Building a Machining Knowledge Base for Intelligent Machine Tools

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Abstract: - Intelligent machines respond to external environments on the basis of decisions that are made by sensing the changes in the environment and analyzing the obtained information. This study focuses on the construction of a knowledge base which enables decision making with that information. Approximately 70% of all errors that occur in machine tools are caused by thermal errors. In order to proactively deal with these errors, a system which measures the temperatures of each part and predicts and compensates the displacement of each spindle has been developed. The system was built in an open type controller to enable machine tools to measure temperature changes and compensate the displacement. The construction of a machining knowledge base is important for the implementation of intelligent machine tools, and is expected to be applicable to the network-based, intelligent machine tools which look set to appear sooner or later.

Key-Words: Machining Knowledge Base, Intelligent Machine Tools, Thermal errors, Offset compensation, Open controller, Multiple linear regression models, Neural Network

1 Introduction

The most recent trend in machine tool development involves intelligent machines that can actively recognize environmental changes, make judgments, and respond to the changes. Intelligent machine tools incorporate a sensing or monitoring function which senses outside environmental changes, a knowledge processing function which makes judgments with the obtained information, and an action implementing part which responds to the environmental changes on the based of a judgment [1]. While the expert systems are being studied in order to implement a knowledge processor, most of the systems are operated an off-line basis, resulting in slow knowledge information processing and various problems in the interfacing with the controllers of machine tools.

To solve such problems, many studies are being conducted on intelligent machine tools which have PC-NC, which is an open controller based on PC, for implementation with the various software developed for intelligence and connected with the open controller.

In this study, a knowledge base was constructed with the machining information used in machine tools and adopted to actual machine tools to implement intelligent machine tools.

2 Building a Knowledge Base

Many studies are being conducted on distributed control and autonomous intelligent machines with the aim of implementing an efficient system structure. To this end, human action is a good example for the structural analysis [2, 5].

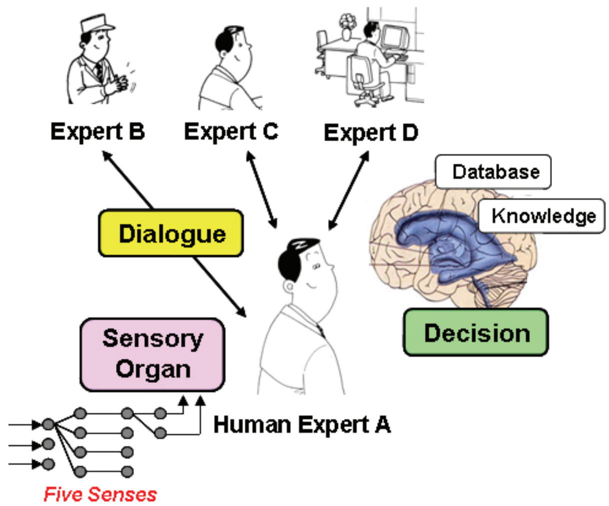

Fig. 1 Process of intelligence of human expert

As shown in Fig. 1, external environments are recognized by the senses and the information is sent to the brain through the nerves; the brain then makes decisions on the basis of the obtained information. The decision making process depends on the knowledge accumulated in the brain, which responds to the external environment in accordance with the decision made.

The knowledge processor, which is the brain of a machine tool, builds a knowledge base with the information required for machining in order to make decisions that respond to the status data taken from the sensors [1]. Fig. 2 shows the structure of a knowledge base in an intelligent machine tool. It is based on the rule basis, having functions which are implemented independently or dependently. Partial knowledge in each part can be used by integration [6].

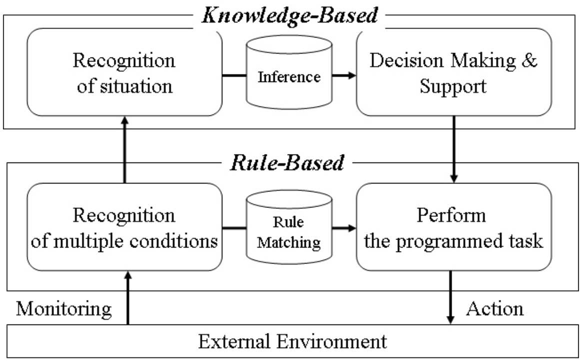

Fig. 2 Structure of a knowledge base

The methods of utilizing the built-up knowledge base efficiently can be classified by the bottom-up and top-down approaches. The top-down approach, which is also known as 'divide and conquer', consists of dividing a problem into sub-problems and then solving them, in order to solve the parent problem. The knowledge for solving problems can be classified into four categories: equations; rules; decision making; and experience data, as shown in Figure 3 [3].

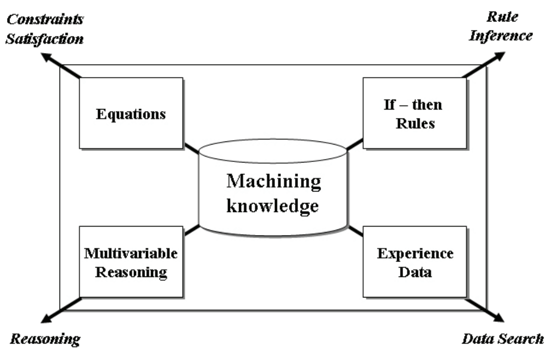

Fig. 3 Classification of four categories on knowledge base

As for the methodologies for utilizing the knowledge in such categories, there are the following constraints: satisfaction, rule inference, reasoning, and data search.

A variety of machining information is present in the machine tools. Various information types, including high-speed machining techniques such as machining conditions, the automatic decision of the tool path which can be applied commonly to all machine tools, and operation techniques such as status monitoring, fault cause analysis and compensation of thermal errors, are used by specific devices.

The thermal errors account for approximately 70% of all the errors that arise in machine tools [4]. In this study, a prediction model capable of compensating the thermal error to minimize it was developed and implemented in the knowledge base in equation form.

To build a thermal displacement prediction model, experiments were conducted on thermal displacement, and the temperature and displacement were recorded. The prediction model provides the displacement values in 3-axes, with the input of the temperature values at the 4 measurement points. Multiple linear regression analysis and neural network analysis methods were used for the model.

The multiple linear regression method is used for prediction and analysis through the model estimation by building a mathematical model which represents the relations between the variables, and then entering the observed values of the variables into the model. To this end, 3 linear regression equations are required, as shown in Fig. 4, because 4 independent variables including X, Y, Z, and the atmosphere to explain the relations among the 1 response variable and several explanatory variables, and the 3 displacements in the x, y, and z axes are produced.

$$Y_1 = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4$$
$$Y_2 = \beta_5 + \beta_6 X_1 + \beta_7 X_2 + \beta_8 X_3 + \beta_9 X_4$$
$$Y_3 = \beta_{10} + \beta_{11} X_1 + \beta_{12} X_2 + \beta_{13} X_3 + \beta_{14} X_4$$

Y_1: X axis displacement, Y_2: Y axis displacement, Y_3: Z axis displacement
X_1: X axis temperature, X_2: Y axis temperature, X_3: Z axis temperature
X_4: atmosphere temperature, $\beta_{0\text{-}14}$: regression constant

Fig. 4 Equations of regression model

While various prediction models utilize neural networks, including the Hopfield neural network, multi-layer percept theory, competitive learning neural network, self-organizing neural network, adaptive resonance theory neural network, a neural network using a multi-layer percept theory was established to build the prediction model for thermal displacement. The multi-layer percept theory model, which is suitable for pattern recognition and function approximation, has one or more hidden layers between the input and output layers, as shown in Fig. 5. The learning algorithm is the error back propagation method which adjusts the weight(s) of the hidden layer(s) and the output layer. This method minimizes error - on the basis of the said adjustment - by varying the weights of the input layer and the hidden layer(s).

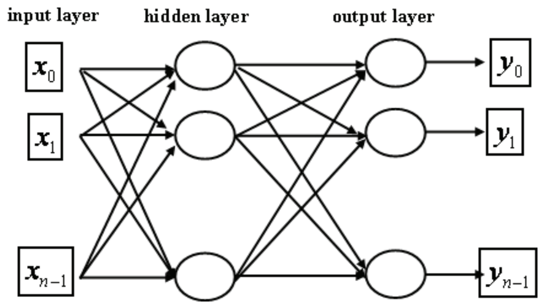

Fig.5 Multi layer percept theory of Neural Network

3 Implementation

The 2 prediction models described above were constructed in the knowledge base in order to compensate the thermal errors. The knowledge base basically controls the rule and is programmed using JAVA.

The open-type controller technology has solved various problems in the closed-type controller. The open-type controller enables the addition of appropriate NC functions as required, and is not restricted to the NC functions provided by the NC developers. It maximizes user convenience in conjunction with other application programs and can increase work efficiency.

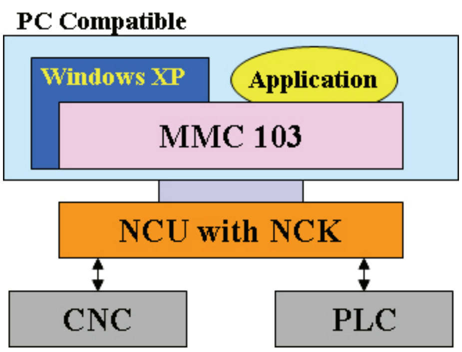

Fig. 6 Software structure of the open controller

Fig. 6 shows the software structure of the open-type controller used in this study. The NC Kernel can send the commands created in the application by MMC (Man Machine Control) to the CNC and PLC. The knowledge base, including the developed prediction model, can be installed in the application area too.

The accuracy of the developed prediction model was tested with a '3-axes milling machine' installed with an open-type controller. Thermocouples were installed in order to measure the temperature. A gap sensor of the eddy current type was installed for comparison with the actual displacement. The thermal displacement test complied with the ISO/DIS 230-3, BS3800 : part3 : 1900 and ASME B5.54-1992 specifications.

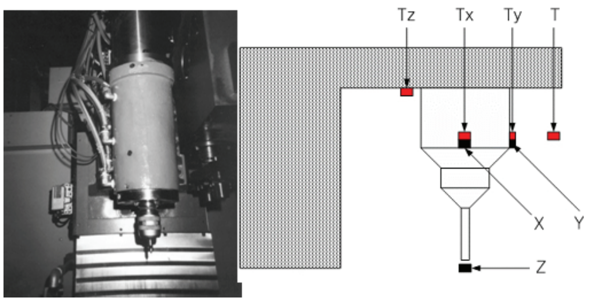

Fig. 7 Test environment at creating thermal errors

As shown in Fig. 7, for the test environment aimed at creating the thermal displacement prediction model, the temperature changes that occurred during the operation of the machining center were measured using the isolated thermocouple input modules installed around the vertical machining center. The temperature was measured at least once every 10 minutes. The measurement data have to be obtained for at least 4 to 6 hours in order to secure reliability. In this test, the thermal displacement was measured, together with the temperature changes, with a gap sensor in the operational range of 4000 to 6000 rpm (which is the most common working range in vertical machining centers) without a load. The measurements were obtained for application to the actual operational conditions of the machine tool.

Through the test, it was analyzed that the thermal displacement in a vertical machining center was larger in the z and y axes than that in the x-axis. Fig. 8 shows the comparison of z axis between the actual displacement value and that predicted value by the linear regression model and the neural network model. Neural network model is learned 50000 times. It was analyzed that the neural network model has better accuracy than the regression analysis model; however, the linear regression model was used for the operation of the actual open-type controller because it is a simple.

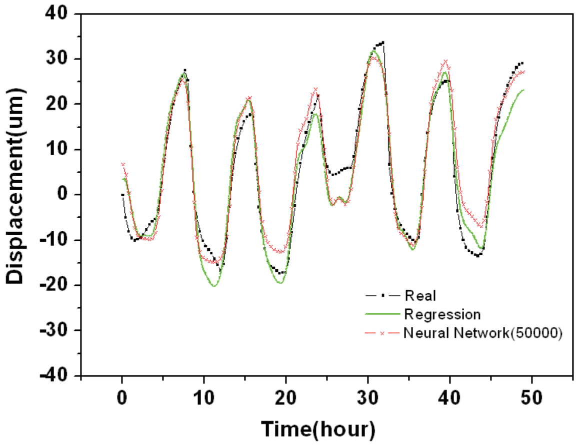

Fig. 8 Comparison between actual value and predicted value using model

Using the model equation thus analyzed, the compensation value was estimated in the computation rule form in the rule base.

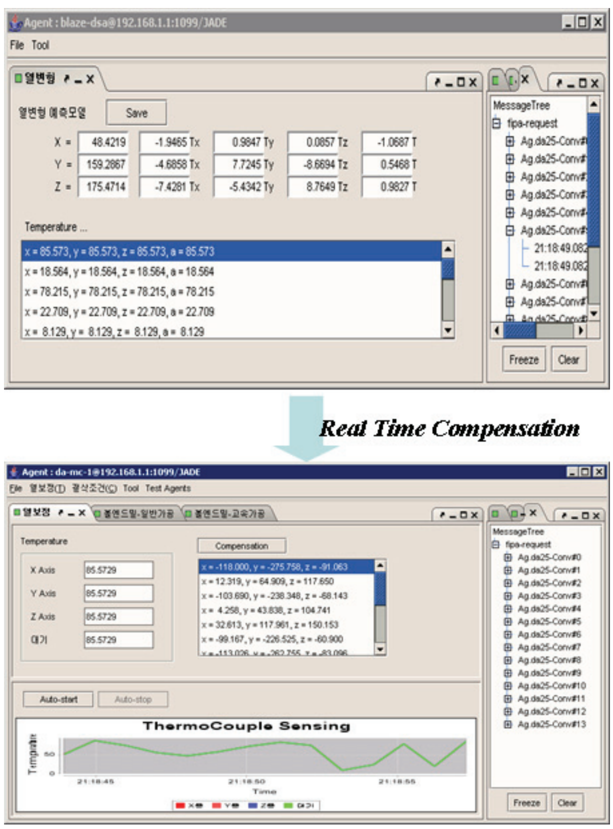

Fig. 9 Real time compensation using regression model

Fig. 9 shows that, the change of prediction model was enabled on a real-time simply based by changing the constants which are entered into the prediction model, when the prediction model is to be changed during the operation or in accordance with the environment. With this method, the open controller can carry out the compensation by calculating the displacement of the machine with the temperature data obtained on a real-time.

The available compensation methods are NC code correction command, analog compensation, which inserts the analog voltage to the position feedback signal of the servo system, digital compensation, which compensates the position values of the servo system by transmitting digital values to the open controller via a communication port, and the offset compensation. The offset value compensation is the easiest method for operators. Fig. 10 shows a window of the automatic compensation of the offset value in an open controller.

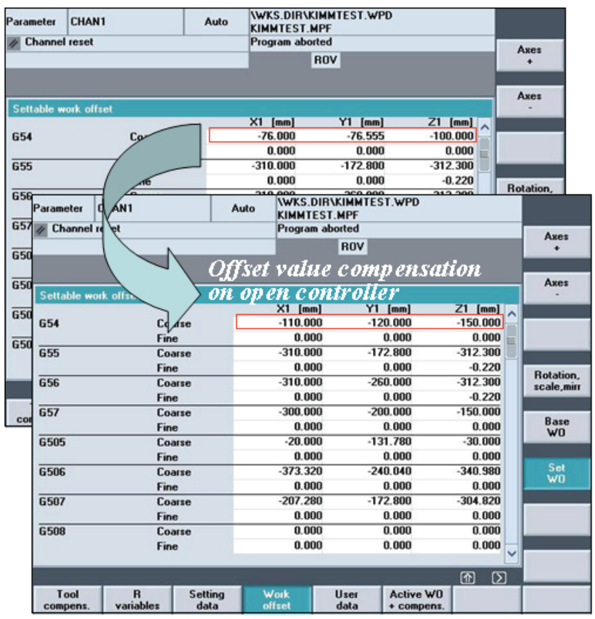

Fig. 10 Offset values compensation on open controller

4 Conclusion

This study was aimed at building a machining knowledge base for the implementation of intelligent machine tools. Two prediction models of compensation for thermal errors were constructed through thermal displacement tests to compensate the thermal error, which represents the largest error in machining tools, on a real-time. A linear regression analysis model and a neural network model were constructed, and a regression analysis model, which is easily applied in open controllers, was constructed as the knowledge base for thermal error compensation through the analysis and comparison with the actual displacement, and the thermal displacement error was compensated through the compensation of the offset value on open controller. Further studies will be conducted to build an infrastructure for the implementation of intelligent machine tools by constructing a knowledge base containing more machining information.

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