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Application of multi sensor data fusion based on Principal Component Analysis and Artificial Neural Network for machine tool thermal monitoring

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Abstract

Due to the various heat sources on a machine tool, there exists a complex temperature distribution across its structure. This causes an inherent thermal hysteresis which is undesirable as it affects the systematic tool –to-workpiece positioning capability. To monitor this, two physical quantities (temperature and strain) are measured at multiple locations. This article is concerned with the use of Principal Component Analysis (PCA) and Artificial Neural Networks (ANN) to fuse this potentially large amount of data from multiple sources. PCA reduces the dimensionality of the data and thus reduces training time for the ANN which is being used for thermal modelling. This paper shows the effect of different levels of data compression and the application of rate of change of sensor values to reduce the effect of system hysteresis. This methodology has been successfully applied to the ram of a 5-axis gantry machine with 90 % correlation to the measured displacement.

1 Introduction

With increased global competition, the manufacturing sector is vigorously working on enhancing the efficiency of manufacturing processes in terms of quality and cost. Consistent product quality is important for both machine tool manufacturers and end users. To improve this quality, the stability and accuracy of the machine tools needs to be enhanced. Machining accuracy is chiefly governed by the relative position between cutting tool and nominal workpiece and this directly affects the dimensional accuracy of machined parts (1). The main causes of errors in manufactured workpiece are low static stiffness of the

machine structure, low dynamic performance of the feed drives, tool wear and thermal deformation of the tool, machine and workpiece (2; 3).

Thermal errors can contribute more than 50 % of the total machine errors (4) and with effective compensation of other error sources, this percentage can be much higher. Thermally induced deformations in machine tools leads to varying displacements between tool and workpiece (5). A non-uniform temperature distribution increases the complexity of thermal errors in CNC machine tool; this distribution becomes non-linear and non-stationary and varies with time. The mutual coupling of the strength of the heat sources and different heat transfer and expansion coefficients of various components of a machine tool structure create complex thermal characteristics (6). Thermal deformations are determined by not only the instantaneous thermal environment, but also the previous thermal status of the machine tool. This thermal memorizing phenomenon leads to a hysteresis effect (7) can reduce the robustness of the static modelling approach, and thus compensation of the error (8). Studies on thermal monitoring of machine tools are carried out based on the application of single or multiple sensors. Application of different sensors provides the ability to detect a wide range of system parameters like temperature, displacement, strain, etc.

Sensor fusion culminates in a more holistic view of the process and in turn the state of the machine (9). For example, by observing the change in the strain of the structure with respect to variation in temperature provides the input-response function of the system, which would be difficult to obtain by simply monitoring either strain or temperature; change in strain can derive from several causes while explicit prediction of distribution from temperature is a major challenge. Sensor fusion refers to the process of integrating data from multiple sensors in a way that enhances the performance of the system overall (10). It can provide more reliable and accurate information with various techniques used for sensor fusion such as Kalman filter, algebraic functions, fuzzy logic, neural network, etc. (11)

In machining, application of sensor fusion is inspired from the perspective where sensors can be used that can operate reliably in an industrial environment and each can sense a different variable. This is because different signals have different correlation efficiency and their effective and cooperative fusion is expected to produce better estimation result (12).

In the current work, data is acquired from two sources: temperature sensors for temperature measurement and Fibre Bragg Grating (FBG) sensors for strain measurement. Neural Network (NN) can map the nonlinear relationship by training with back-propagation algorithm (13). As the relationship between thermal deformation of the machine and temperature measurement is nonlinear (8), it is reasonable to use Artificial Neural Network (ANN) to build the thermal deformation estimation model. However ANN sometimes loses its generalization capability due to the over fitting which reduces the robustness of its estimation ability. To make sensor fusion useful, it is essential to pre-process data and to consider temporal development of data in an appropriate way (14). In this case, Principal Component Analysis (PCA) is used for dimensionality

reduction of the data and to improve the ANN's estimation performance while reducing the training time.

This paper also demonstrates different levels of data compression i.e. comparison of ANN performance is made with various kinds of inputs. Inputs being: i) all available sensors, ii) principal components of all sensors, iii) sensors having good correlation with the measured output and iv) principal components of these correlated sensors. This methodology is then applied to the ram of a 5-axis gantry machine.

2 System architecture

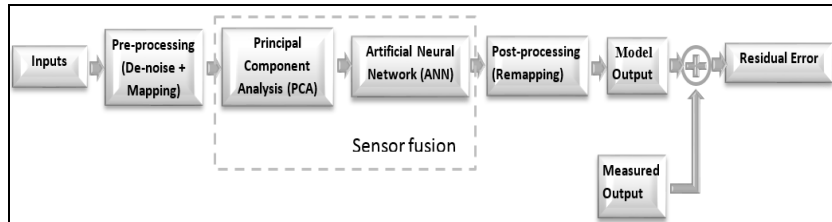


Figure 1. System architecture of the PCA-ANN based prediction model.

A block diagram of the system architecture is shown in figure 1. Eight FBG and six temperature sensors were used as a system input. A Laser position sensor was used to measure the displacement in the ram of a machine. Technical specifications of all the sensors used can be found in (15). Data obtained from measurements was pre-processed using a moving average filter with window size of five to remove any undesired noise signal before normalising it. This processed input data was used for PCA which was further on used to train the ANN model and after the completion of training, used as input layer to test the model with a completely new and independent set of inputs. The ANN's predicted output was compared with the measured thermal displacement response in terms of percentage correlation (% R) and Root Mean Square Error (RMSE) between them to check the performance of the thermal model.

PCA is a statistical technique and is used to transform a set of inter-dependent variables into significant and independent ones called Principal Components (PCs). This transformation is performed in such a way that the first PC has the largest possible variance and each succeeding PC in turn has the highest variance possible while being orthogonal to the preceding one. The detailed mathematical background of PCA is given by Jolliffe (16).

Experimentally obtained measurement data was represented by a 720×14 sensor data matrix. The fourteen columns correspond to the eight FBG and six temperature sensors and the 720 rows are data samples for each sensor. This data matrix is the input data set for PCA. Figure 2 illustrates the percentage of total variance by fourteen principal components, corresponding to fourteen sensors, obtained by PCA of three tests. First PC represents the maximum information which explains more than 90 % of total variance and the combined

PC1, PC2 and PC3 holds more than 99 % of the information while remaining PCs account for less than 1 % of the total data. Hence, to ensure the dimension reduction and integrity of the original data, first three PCs were selected. Thus the new data set is of the dimension 720×3 . This is the new input set for the ANN model.

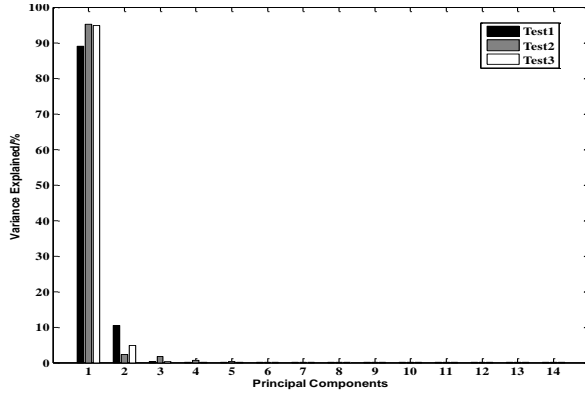


Figure 2. Percentage of total variance illustrated by all the principal components for three tests.

For thermal modelling using sensor fusion, a three layer feed forward ANN based on multilayer perceptron was selected. To reduce the training time of the ANN and to check its performance with reduced data set obtained using PCA, four models were created. Model 1 was trained with all available input sensors i.e. fourteen sensors and model 2 was trained with three PCs extracted from fourteen sensors.

Table 1. Table presenting % correlation of all the sensors with the measured thermal displacement.

| FBG Sensor | % correlation with measured displacement | Temperature sensor | % correlation with measured displacement |
|------------|--|--------------------|--|
| 1 | 98.04 | 1 | 96.5 |
| 2 | 91.86 | 2 | 79.32 |
| 3 | 99.31 | 3 | 81.05 |
| 4 | 69.28 | 4 | 81.14 |
| 5 | 81.62 | 5 | 64.16 |
| 6 | 86.68 | 6 | 44.69 |
| 7 | 82.81 | | |
| 8 | 77.77 | | |

Model 3 consisted of only those sensors which had the highest correlation among all sensors with measured displacement. From table 1 we can comment that the first three FBG sensors have highest correlation with the measured data as well as temperature sensor one, three and four. Hence we selected three FBGs and three temperature sensors for this model. PCA was performed on

these correlated sensors and three PCs extracted from them were used to train model 4.

The size of the input layer was either fourteen, three or six depending on the model. The hidden layer was made up of ten neurons and one neuron in the output layer. The method of supervised learning using back propagation strategy with Levenberg-Marquardt algorithm was used. For learning purposes each data matrix was divided into three sets: a training set consisting of 70 % of data; a validation set using 15 %; and a testing set of 15 %. The training data set was used to train the ANN by adjusting its weights, the validation set was used to minimize over-fitting and the test set was used to evaluate the performance of the ANN after completion of the training phase. Once the learning of the ANN was completed, an independent data set was presented to the ANN model and the performance of all the four models was checked.

MATLAB was used for all the PCA, ANN training, testing and analysis of the data.

3 Experimental setup

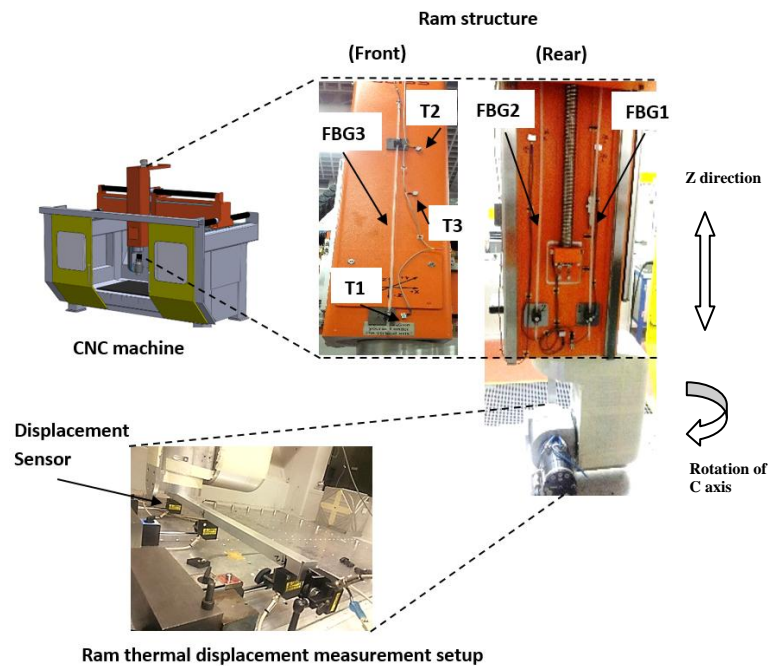


Figure 3. CNC machine and ram structure with sensors location.

The experimental setup is described in figure 3. Tests were performed on a 5-axis gantry machine, the aim of which was to monitor thermal displacement in the Z direction due to C-axis motor heating while in operation. Temperature sensors (T1, T2, T3 etc.) were mounted on front and rear faces of the ram.

Location of temperature sensors was decided after examining the heat distribution measured using a thermal imaging camera. Additionally, FBG sensors were also mounted on the ram structure. Displacement in the Z direction is measured by laser triangulation sensors. For data acquisition and logging, applications using LabVIEW were developed. This is reported in Potdar et al (15).

Tests consisted of a heating and cooling cycle lasting for approximately three hours each. During the heating period, the C-axis motor was rotated at 60 revolutions per minute to simulate 5-axis machining and held stationary during the cooling phase. To facilitate the laser measurement during the heating phase the C axis was stopped intermittently. Sampling rate for FBGs and temperature sensor was 30 seconds. Results of the experiment are discussed in the next section.

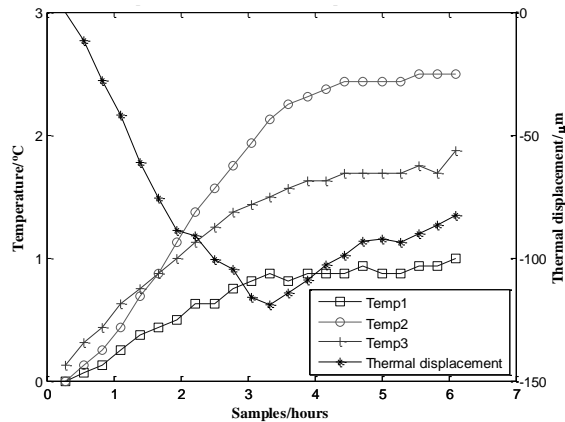


Figure 4. Temperature variation and corresponding thermal response in Z direction of the ram.

The data represented in both figure 4 and figure 5 belongs to test number 3, which was completely independent to the training phase of the ANN.

Figure 4 demonstrates the variation of temperature change taking place during the test duration of six hours. Data from only three temperatures sensors with highest correlation is selected for the demonstration purposes based on table 1. As expected an increase in temperature can be observed due to the heat induced by the C-axis motor located inside the bottom of the ram. Surprisingly the thermal time constant was high, evident from the gradient after three hours. During the cooling cycle increase in temperature slows but no typical exponential cooling occurred. Figure 5 shows the thermal displacement in the negative Z direction indicating expansion that reached a maximum of 120 μm after three hours. A further analysis revealed that the thermal displacement decreased when the motor was non-operational.

Similarly, figure 5 shows the expected response of the FBG sensors. During the heating increased strain due to expansion can be observed and steady reduction during the cooling stage. The FBG's provide the overall strain over the length of ram structure, but not localised distortion.

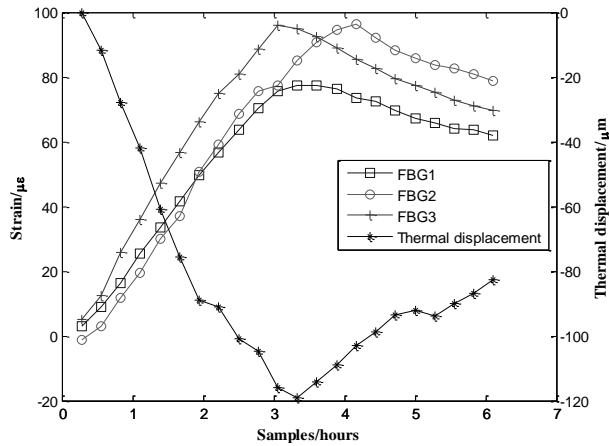


Figure 5. Variation in strain and corresponding thermal response in Z direction of the ram.

4 Result

Estimated thermal displacements obtained from the four models were compared with the actual measured displacement. Table 2 compares percentage correlation between measured output and predicted output by four models. Although model 4 training is marginally worse than the other 3 models, it is appreciably better than them for both the validation trials. It can be clearly seen that the model 4 output has better than 90 % correlation to the measured displacement compared to the other models.

Table 2. Table showing percentage correlation (R) between ANN output and measured output .

| Test no. | Model 1 R/% | Model 2 R/% | Model 3 R/% | Model 4 R/% |
|---------------------|----------------|----------------|----------------|----------------|
| 1 (Training) | 99.99 | 99.83 | 99.83 | 99.28 |
| 2 | 26.85 | 77.56 | 88.41 | 94.20 |
| 3 | 26.74 | 57.56 | 82.58 | 96.14 |

The RMSE for all the four models is presented in table 3. Again, excluding the training (test one), model four shows lowest RMSE, 8 µm for test two and 12 µm for test three.

Table 3. Table showing root mean square error (RMSE) between ANN output and measured output.

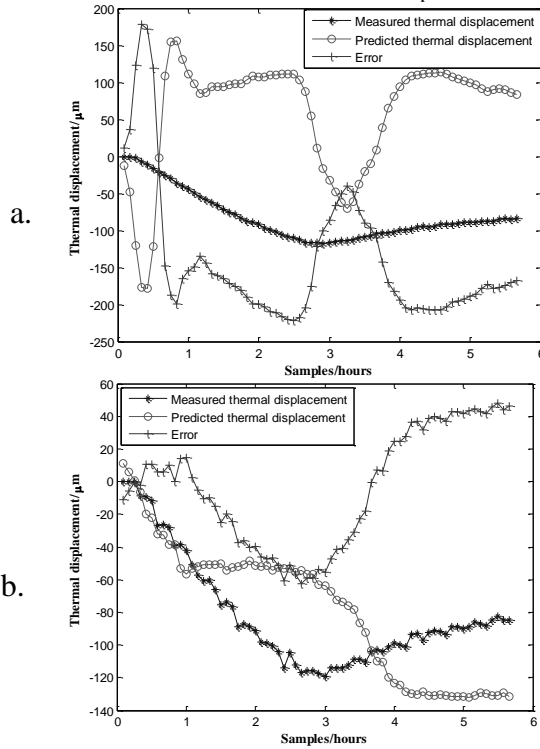
| Test | Model 1 RMSE/µm | Model 2 RMSE/µm | Model 3 RMSE/µm | Model 4 RMSE/µm |
|---------------------|--------------------|--------------------|--------------------|--------------------|
| 1 (Training) | 2 | 2 | 2 | 4 |
| 2 | 51 | 16 | 12 | 8 |
| 3 | 168 | 36 | 36 | 12 |

From table 4, it can be seen that training time for the ANN is reduced from 59 seconds for model 1 to 1.28 seconds for model 4. This is mainly due to the reduction in the dimension of the input dataset from 720×14 to 720×3 , showing the validity of the technique. Applying this method to a full machine model would have greater benefits.

Table 4. ANN training time required for all models.

| | Model 1 | Model 2 | Model 3 | Model 4 |
|-----------------------------|---------|---------|---------|---------|
| Training Time/Second | 59 | 0.53 | 1.87 | 1.28 |

Figure 6 (a, b, c and d) shows outputs of the four models with measured thermal displacement. Additionally it also shows the residual error, obtained by calculating the difference between predicted and measured output. Maximum residual error for model 1 is $220 \mu\text{m}$, model 2 is $50 \mu\text{m}$, model 3 is $40 \mu\text{m}$ and for model 4 is $26 \mu\text{m}$. Thus model 4 shows improvement of 78 % (absolute error) over the original measured thermal displacement of $120 \mu\text{m}$.



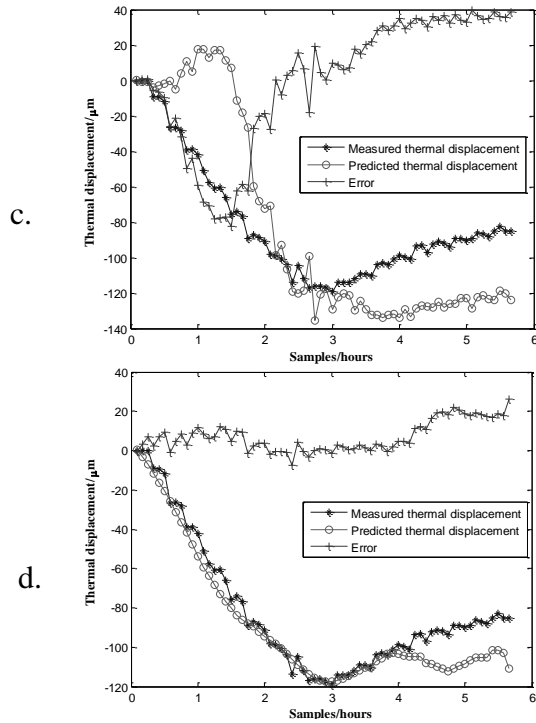


Figure 6. Comparing measured output and predicted output of test 3 for all models; a) model 1 b) model 2 c) model 3 d) model 4.

5 Conclusion

In this paper, output scores of the PCA used to train a sensor fusion model developed using ANN for thermal error modelling. ANN model output with correlated sensors with extracted PCs showed better than 90 % correlation with the measured data compared to other models and least RMSE. Thus it can be concluded that predication and generalization capability of the ANN was improved. The method of correlation analysis used for temperature and FBG sensors reduces the number of variables in modelling and thus can reduce the cost of the system.

PCA further reduces the dimensionality of the measured input data, thus reducing the computation time of the ANN. This can be especially useful in case of large amount data obtained for a long period of time or if close to real time calculations are needed for active compensation.

The modelling and analysis technique mentioned in this paper is a preliminary work with a scope to be extended further by considering a variety of real production conditions such as variations in environmental temperature, addition of cutting fluids, presence of swarf and variable operational cycle time periods.

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