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Method for Online Identification of the Dimensional Deviation - State Variables Relation Applied to Manufacturing Machines

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ABSTRACT

In this work a new method for online identification of the relation between the dimensional deviation and the cutting force, with the object of building a mathematical model to be used for online compensation of the dimensional error. The key idea is to identify this relation separately for each one of the two generating curves (the generatrix and the directrix) using the SVM regression technique. The resulting mathematical model can be used in order to predict the values for the dimensional deviation based on the current position of the tool and on the measured values of the cutting force. The identification method was tested for an entire batch of turned workpieces. The results showed that by using the proposed method the machining error can be reduced by 2,5 times.
Keywords*: machining system identification, SVM regression, dimensional error compensation, surface generatrix and directrix.*

1. Introduction

Dimensional deviation depends on a set of state variables of the manufacturing systems. Identifying the model of dimensional deviation is a difficult task because of the diversity of the state variables nature: cutting forces, temperature field and tool position. Because of the diverse nature of the state variables often, a sensor fusion system is required. The identification process must be rapid in order to generate a model to be used for dimensional error compensation. The workpieces resulted from the manufacturing process must be measured using a measuring system that can transmit data back to the control system of the machine tool. A better approach is to use measuring system built in the machine. "On machine measurement" is not a new concept. Cho [1] proposed a dimensional error compensation system equipped with an OMM system. The system modeled the dimensional deviation based only on the process parameters using a polynomial neural network.

The identification of the dimensional dimension was also used for predictive control by the researchers for NIST. They developed a method for compensating the errors based on intermittent inspection [2]. The error model was based on spline functions.

Fung developed a predictive system [3] that uses on machine measurement system for predictive control of dimensional deviations. The system uses the measured values of the cutting forces and the measured dimension of the semi finished in order to predict the dimensional deviation using ARMAX and NARMAX models.

Similar predictive systems were also proposed in [4, 5, 6]

All these approaches have a main drawback: the generation process is not taken in account.

In this paper a new concept is proposed identification of the relation between the dimensional deviation across each of the generating curves and the manufacturing process state variables.

2. Problem formulation

If we consider a manufacturing batch consisting in several workpieces, the dimensional deviation differs for each workpiece. This inconsistency is caused by the dimensional, geometric and material inconsistencies. Moreover, the machining system behavior is changing in time, implying another variation of the dimensional deviation. The slow evolution in time and space of the dimensional deviation can be compensated by frequent modification of the compensation value. The rapid evolution of the can be compensated by using a control loop. Based on these observations a solution to the dimensional deviation compensation arises. This solution implies the online identification of the relation between the dimensional deviation and the state variables which are changing in time, associated with an adaptive control loop for correction control. Practically, it can be seen that the dimensional deviation evolution by the direction of the generatrix (the profile of revolution surface) is slow varying in time, whereas the evolution by the direction of the directrix (workpiece rotation) is more rapid.

3. The experimental stand

With a view to development of a method for prediction and online compensation of the dimensional deviations an experimental stand was used. This stand consisted in an experimental lathe equipped with a numerical control system. The control system was connected by an Ethernet network to a data acquisition system. From the machine control system, the data acquisition system acquires data regarding the machine axis position.

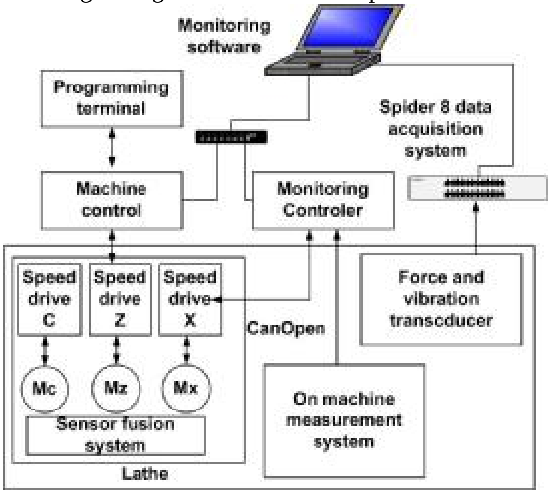

Fig. 1. The experimental stand structure

Strain gauges were fixed on the tool in order to measure the cutting force components. In order to measure the cutting force using strain gauges a data acquisition system type Spider 8 produced by Hottinger Baldwin Messtechnik GmbH. Also in order monitor the lathe motor speed drives parameter,s a second controller was used. This controller is a CanOpen master controller which can communicate with the speed drives which are CanOpen slaves. The master controller acquires from each slave the following parameters: motor current, torque, supplied power, energy absorbed. Also this controller is connected to a measuring system (on machine measuring function).

After each workpiece was manufactured, its dimension was measured using two length gauges manufactured by Heidenhain. The resolution of these length gauges was 1µm and their accuracy was ± 1µm. The length gauges were placed in contact with the workpiece and then moved across the workpice length. The spindle was rotated with 30 revolution per minute.

The following state variables were measured and their values were recorded:

- two of the force components, namely Fx and Fz
- the current and the energy absorbed by the lathe motors,
- the tool coordinates during the operation,
- the measured diameter of the worpieces.

4. The experimental program

A batch of 40 workpieces was processed. Each workpiece surface was divided in 7 zones with the length of 8mm. For each zone a conic surface was turned. The shape and the dimension of the workpieces and of the semi finished is presented in figure 2.

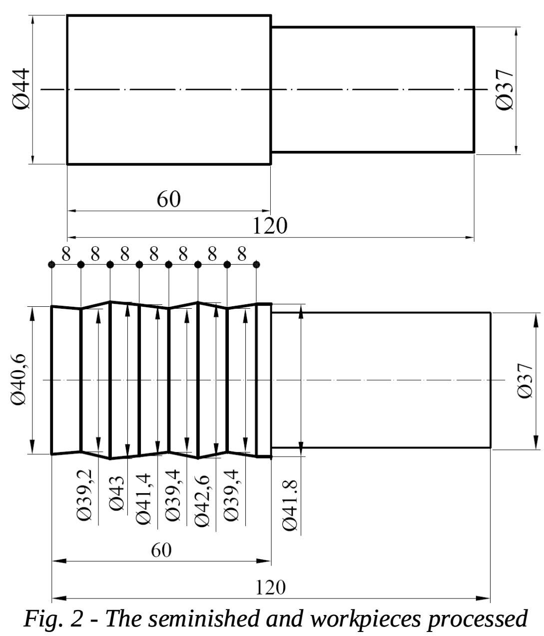

Fig. 2 - The seminished and workpieces processed

Data was recorded during the manufacturing and measuring process and then analyzed. The main aspect of the analysis was to determine the dependencies between the dimensional deviation and the state variables. The evolution of the dimensional deviation in respect with cutting force, the spindle motor absorbed current and the spindle torque or an workpiece is represented in figure 3.

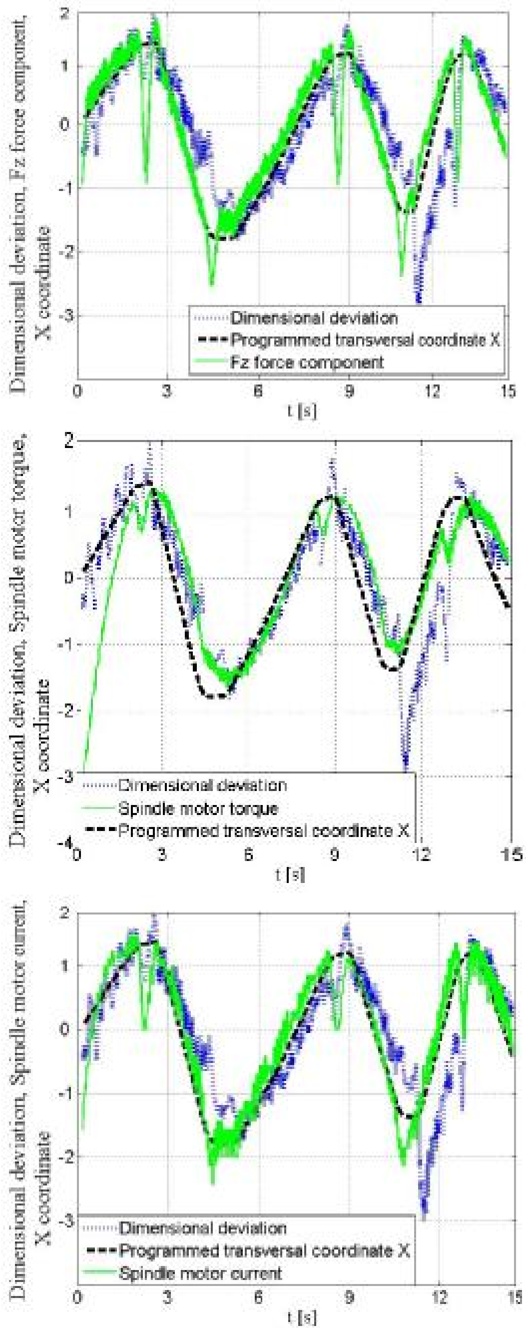

Fig.3 –The dependecies betwen the dimensional deviation and force, C motor current and C motor torque

In order to graphically analyze the dependency between the state variables and the dimensional deviation, each state variable was normalized using this transformation:

$$m^*(t) = \frac{m(t) - \overline{m}}{s_m}$$

where *m(t)* represent the variable at *t* time, $\overline{m}$ and s_m represents the variable average value and respectively, the variable standard deviation over the entire workpiece manufacturing process. After this transformation each state variable will have the average value equal to 0 and standard deviation equal to 1. For this reason the variables shown in figure 3 don't have associated units.

From this figure it can be seen that the dimensional deviation is well correlated with the state variables associated with the spindle motor, but the force is a better indicator.

5. The prognosis of the dimensional deviation

The problem of dimensional deviation prognosis can be dived in two sub problems:
-the problem of the dimensional deviation in respect with the directrix programmed profile,
-the problem of the dimensional deviation in respect with the generatrix programmed profile.
By analyzing the data referring to the dimensional deviation and force over time we can determine that both this signals present an harmonic component. Using Fourier analysis (FFT algorithm) we determined the frequencies or each component. The frequency of the harmonic component with the highest amplitude was 15 Hz force and 0,5 Hz for the dimensional deviation. The dominant frequency of force signal is caused by fixing error of the semi finished, it corresponds to the spindle number of revolution per minute 800 rpm=800/60=15Hz. The dominant frequency for dimensional deviation was about 0.5 Hz which also corresponds to the spindle number of revolution during the measuring stage 30rpm=30/60=0,5Hz. The amplitudes values differ from each workpiece this ratio is dependent with the excentricty of the workpice. This error component corresponds to the dimensional deviation across the directrix direction. In order to analyze the component of the dimensional deviation across the generatrix the directrix component must be removed.

We consider the first workpiece of the batch. This workpiece will be used in order to determine in a first phase the dimensional dependencies between the force value and the dimensional deviation. In order to do this, the first workpiece will be considered as a test workpiece. The machining allowance for this first workpiece will divided in two parts, the first part will be used for the test, while the last part will be used for finishing the part. The test workcycle result will be the same shape but slightly larger.

During the workcycle the time evolution of the cutting force, of the dimensional deviation in respect with the *Z* axis coordinate of the lathe

In figure 3 it can be seen that the dimensional deviation evolution is different for different parts of the workpiece characterized by different conicities. Also the rigidity of the technological system is different across the Z axis. Given these observations we modeled the dimensional deviation and the cutting force using Support Vector Machine regression technique in relation with the Z coordinate.

Support Vector Machine was developed at AT&T Bell laboratory by Vapnik and co-workers [7, 8]. Initially this technique was used for classification problems. The technique was used with great success in practice to solve difficult task such as optical character recognition, face recognition, spam detection, genetic research. The first technique for regression was also developed by Vapnik [9] and was called ε-SV. Suppose that after we monitor a process we have a dataset composed by pairs of values $\{(\mathbf{x_1}, y_1),...(\mathbf{x_n}, y_n)\} \subset c \times \mathrm{R}$. c defines the space of the input variable (the input variable is a vector $\mathbf{x}_i$) and could be for instance R^n if the dimension of input variable is *n*. The variable that will be predicted is y. Initially the algorithm is trained using data obtained from monitoring stage. The purpose to determine a function *f(x)* that would approximate the target outputs y_i with a maximum deviation equal with ε and also the function must be as flat as possible. In linear case of the problem the function was this form:

$$f(x) = \langle w, x \rangle + b \text{, with } w \in c, b \in \Re .$$

The objective is to find the proper parameters *w*, *b* in order to keep the empirical loss function defined as:

$$R_{emp}(w,b) = \left| y - \langle w, x \rangle - b \right|$$

bellow a fixed value ε.

This is equivalent to solve this optimization problem:

- minimize $\frac{1}{2}\|w\|^2$
- subject to $\begin{cases} y_i - \langle w, x_i \rangle - b \le e \\ \langle w, xi \rangle + b - y_i \le e \end{cases}$

A function that could meet all this conditions does not always exists, so in order to find the best function that can approximate the training outputs, the soft margin approach introduced by Vapnik and Cortes was used:

- minimize $\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(x_i + x_i^*)$
- subject to $\begin{cases} y_i - \langle w, x_i \rangle - b \le e + x_i \\ \langle w, xi \rangle + b - y_i \le e + x_i^* \\ x_i , x_i^* \ge 0 \end{cases}$

The Lagrangian for which a saddle point must be found is:

$$L = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(h_i x_i + h_i^* x_i^*) -$$

$$\sum_{i=1}^{n} a_i (e + x_i^* + y_i - \langle w, x_i \rangle - b)$$

$$-\sum_{i=1}^{n} a_i (e + x_i - y_i + \langle w, x_i \rangle + b)$$

With $a_i^{(*)}, h_i^{(*)} \ge 0$. Some of this lagrangian multipliers will be 0. So the solution will be determined by some vectors from the training data, vectors for which the lagrangians multipliers will be different from 0. This vector are called support vectors. The model parameters will depend on this parameters. The solution will be:

$$f(x) = \sum_i (a_i - a_i^*)\langle x, x_i \rangle + b$$

For non-linear problems like our problem the scalar product $\langle x_i, x \rangle$ can be replaced with a nonlinear function called kernel function. This kernel function is a function that can be expressed as a dot product of similar functions: $k(x, x_i) = \langle f(x), f(x_i) \rangle$. The kernel trick is to map the data in a space with a higher dimension using a transformation x-> $f(x)$.

We trained the algorithm (implemented in Weka package [10]) using pair of data obtained from process and we obtained two functions: *F(Z)* and *d(Z)*.The kernel function used was the radial basis function RBF.

$$k(x, x_i) = e^{-g\|x_1 - x_2\|}$$

The γ parameter value was set to 10 after testing different parameter values using 10 fold cross validation technique. Also using the same technique the models C parameter was set to 100 and ε parameter to 0,01.

Using SVR technique was preferred because it's resistance to outliers presence. In figure 4 the cutting force evolution is presented along with the cutting force evolution modeled with SVM.

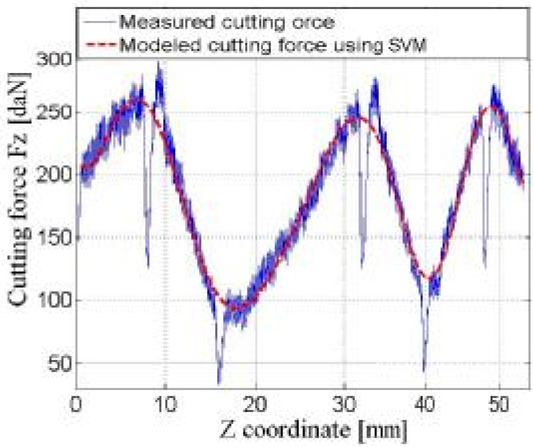

Fig.4 –The cuting force evolution and the model using SVM

In figure 5 the dimensional deviation evolution is presented along with the result of the model using SVM. As depicted in the picture bellow the oscillations of the measured signal, oscillations which are dimensional deviations across the direction of the directrix, are removed and the modeled deviation signal represents the dimensional deviation accros the direction of the generatrix.

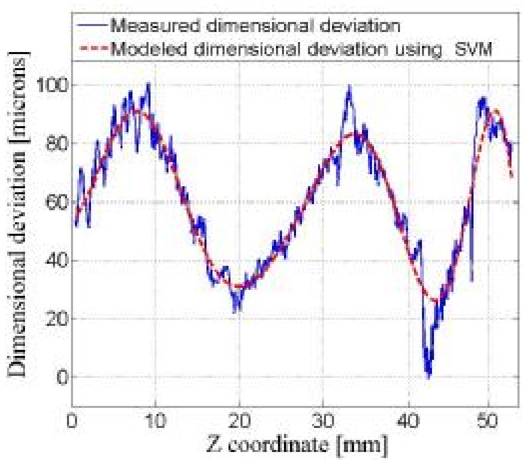

Fig.5 –The dimensional deviation and the model using SVM

Using the data obtained by the SVM models a third model was trained, a model that will approximate the relation between the dimensional deviation, cutting force and the Z coordinate $\delta=\delta(Z,F)$ (figure xx).

The obtained model was used for predicting the error of the next workpiece. During the next workpiece the Z coordinate is known, also the average value of the force is computed. These values are inputted in $\delta=\delta(Z,F)$.

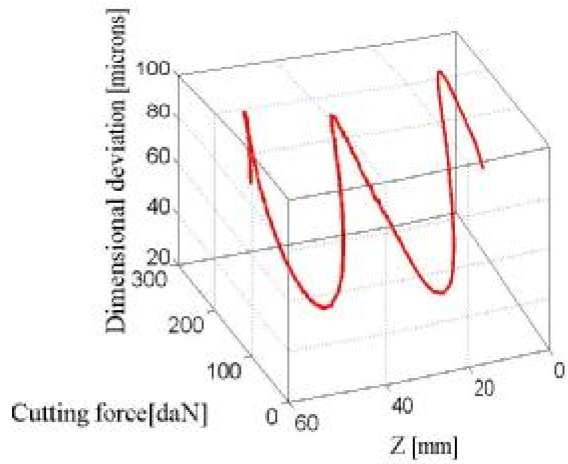

Fig.6 –The grafical representation of the relation between Z coordinate, cutting force and dimensional deviation

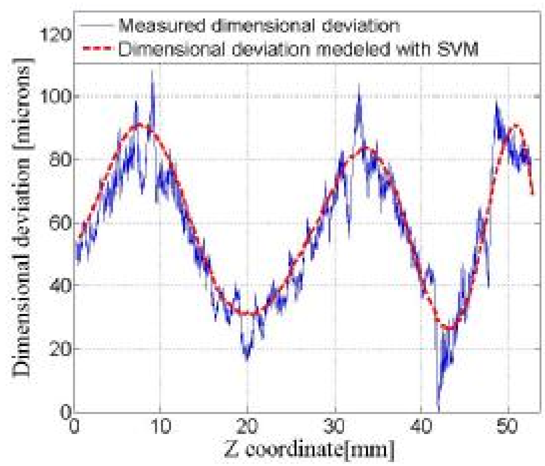

Fig.7 –The predictions made using SVM

As depicted in above picture the prediction performance was fairly good. The prediction was three times better then the case of prediction made by the average value of the error of the previous part.

5. Conclusions

In this work a new method for online identification and prediction is proposed. The identification of the dimensional deviation in relation with the state variables was applied for a real manufacturing system, a lathe.

The identification method is different among two direction: directrix and generatrix. Predictions were made for the dimensional deviation on the generatrix direction. The prediction was made using an algorithm that uses SV regression.

The prediction results were good the prediction precision increased 2 times.

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Metodă pentru identificarea liniilor de deviație dimensională – relația variabilelor de stat aplicate la maşinile unelte

Rezumat

In lucrare se prezinta o metoda de identificare online a relatiei dintre deviatia dimensionala si forta de aschiere, in scopul constructiei unui model destinat compensarii online a erorii dimensionale. Ideea de baza a metodei este identificarea acestei relatii separat pentru fiecare dintre cele doua curbe generatoare ale suprafetei (generatrix and directrix) folosind tehnica SVM regression. In concret, modelul matematic obtinut permite prognoza deviatiei dimensionale pornind de la valoarea masurata a fortei de aschiere si coordonata punctului curent. Metoda de identificare a fost testata experimental in cazul strunjirii unui lot de piese. Rezultatele obtinute au aratat ca prin aplicarea metodei eroarea de prelucrare eroarea de prelucrare poate fi diminuata in medie de 2.5 ori.

Méthode pour l'identification en ligne de la déviation dimensionnelle - relation de variables d'état appliquée aux machines de fabrication

Résumé

Dans ce travail une nouvelle méthode pour l'identification en ligne de la relation entre la déviation dimensionnelle et la force de découpage, avec l'objet d'établir un modèle mathématique à employer pour la compensation en ligne de l'erreur dimensionnelle. L'idée principale est d'identifier cette relation séparément pour chacune des deux courbes se produisantes (la génératrice et le directrix) utilisant la technique de régression de SVM. Le modèle mathématique en résultant peut être employé afin de prévoir les valeurs pour la déviation dimensionnelle basée sur la position actuelle de l'outil et sur les valeurs mesurées de la force de découpage. La méthode d'identification a été examinée pour une série entière d'objets tournés. Les résultats ont montré que cela en employant la méthode proposée l'erreur d'usinage peut être réduite par 2.5 fois.