tf. keras. Sequential function of TensorFlow in pychar. The pseudocode of error compensation algorithm model is as follows:

model = tf. keras. Sequential {[

layers. Dense (512, input_dim = train_features.shape [1], activation = “relu”),

layers. Dense (512, activation = “relu”),

layers. Dense (512, activation = “relu”),

layers. Dense (train_labels.shape [1])]}

model. compile (optimiser = tf. keras. optimisers. SGD (learning_rate = lr, momentum = 0.9, loss = “mse”, nesterov = True, clipvalue = 0.5, decay = lr/epochs_number), metrics = [’acc’])

Step 4: Error compensation algorithm model training deployment. Deploy the trained error compensation algorithm model to the cloud platform for processing error accuracy compensation, thus reducing machine tool processing error.

4.3 Realisation of Vision Detection Algorithm Based on Neural Network

Conduct workpiece training through industrial vision, collect qualified and unqualified samples, carry out data preprocessing and cloud platform storage, and use the neural network algorithm in Section 2.3 to conduct model training and deployment by setting corresponding parameters. The trained model can return the similarity between the workpieces to be tested and the standard parts, so that the equipment has the function of identifying qualified and unqualified workpieces.

The specific implementation steps of visual detection algorithm are as follows:

Step 1: Data collection. Use the vision system to collect several workpiece image data and determine the workpiece sample image database.

Step 2: Data preprocessing. Conduct relevant processing on the images and select high-quality images for training.

Step 3: Visual inspection model training. Call the tf. keras. Sequential function of TensorFlow in Pycharm, and obtain the optimal model by constantly updating the network parameters. The pseudocode of visual detection model is as follows:

```
Model = tf. keras. Sequential {[
layers. experimental. preprocessing. Rescaling (1./127.5,offset = -1),
layers. MaxPooling2D (),
layers. Conv2D (64, 3, activation = ‘relu’),
layers. MaxPooling2D (),
layers. Conv2D (128, 3, activation = ‘relu’),
layers. MaxPooling2D (),
layers. Conv2D (256, 3, activation = ‘relu’),
layers. Conv2D (512, 3, activation = ‘relu’),
layers. MaxPooling2D (),
layers. Flatten (),
layers. Dense (128, activation = ‘relu’),
layers. Dense (num_classes), ]}
model. compile (optimiser = ‘adam’,
loss = ‘sigmoid’, metrics = [‘accuracy’])
```

Activation = ‘relu’ is the activation function of the neural network, loss = ‘sigmoid’ is the loss function, and optimiser = ‘adam’ is the selector.

Step 4: Visual inspection model deployment. Deploy the trained visual inspection model to the cloud platform to identify qualified and unqualified artefacts.

5. Result Test

5.1 Error Compensation Model Simulation Test

By adjusting the neural network model structure and various parameters, the optimal solution of the model can be found. Tested by simulation. The Fig. 5 shows that if no data is processed, the accuracy of the training set and test set will set increases with increasing training time, while the maximum accuracy of the training set and test set is only 0.275 and 0.247, respectively. When the data set is correlated and normalised, using the trained intelligent error compensation algorithm that is mentioned in Section 4.2, The Fig. 6 shows that the maximum accuracy of the training set and the test set can reach 0.97 and 0.96, respectively, and the accuracy is 0.695 and 0.713 higher than before. Where train stands for the data of the training set, test for the data of the test set, and the ordinate for the accuracy. The higher the accuracy, the better the stability; the abscissa is the number of model trainings.

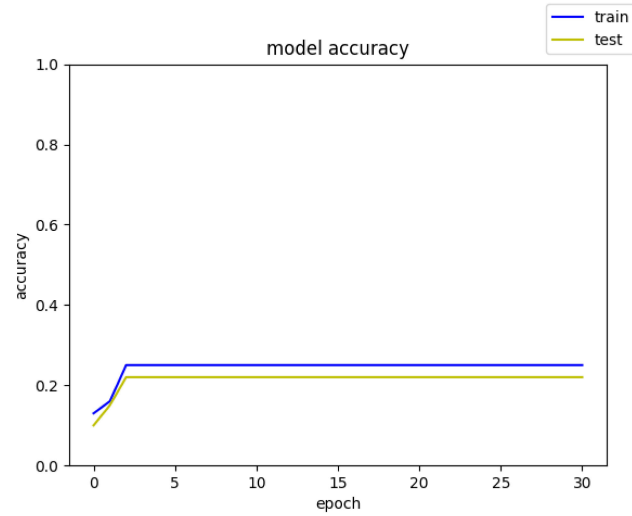

Figure 5. Data set is not processed.

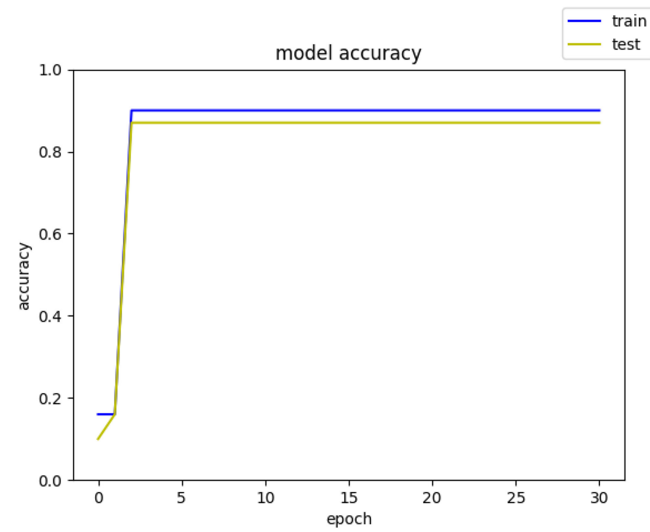

Figure 6. Result after processed the data set.

From this, on the one hand, by using the Apriori algorithm to mine the data correlations and normalise the data, a more effective data set can be obtained and the convergence of data can be increased. On the other hand, by adjusting the parameters of accuracy, loss function, learning rate, precision, and recall of the neural network, the optimal intelligent error compensation model is found for the lathe under different situations,

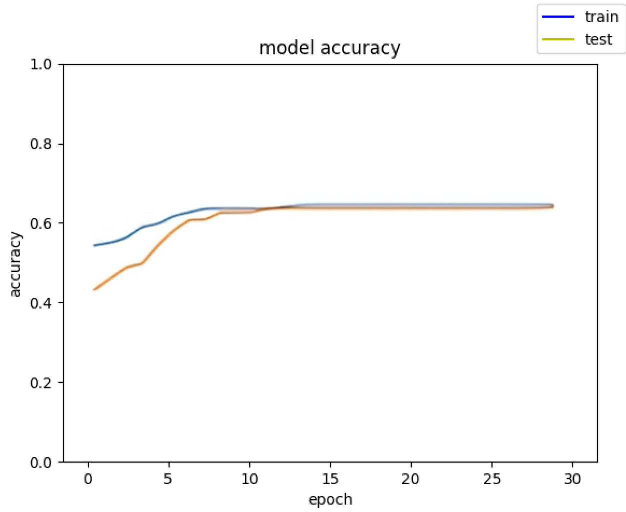

Figure 7. Picture not processed.

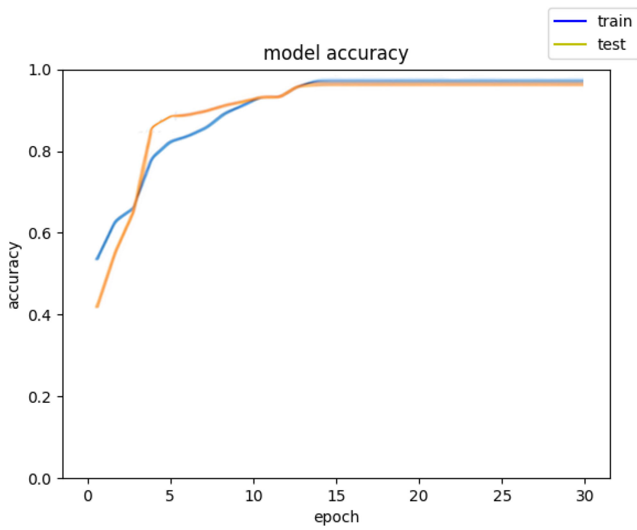

Figure 8. Picture related processed.

thereby improving the stability of workpiece machining accuracy.

5.2 Visual Inspection Model Simulation Test

The visual inspection algorithm is used to identify whether the workpiece is qualified or not after the error compensation, and the training of the visual algorithm needs to collect a large number of qualified and unqualified sample data sets. In the process of data collection, if no processing is done to the collected images, directly call the tf. keras. Sequential function of TensorFlow in Pycharm, and continuously update network parameters, with the increase of model training times, the accuracy of training data set and test data set can reach up to 0.65 and 0.635, as shown in Fig. 7. If relevant image processing is carried out and parameters of the visual detection algorithm in Section 4.3 are adjusted, the accuracy of the training set and test set data can reach

Figure 9. Material processing tank.

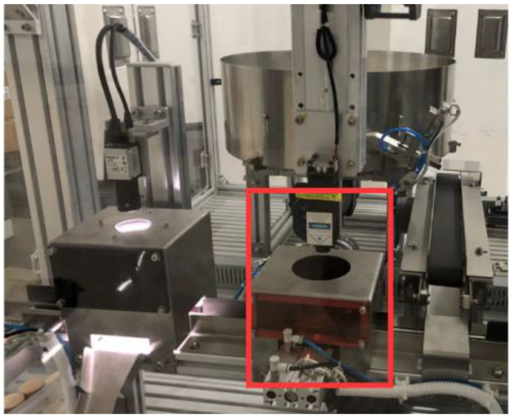

Figure 10. Material carving.

0.99 and 0.91, respectively, which is 0.34 and 0.275 higher than before, as shown in Fig. 8. It can be seen that the neural network vision detection algorithm can effectively identify qualified processing and unqualified processing.

5.3 Actual Test

Prepare 30 materials for actual processing. The material processing slot is shown in Fig. 9. The materials are transported to the carving table *via* the conveyor belt and carved one by one. The processing of the material is shown in Fig. 10. During the carving process, the cloud platform uses the intelligent error compensation algorithm to compensate for the accuracy of processing errors, to improve the product qualification rate. After the carving is completed, the visual inspection and calculation method is used to verify whether the workpiece image is qualified. The final result shows that 30 carving materials are qualified, with a qualification rate of 100%, as shown in Fig. 11.

6. Conclusion

To solve the problem of stability of machining accuracy of CNC machine tools, an intelligent model based on Apriori algorithm and neural network is proposed. To

Figure 11. Material qualification verification.

improve the validity of the data, the Apriori algorithm is used for data association mining. To solve the problem that the machining accuracy is affected by the machine parts, external environment, and other factors in the actual machining, an intelligent error compensation model is established using a neural network, which provides an instant, intelligent and accurate compensation scheme. To verify the influence of error compensation model on the stability of CNC machine tools, the neural network is used to build a visual inspection model that identifies the machined products, judges whether they are qualified, and counts the qualified rate. The simulation results show that the error compensation model established in this paper can increase the accuracy of training set and test set to 0.97 and 0.96, respectively, and the visual recognition model established in this paper can effectively identify test set data and training set data, with the accuracy of 0.99 and 0.91, respectively. The experimental results show that all products meet the accuracy requirements, and the above models can solve the stability problem in NC machining. For further research, we can consider adding clustering algorithm, combining neural network training data set, and introducing a larger data set for experimental testing to analyse its stability.

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References

[1] J. He, Z.L. Guo, S.B. Luo, *et al.*, Ultra-precision machining technology of off-axis paraboloid surface based on PMAC time-based control, *Optics and Precision Engineering, 29*(8), 2021, 7–8.

[2] D. Lv, J.H. Zhang, D.W. Wang, *et al.*, Technical status and countermeasures of dynamic accuracy of domestic CNC machine tools, *Aeronautical Manufacturing Technology, 65*(6), 2022, 22–33.

[3] H. Zhao, X. Zhou, and S.T. Zhang, Local optimization of five-axis machining tool orientation based on angular acceleration of machine tool, *Machine Tool & Hydraulics, 50*(11), 2022, 94–97.

[4] X. Feng, H. Mao, Z. Xin, *et al.*, Study on engineering application of servo control system in giant friction welding machines, *Mechatronic Systems and Control,* (3), 2023, 122–132.

[5] K. Liu, W. Han, Y.Q. Wang, H. Liu, and L. Song, Review on thermal error compensation for feed axes of CNC machine tools, *Journal of Mechanical Engineering, 57*(3), 2021, 156–173.

[6] K. Bai, Z. Li, and L.H. Wu, Triggered probe error speed compensation in on-machine measurement of machine tool, *Modular Machine Tool & Automatic Manufacturing Technique, 2*(22), 2021, 91–98.

[7] Z. Zhao, Z.F. Lou, Z.N. Zhang, *et al.*, Geometric error model of CNC machine tools based on Abbe principle, *Optics and Precision Engineering, 28*(4), 2020, 885–897.

[8] F. Tan, C.N. Li, H. Xiao, Z.Q. Su, and K.A. Zhen, A thermal error prediction method for CNC machine tool based on LSTM recurrent neural network, *Chinese Journal of Scientific Instrument, 41*(9), 2020, 79–87.

[9] H.R. Patel, Fuzzy-based metaheuristic algorithm for optimization of fuzzy controller: fault-tolerant control application, *International Journal of Intelligent Computing and Cybernetics, 15*(4), 2022, 599–624.

[10] H.R. Patel and V.A. Shah, Type-2 fuzzy logic applications designed for active parameter adaptation in metaheuristic algorithm for fuzzy fault-tolerant controller, *International Journal of Intelligent Computing and Cybernetics, 16*(2), 2023, 198–222.

[11] A. Kumar, Reinforcement learning: Application and advances towards stable control strategies, *Mechatronic Systems and Control,* (1), 2023, 53–57.

[12] A. Kukker and R. Sharma, Stochastic genetic algorithm-assisted fuzzy q-learning for robotic manipulators, *Arabian Journal for Science and Engineering, 46*, 2021, 9527–9539.

[13] A.K. Yadav, V. Kumar, A.S, Pandey, *et al.*, Wind farm integrated fuzzy logic-based facts controlled power system stability analysis, *Mechatronic Systems and Control,* (4), 2023, 172–181.

[14] K. Amit and S. Rajneesh, Neural reinforcement learning classifier for elbow, finger and hand movements, *Journal of Intelligent and Fuzzy Systems, 35*, 2018, 1–11.

[15] R.L. Kumar, F. Khan, S. Din, *et al.*, Recurrent neural network and reinforcement learning model for COVID-19 prediction, *Frontiers in Public Health, 9*, 2021, 744100.

[16] N.A. Vishnu, M.L.G. Rubell, and P. Gopakumar, Reinforcement learning based energy management system for hybrid electric vehicles, *Proc. 2023 3rd International Conf. on Advances in Computing, Communication, Embedded and Secure Systems (ACCESS),* Kalady, 2024-03-16, DOI: 10.1109/ACCESS57397.2023.10200701.

[17] K.N. Fang and B.C. Xie, Research on dealing with missing data based on clustering and association rule, *Statistical Research, 28*(2), 2011, 87–92.

[18] M.W. Tian, L. Zhang, P. Guo, H. Zhang, Q. Chen, Y. Lei, and A. Xue, Data dependence analysis for defects data of relay protection devices based on Apriori algorithm, *IEEE Access, 8*, 2020, 120647–120653.

[19] B.A. Khuwaileh, M. Al-Shabi, and M. Assad, Artificial neural network based particle swarm optimization solution approach for the inverse depletion of used nuclear fuel, *Annals of Nuclear Energy, 4*(22), 2021, 108–116.

[20] Z. Shi, W. Zheng, and W. Yin, Improving the reliability of the prediction of terrestrial water storage in Yunnan using the artificial neural network selective joint prediction model, *IEEE Access, 1*(12), 2021, 305–311.

Biographies

Jun Guo was born in Hunan, China, in 1992. He received the bachelor's degree in communication engineering from Jinggangshan University in June 2015, and the master's degree in electronic and communication engineering from Nanchang Hangkong University in June 2018. Since July 2018, he has been affiliated with Hunan Automotive Engineering Vocational College. His research interests include artificial intelligence and big data.

Lei Xiang was born in Hunan, China, in 1982. He received the bachelor's degree in computer science and technology from Xiangtan University in June 2006, and the master's degree in engineering from Huazhong University of Science and Technology in December 2010. Since July 2006, he has been with Hunan Automotive Engineering Vocational College, where his research interests include information security and big data.

Ying Wang was born in Taojiang, Hunan Province, China, in 1975. He received the Ph.D. degree in land resources information engineering from Central South University, Changsha, China, in 2009. Since 2019, he has been a Professor with Hunan Automotive Engineering Vocational University, Zhuzhou, China, where he also serves as the Director of the Joint Laboratory for High-Precision Positioning of Beidou and Intelligent Connected Vehicles. His research interests encompass intelligent driving, geographic information systems (GIS) and high-precision mapping, computer graphics, and digital image processing.