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Thermal error modelling of machine tools based on ANFIS with fuzzy c-means clustering using a thermal imaging camera

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ABSTRACT

Thermal errors are often quoted as being the largest contributor to CNC machine tool errors, but they can be effectively reduced using error compensation. The performance of a thermal error compensation system depends on the accuracy and robustness of the thermal error model and the quality of the inputs to the model. The location of temperature measurement must provide a representative measurement of the change in temperature that will affect the machine structure. The number of sensors and their locations are not always intuitive and the time required to identify the optimal locations is often prohibitive, resulting in compromise and poor results.

In this paper, a new intelligent compensation system for reducing thermal errors of machine tools using data obtained from a thermal imaging camera is introduced. Different groups of key temperature points were identified from thermal images using a novel schema based on a Grey model GM (0,N) and fuzzy c-means (FCM) clustering method. An Adaptive Neuro-Fuzzy Inference System with fuzzy c-means clustering (FCM-ANFIS) was employed to design the thermal prediction model. In order to optimise the approach, a parametric study was carried out by changing the number of inputs and number of membership functions to the FCM-ANFIS model, and comparing the relative robustness of the designs. According to the results, the FCM-ANFIS model with four inputs and six membership functions achieves the best performance in terms of the accuracy of its predictive ability. The residual value of the model is smaller than ±2 μm, which represents a 95% reduction in the thermally-induced error on the machine. Finally, the proposed method is shown to compare favourably against an Artificial Neural Network (ANN) model.

1. Introduction

Thermal errors can have significant effects on CNC machine tool accuracy. They arise from thermal deformations of the machine elements created by external heat/cooling sources or those that exist within the structure (i.e. bearings, motors, belt drives, the flow of coolant and the environment temperature). According to various publications [1,2], thermal errors represent approximately 70% of the total positioning error of the CNC machine tool. Spindle drift is often considered to be the major error component among them [1]. Thermal errors can be reduced by amending a machine tool's structure using advanced design and manufacture procedures, such as structural symmetry or cooling jackets. However, an error compensation system is often considered to be a less restrictive and more economical method of decreasing thermal errors. An extensive study has been carried out in the area of thermal error compensation [3]. There are two general schools of thought

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related to thermal error compensation. The first uses numerical analysis techniques such as the finite-element method [4] and finite-difference method [5]. These methods are limited to qualitative analysis because of the problems of establishing the boundary conditions and accurately obtaining the characteristics of heat transfer. The second approach uses empirical modelling, which is based on correlation between the measured temperature changes and the resultant displacement of the functional point of the machine tool, which is the change in relative location between the tool and workpiece. Although this method can provide reasonable results for some tests, the thermal displacement usually changes with variation in the machining process. An accurate, robust thermal error prediction model is the most significant part of any thermal compensation system. In recent years, it has been shown that thermal errors can be successfully predicted by empirical modelling techniques such as multiple regression analysis [6], types of Artificial Neural Networks [7], fuzzy logic [8], an Adaptive Neuro-Fuzzy Inference System [9,10], Grey system theory [11] and a combination of several different modelling methods [12,13].

Chen et al. [6] used a multiple regression analysis (MRA) model for thermal error compensation of a horizontal machining centre. With their experimental results, the thermal error was reduced from 196 to 8 μm. Yang et al. [14] also used the MRA model to form an error synthesis model which merges both the thermal and geometric errors of a lathe. With their experimental results, the error could be reduced from 60 to 14 μm. However, the thermal displacement usually changes with variation in the machining process and the environment; it is difficult to apply MRA to a multiple output variable model. In order to overcome the drawbacks of MRA models, more attention has subsequently been given to the Artificial Intelligence (AI) techniques such as Artificial Neural Networks (ANNs). Chen et al. [7] proposed an ANN model structured with 15 nodes in the input layer, 15 nodes in the hidden layer, and six nodes in the output layer in order to drive a thermal error compensation of the spindle and lead-screws of a vertical machining centre. The ANN model was trained with 540 training data pairs and tested with a new cutting condition, which was not included within the training pairs. Test results showed that the thermal errors could be reduced from 40 to 5 μm after applying the compensation model, but no justification for the number of nodes or length of training data was provided. Wang [13] used a neural network trained by a hierarchy-genetic-algorithm (HGA) in order to map the temperature variation against the thermal drift of the machine tool. Wang [10] also proposed a thermal model merging Grey system theory GM(1,m) and an Adaptive Neuro-Fuzzy Inference System (ANFIS). A hybrid learning method, which is a combination of both steepest descent and least-squares estimator methods, was used in the learning algorithms. Experimental results indicated that the thermal error compensation model could reduce the thermal error to less than 9.2 μm under real cutting conditions. He used six inputs with three fuzzy sets per input, producing a complete rule set of 729 (3^6) rules in order to build an ANFIS model. Clearly, Wang's model is practically limited to low dimensional modelling. Eskandari et al. [15] presented a method to compensate for positional, geometric, and thermally induced errors of three-axis CNC milling machine using an offline technique. Thermal errors were modelled by three empirical methods: MRA, ANN, and ANFIS. To build their models, the experimental data was collected every 10 min while the machine was running for 120 min. The experimental data was divided into training and checking sets. They found that ANFIS was a more accurate modelling method in comparison with ANN and MRA. Their test results on a free form shape show average improvement of 41% of the uncompensated errors. A common omission in the published research is discussion or scientific rigour regarding the selection of the number and location of thermal sensors.

Other researchers have shown that a precise selection of thermal sensors and their position is needed to ensure the prediction accuracy and robustness of compensation models. Poor location and a small number of thermal sensors will lead to poor prediction accuracy. However, a large number of thermal sensors may have a negative influence on a model's robustness because each thermal sensor may bring noise to the model as well as bringing useful information. Additionally, issues of sensor reliability are commercially sensitive; the fewer sensors installed the fewer potential failures. Engineering judgment, thermal mode analysis, stepwise regression and correlation coefficient have been used to select the location of temperature sensors for thermal error compensation models [3]. Yan et al. [14] proposed an MRA model combing two methods, namely the direct criterion method and indirect grouping method; both methods are based on the synthetic Grey correlation. Using this method, the number of temperature sensors was reduced from sixteen to four sensors and the best combination of temperature sensors was selected. Jan Han et al. [16] proposed a correlation coefficient analysis and fuzzy c-means clustering for selecting temperature sensors both in their robust regression thermal error model and ANN model [17]; the number of thermal sensors was reduced from thirty-two to five. However, these methods suffer from the following drawbacks: a large amount of data is needed in order to select proper sensors; and the available data must satisfy a typical distribution such as normal (or Gaussian) distribution. Therefore, a systematic approach is still needed to minimise the number of temperature sensors and select their locations so that the downtime and resources can be reduced while robustness is increased. It is notable that most publications deal only with the reduction in sensors, but not the means by which the original set were determined. As a result the system is only shown for situations where the possible solutions are a subset of all potential locations, which requires non-trivial preconditioning of the problem. This is a situation where some aspects of the machine spatial temperature gradients might already have been missed and is typical when a machine model is being adapted, rather than evaluated from a new perspective.

In order to overcome the drawbacks of traditional Artificial Intelligence techniques such as ANNs and fuzzy logic, more attention has been focussed on hybrid models. For instance, in the fuzzy system's applications, the membership functions (MFs) typically have to be manually adjusted by trial and error. The fuzzy model performs like a white box, meaning that the model designers can explicitly understand how the model achieved its goal. However, such models that are based only on expert knowledge may suffer from a loss of accuracy due to engineering assumptions [8]. Conversely, ANNs can learn