GEOMETRIC ERROR COMPENSATION FOR MULTI-AXIAL PRECISION MOTION SYSTEMS USING SUPPORT VECTORS

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ABSTRACT

A new method for geometrical error compensation of precision motion systems using support vector machines (SVMs) will be developed in this paper. The compensation is carried out with respect to an overall geometrical error model which is constructed from measurements made with respect to each axis of the machine. These error components are modeled using support vector regression method, thus dispensing with the conventional look-up table. The adequacy and clear benefits of the proposed approach are illustrated from an application to a two-axial precision motion platform.

Key Words: Geometric error compensation, support vector machine, gantry stage

I. INTRODUCTION

Precision motion systems play an important and direct role in many industries, including the microelectronics manufacturing, aerospace, biomedical and storage media. In these automated positioning machines and other machine tools, the relative position errors between the end-effectors of the machine and the workpiece directly affect the quality of the final product or the process concerned. Furthermore, as a result of the products' shrinking sizes, tighter specifications and very large production volumes of the final products, the tough demands on the final products translates to different high precision and high speed requirements of precision motion systems in the manufacturing processes.

One important observation at this point is that there should be a balance between machining performance and cost. Either should not be pursued at the total expense of the other. An important criterion for determining the trade-off between performance and cost lies in the area of application of the machine to be constructed.

Thus, rather than relying purely on the precision design and construction of the hardware which is costly, it would be highly desirable to adopt a corrective approach to improve the performance of precision motion system. Error modeling and compensation is a viable candidate to improve system performance at a much reduced cost as compared to purely constructing the machine at high precision.

The early developments in error compensation are well-documented in Evans [1]. Different methods were reported in the literature to model and compensate the errors. These methods include neural-based approaches [2-4], use of genetic algorithms [5], finite element analysis [6] and other analytical tools [7-9]. In the industry, many of the manufacturers (e.g. Mitutoyo, Japan) have incorporated geometrical compensation within their systems [10]. Common to all these works and more is a model of the machine errors, which is either implicitly or explicitly used in the compensator. The error model is normally used off-line to analyze and correct the measurement data in the final displayed look-up table form. The look-up table is built based on points collected and calibrated in the operational working space of the machine to improve its precision and accuracy. It has several associated disadvantages; such as computational requirements and memory storage, which become clearly significant with increasingly stringent requirements.

In this paper, geometrical compensation is used to
improve the accuracy of the precision motion system using a dual-axis high-grade analog optical encoder and Support Vector Machines (SVM) to calibrate and model the geometrical errors respectively. This proposed approach will reduce sufficiently the setup time required to perform the experiment as geometrical compensation of the precision motion system can be performed concurrently for both set of axis. The proposed approach uses the support vector regression (SVR) method as the basis for modeling; with motivation from the reported problems associated with the look-up table and the other approaches. Experimental and simulation results are provided to highlight the principles and practical applicability of the proposed method resulting from such an approach, as compared to other approaches reported in the literature. Finally, diagonal tests will be performed to demonstrate that the proposed compensation approach is able to reduce the geometrical errors effectively.

II. SUPPORT VECTOR REGRESSION

Neural networks, being universal approximators, are good candidates for geometric compensation purposes [11]. But neural networks pose some shortcomings that can be effectively overcome using SVMs. These shortcomings include the constraints associated with dimensionality and difficulty in determining the optimum number of neurons. Given the natural sparseness property of SVMs, the decision boundary can be expressed in terms of a limited number of support vectors. The solution to a convex QP problem provides the regression/mapping function. SVMs can be said to be closely related to learning in reproducing kernel hilbert spaces (RKHS). Nonlinear classification and regression by convex optimization with a unique solution and primal-dual interpretations. The optimum number of neurons automatically follows a convex solution. SVMs are thus strong candidates for learning and generalization in huge dimensional input spaces, avoiding the dimensionality constraint.

The support vector machine (SVM), originated from the Statistic Learning Theory [12,13], is mostly used in regression and classification applications. The SVM is able to select the number of the basis functions systematically without the dimensionality constraint and the number of data points available. The common optimization problem of being trapped in local minimas is also avoided in SVM applications due to its fundamental Structural Risk Minimization (SRM) principle [13]. SVMs are believed to be able to generalize well on unseen data and overcome the problem of overfitting, considering the many outstanding results reported in the literature [14-16]. All these attractive features suggest that SVMs are strong candidates for regression purposes.

The SVM is derived from the statistical learning theory to approximate the non-linear function \( f(x) \) for a given precision [13]. (The equations developed here shall be adapted to suit our purpose, since our output is one-dimensional.) The current output \( y_k \) may be approximated by

\[
y_k = w \phi(x_i) + b,
\]

where \( x_i \) represents the current input, \( \phi(x) \) is a nonlinear basis function, \( b \) is the bias, and \( w \) is the weighting. Posing as a constrained optimization problem, the formulation in primal space is

\[
\min J(w, \xi, b) = \frac{1}{2} w^T w + C \sum_{i=1}^{m} \xi_i,
\]

where \( \xi_i \), equated to \( y_i - (w \phi(x_i) + b) \), are the slack variables, and \( C \) is the regularization parameter. Subjecting it to the constraint \( 0 \leq \alpha_i \leq C \), for \( i = 1, ..., N \), where \( \alpha_i \) are the Lagrangian multipliers, the problem can be expressed (in the dual space) using the Langrangian function

\[
J(w, \alpha, b) = \frac{1}{2} w^T w + \sum_{i=1}^{N} \alpha_i (y_i - (w \phi(x_i) + b)),
\]

with a set of \( N \) training data pairs \( \{x_i, y_i\} \), for \( i = 1, ..., N \). By performing the optimization and satisfying the KKT conditions,

\[
\frac{\partial J}{\partial w} = 0 \Rightarrow w = \sum_{i=1}^{N} \alpha_i \phi(x_i),
\]

\[
\frac{\partial J}{\partial b} = 0 \Rightarrow \sum_{i=1}^{N} \alpha_i = 0,
\]

the parameters \( \alpha_i \) and \( b \) are obtained. We specified the following transformation pair:

\[
K(x_i, x_i) = \phi(x_i) \cdot \phi(x_i),
\]

where \( K(x_i, x_i) \) is a symmetrical kernel satisfying Mercer’s condition [13,17]. For our purpose, we have selected the RBF for the kernel, i.e.

\[
K(x_i, x_j) = \exp\left(-\frac{(x_i - x_j)^T (x_i - x_j)}{\sigma}\right),
\]

where \( \sigma \) is a user-specified constant. Thus, noting (4) and (6), the output may finally be expressed as

\[
y_k = f(x_k) = \sum_{i=1}^{N} \alpha_i K(x_i, x_k) + b,
\]
III. CALIBRATION OF THE TESTBED — TWO-AXIAL PRECISION MOTION SYSTEM

In certain cases, for specific precision-dependent operations, the inherent accuracy of a commercial machine may be insufficient. This has resulted in the usage of a higher precision measurement system to assess the deviation of the tool-tip position from its true value and provide the necessary compensation. In this paper, for an efficient and cost-effective solution, a Heidenhain two-coordinates encoder is used as the reference to calibrate a two-axial precision motion stage. The stage is manufactured by Anorad. Figure 1 shows a picture of the precision motion stage used, while Table 1 details its specifications.

3.1 Reference encoder

Normally, a laser interferometer is used to calibrate the machine. Today, laser interferometers can readily yield a measurement resolution of down to one nanometer. However, although highly accurate, the laser interferometer requires stringent conditions to operate under; it is highly susceptible to pressure, temperature and humidity. Furthermore the calibration process is rather tedious and a high level of expertise is required to operate the laser interferometer. In addition, the high cost of a laser interferometer implies that probably only large companies can afford one. Hence, we propose the usage of a low-cost dual-axis encoder to simultaneously calibrate both axes.

A picture of the encoder used is shown in Fig. 2. Its specifications are given in Table 2 below. The encoder features as measuring standard a planar phase-grating structure on a glass substrate. This makes it possible to ensure positions in a plane. The precision graduations are manufactured in a process (DIADUR) invented by Heidenhain, which involved graduations that are composed of an extremely thin layer of chromium on a substrate of glass. This allows the accuracy of the graduation structure to lie within the micron and submicron range.

The accuracy of the motion achieved by the machine is mainly limited by the characteristics of the encoder used. These performances include (1) the accuracy of the graduation, (2) the interpolation error during signal processing in the incorporated or external interpolation and digitizing electronics, (3) the error from the

Table 1. Specifications of G5300M1 Anorad gantry platform

<table>
<thead>
<tr>
<th>Specifications</th>
<th>X</th>
<th>Y</th>
</tr>
</thead>
<tbody>
<tr>
<td>Travel</td>
<td>250mm</td>
<td>400mm</td>
</tr>
<tr>
<td>Drive Interface</td>
<td>LEA-S-2-S-NC</td>
<td>LEB-S-4-S-NC</td>
</tr>
<tr>
<td>Velocity</td>
<td>1.0m/s</td>
<td></td>
</tr>
<tr>
<td>Acceleration</td>
<td>&gt;1.0g/s</td>
<td>&gt;0.7g/s</td>
</tr>
<tr>
<td>Resolution</td>
<td>1µm</td>
<td></td>
</tr>
<tr>
<td>Straightness of Travel</td>
<td>±3µm</td>
<td></td>
</tr>
<tr>
<td>Flatness of Travel</td>
<td>±6µm</td>
<td></td>
</tr>
<tr>
<td>Repetitability</td>
<td>±2.5µm bi-directional</td>
<td></td>
</tr>
<tr>
<td>Orthogonality (X to Y)</td>
<td>±10 arc seconds</td>
<td></td>
</tr>
</tbody>
</table>

Table 2. Heidenhain dual-axial encoder’s specifications

<table>
<thead>
<tr>
<th>Specifications</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Measuring standard</td>
<td>Two-coordinate DIADUR phase grating on glass</td>
</tr>
<tr>
<td>Grating period</td>
<td>8µm</td>
</tr>
<tr>
<td>Signal period</td>
<td>4µm</td>
</tr>
<tr>
<td>Thermal expansion coefficient</td>
<td>8ppm/K</td>
</tr>
<tr>
<td>Accuracy grade</td>
<td>±2.2µm</td>
</tr>
<tr>
<td>Measuring step</td>
<td>0.1µm</td>
</tr>
<tr>
<td>Measuring range</td>
<td>68mm × 68mm (1.38in. × 1.38in.)</td>
</tr>
<tr>
<td>Reference mark</td>
<td>One reference mark 3mm after beginning of measuring range</td>
</tr>
<tr>
<td>Max. traversing speed</td>
<td>30m/min (1181ipm) depending on the subsequent electronics</td>
</tr>
<tr>
<td>Vibration (50 to 2000Hz)</td>
<td>≤80m/s²</td>
</tr>
<tr>
<td>Shock (11ms)</td>
<td>≤100m/s²</td>
</tr>
</tbody>
</table>
scanning unit guideway along the scale, and (4) mechanical deficiency during setup which results in orthogonal error and Abbe error.

Hence, the usage of the Heidenhain encoder as a superior measurement system is justified by comparison of the encoder specifications on the Anorad (the mer-50 encoder) with the Heidenhain encoder. The advantages arise from the fact that the Heidenhain encoder has a higher accuracy grade, and a smaller grating pitch (which resulted in smaller interpolation error, hence a better representation of the actual position). Furthermore, with the scanning head mounted at the tool tip, the resulting Abbe error is minimized. Also, by having a two-axis scale housing, mounting guideway error and the effect of orthogonal error are also reduced significantly.

3.2 Calibration methodology

Error modeling typically begins with a calibration of the errors at selected points within the operational space of the machine. These errors are subsequently cumulated using the overall error model to yield the overall positional error and create the error map.

For the Anorad Machine, the tool attached to the table may move in either X or Y direction. The X and Y travel is capable of spanning a 250mm × 400mm 2D space. The present set of Heidenhain measuring range is 68mm × 68mm. Accordingly, we have set the calibration area to a 50mm × 50mm 2D space. Calibration is done at 1mm intervals along the 50mm travel for the Y-axis and 10mm intervals along the 50mm travel for the X-axis. The start position for X-axis and Y-axis is defined as the origin (0, 0) while the end position was (0, 50), (10, 50), (20, 50), (30, 50), (40, 50), and (50, 50) respectively for each of the six calibration line. A schematic diagram showing the calibration profiles of the table is shown in Fig. 3. A clear representation of the data collation process is illustrated by the schematic shown in Fig. 4. A PID controller was used to ensure zero steady-state error. The output was allowed time to settle and various samples were taken and averaged to minimize the influence of noise.

The final error map of both the X-axis and Y-axis is plotted on the left half of Figs. 5 and 6 respectively. The error map obtained is highly non-linear which justified the application of support vectors to model the geometrical error. The SVM map of the X-axis and Y-axis thus obtained is shown on the right half of Figs. 5 and 6 respectively. The adequacy of the resultant models is verified by the close fit of the model to the calibration lines.
IV. REAL-TIME ERROR COMPENSATION

The error compensation (1) is implemented with the SVM as a S-function block in MATLAB/SIMULINK. Error compensation was then executed with servo control. A clear representation of the process is illustrated with the schematic diagram in Fig. 7 below.

To assess the performance of the proposed method, the two actuators were made to move through the body diagonals of the working volume as shown in Fig. 3. 50 tested positioning points (1mm apart) along each diagonal were collected and the resultant positional errors, before and after geometrical compensation, are shown in Figs. 8 and 9. The results showed that the diagonal errors have been reduced from a maximum of 4µm to less than 1.8µm.

It should be noted that there are two main factors which determines the compensation results, (1) the repeatability of the machine and (2) the accuracy of the error map. From experimental runs, the repeatability of the Anorad machine is less than 1µm, while the SVM error mapping obtained (comparing the two diagrams in Figs. 5 and 6) showed that the compensation deviate from the measured position by approximately ±0.8µm (maximum). Lastly, it is noted that the SVM map obtained in Figs. 5 and 6 are also influenced by the repeatability of the Anorad machine. Hence, we can only ensure that the overall compensation will lie between a ±2.8µm (1 ± 0.8 + 1) error region as the worst case scenario. This also implies that for an initially uncompensated positional error which is small, it is possible for the compensated error to increase, but constrained within the ±2.8µm error region.

V. CONCLUSIONS

A new method for geometrical error compensation of precision motion systems using support vector machines is proposed in this paper. The compensation is carried out with respect to an overall geometrical error model which is constructed from the individual error components associated with each axis of the machine. These error components are modeled using support vector regression method, thus dispensing with the conventional look-up table. The adequacy and clear benefits of the proposed approach are illustrated from an application to a dual-axial precision motion platform.

REFERENCES


Chek-Sing Teo received his B. Eng. in Electrical Engineering from the National University of Singapore in 2003. He is currently pursuing his Ph.D. degree at the National University of Singapore under the Agency for Science Technology and Research (A-STAR) Scholarship Scheme. His research interests focus on various aspects of the development of high-speed, high-bandwidth motion control systems for ultra-precision motion stages, with applications for semiconductor equipment.

Kok-Kiong Tan received his B. Eng. in Electrical Engineering with honors in 1992 and Ph.D. in 1995, from the National University of Singapore. He is currently an Associate Professor with the Department of Electrical and Computer Engineering, National University of Singapore. His research interests are in the applications of advanced control techniques to industrial control systems and mechatronic systems, advanced process control and auto-tuning, precision motion control and instrumentation.

Ser-Yong Lim received the B. Eng. degree from the National University of Singapore in 1984, the M.Sc. and Ph.D. degrees in Electrical Engineering from Clemson University, Clemson, SC, in 1988 and 1994, respectively. He is currently the Deputy Executive Director of the Singapore Institute of Manufacturing Technology, Singapore. His main research interests are in nonlinear control of robotic manipulators, high-speed and high-precision robots, force-controlled robots, and new-generation DSP-based robot controllers.

Sunan Huang received his Ph.D. degree from Shanghai Jiao Tong University, Shanghai, China, 1994. He is a Research Fellow in the Department of Electrical and Computer Engineering, National University of Singapore. His research interests include adaptive control, neural network control and automated vehicle control.

Kok-Zuea Tang received a B. Eng. in 1998, a M. Eng. in 2000 and a Ph.D. in Electrical and Computer Engineering in 2004 from the National University of Singapore. His research interests include intelligent precision control and diagnostics, and system optimization.