NONLINEAR POSITION ESTIMATORS BASED ON ARTIFICIAL NEURAL NETWORKS FOR LOW COSTS MANUFACTURING SYSTEMS

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Abstract:

The accurate control of CNC machine axis requires relatively expensive direct measurement sensors. In this paper, artificial neural network based position error estimators are comparatively evaluated as a part of a low-cost (but high performance) manufacturing system. Such schemes are very effective when the system is not subjected to external loads as well as widely changing operating conditions such as ambient temperature.

Keywords: *neural networks, estimators*

1. Introduction

Precision axis motion control is vital for CNC machine tools as the resulting performance affects the dimensional tolerance, form, and the surface accuracy of the manufactured goods. When the characteristic travel-span ("stroke") of the machine is relatively long (>> 0.5 m); the use of direct measurement techniques employing traditional sensors (such as potentiometers, LVDTs, linear scales, laser interferometers) leads to both bulky and relatively expensive solutions.

The main motivation of this paper is to propose feasible estimation schemes based on artificial neural networks that utilize the secondary information sources located on the actuator side of the machine so that the position of the carriage could be estimated to the desired accuracy for "not-so-demanding" applications like CNC laser/plasma cutters, filament winding machines, and rapid prototyping machines.

The organization of the paper is as follows: The proceeding article gives background information on neural networks and their corresponding use as estimators in manufacturing industry. The following section introduces the experimental setup along with number accompanying tests to investigate the error sources of a generic machine axis. Section 4 focuses on suitable neural network architectures and their training using the collected data. The next article illustrates the estimation performance of the neural networks. Finally, the key points of the paper are briefly discussed.

2. Background

The position errors for most CNC machinery are said to be quasi-static [1]. A large portion of such errors are attributed to

- Manufacturing (form, dimension, tolerance) errors of machine elements,
- Misalignment/installation errors of parts in assembly,
- Structural errors induced by static forces,
- Thermal expansions of machine parts and workpiece.

When the afore-mentioned errors are repeatable in spatial and temporal domain, they can be estimated and reduced (if not totally eliminated) through passive error compensation techniques [2]. Unfortunately, developing analytical models for inherently nonlinear error sources in a machine turns out to be a tremendously challenging task. Furthermore, even with the processing power of modern computers, online error estimation using sophisticated models is proven to be very difficult.

The researchers in this field mostly turn their attention to empirical techniques for model construction. Since Artificial Neural Networks (ANN) are known to be universal approximators, they appear to be natural choice for error prediction in production machinery [1, 3-5, 7, 8].

For instance, the dilation caused by the local heating while machining is considered in [3]. The change in workpiece dimensions is estimated by neural networks and the tool path is corrected accordingly. While [4] employs a Radial Basis Function (RBF) network estimate the machining errors. In [5] the compensation required for the next part on a CNC machine tool is studied by a neuro-fuzzy network and tested for cylindrical parts. Likewise, [6] investigates the error sources in bar turning. In [7] the thermally induced errors are estimated by RBF. In reference [8] the relationship between cutting force and the deflection of machine structure is modeled by RBF, to predict the dimensional deviation of the finished part.

3. Experimental setup

As shown in Fig 1, the setup of this study is specifically designed to represent the axis of a generic machine where a DC servomotor with a built-in gearbox drives the carriage via a timing belt. Due to the elements used system, there exist several hard- and soft-nonlinearities associated with the elements including backlash (gearbox + timing belt), time delay (timing belt), friction (bearings), viscoelastic behavior of the belt, and more. Thus, estimating the position of the carriage using indirect measurement techniques is proven to be quite challenging and requires extensive modeling efforts, if universal approximators like neural networks are not employed.

Note that for modeling and verification purposes, a high-resolution linear scale is present in this setup. Thus, the displacement (position) errors introduced by the transmission system are represented as the difference between position measurements of the primary encoder and those of the high-resolution linear scale.

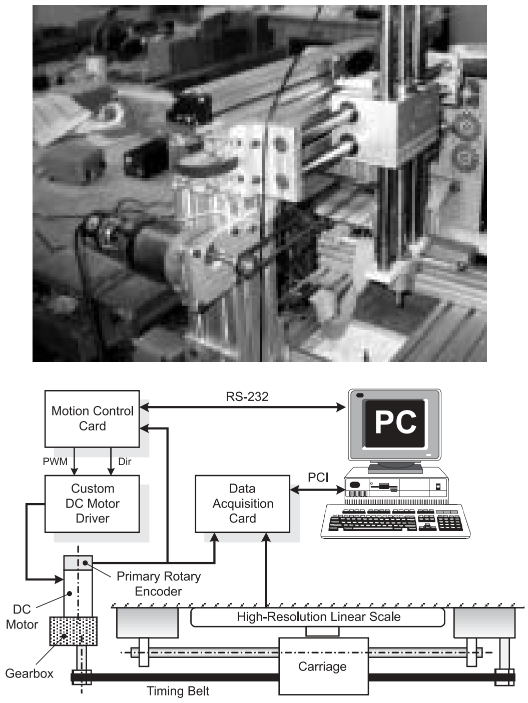


Figure 1. Experimental setup and its schematic.

3.1 Experiments

Within the scope of this study, several tests are conducted. First of all, the repeatability of the motion must be studied as a prerequisite to train various ANNs. In all tests considered, the motor's velocity is accurately controlled along a trapezoidal path as shown in Figure 2 where the resulting (position) tracking error in Figure 3 (that essentially go to zero at the steady state) can be assumed low for all intensive purposes.

Under the above-mentioned conditions, the positioning error patterns for twelve different (overlaid) trajectories are illustrated in Figure 4. As can be verified frequency chart in Figure 5, the positioning errors, which exhibit hysteresis character, are quite repeatable which in turn encourages the development of ANN based estimator models.

To reveal the basic nonlinear relationships, several experiments are performed:

- Full bidirectional travel of the carriage with different steady-state speeds and acceleration profiles,
- Intermittent bidirectional travel of the carriage with different speed and acceleration profiles,
- Intermittent bidirectional travel of the carriage with random speed and acceleration profiles.

The following section concentrates on the suitable neural network architectures and their corresponding training phase utilizing the acquired data.

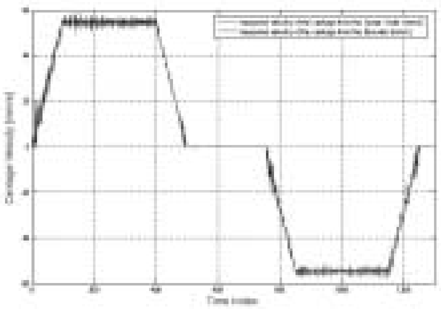


Figure 2. Velocity profile of the carriage.

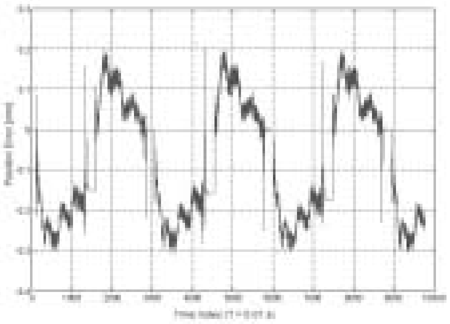


Figure 3. Position tracking error.

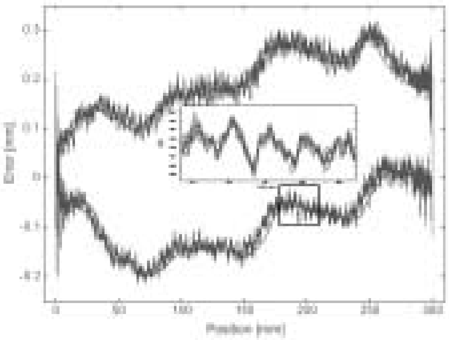


Figure 4. Position errors for 12 cases.

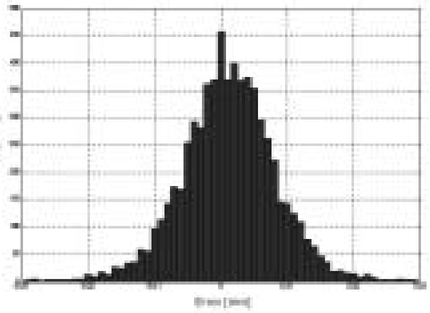


Figure 5. Frequency of positioning errors.

4. Neural network architectures and training

To estimate the position of the carriage, three ANNs, which are to receive inputs from the primary encoder, are considered [9]:

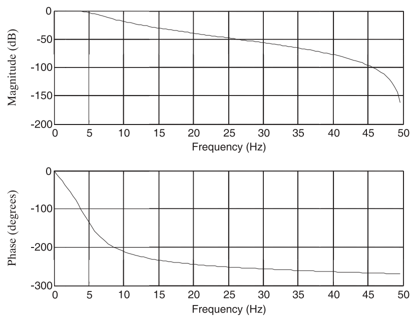
- Feedforward Neural Network (FNN),
- Radial Basis Function Network (RBF),
- Recurrent Neural Network (RNN).

Table 1 summarizes the important attributes of these ANNs. Data collected for the carriage velocity of 100 mm/s is first conditioned (low-pass filtered) to eliminate the high-frequency harmonics introduced by the transmission system (gearbox + timing belt). Figure 6(a) illustrates the Bode plot of this low-pass filter while Figure 6(b) shows the resulting data sequence composed of 1020 data points.

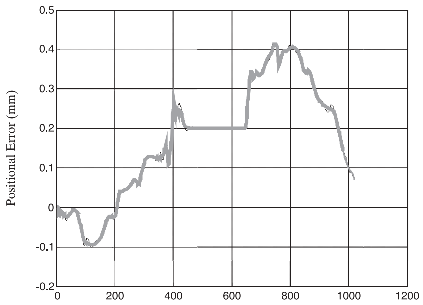
With conditioned training set, the above-mentioned neural networks are trained utilizing Matlab Neural Network toolbox. The training performances of these neural networks are illustrated in Figure 7 while Table 2 summarizes the key results. Note that in Table 2 data compression ratio refers to data points in the training set versus the free parameters of the network (aka "weights"). As can be seen, the FNN yields the best approximation. Surprisingly, the RBF demonstrates a rather poor approximation performance despite its large number of free weights.

Table 1. Neural network architectures used in the study.

FNN *	RBF *	RNN *
Input Layer :Pos, Vel	**Input Layer** :Pos, Vel.	**Input Layer** :Pos., Vel.
First Layer # Neurons: 3 Act. Fcn: Bipolar Sig.	**First Layer** # Neurons: 50 Act. Fcn: Gaussian	**First Layer** # Neurons: 3 Act. Fcn: Bipolar Sig.
Second Layer # Neurons: 6 Act. Fcn: Bipolar Sig.	**Output Layer** # Neurons: 1 Act. Fcn: Linear	**Output Layer** # Neurons: 1 Act. Fcn: Linear
Output Layer # Neurons: 1 Act. Fcn: Linear	N/A	N/A
Training Method: EBP / Gradient Descent	**Training Method:** Gradient Descent	**Training Method:** Levenberg-Marquardt
# Training Data : 1020 samples (Input: *Position, Velocity*; Output: *Position Error*)		

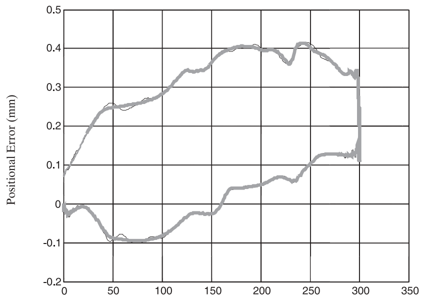


(a) Low-pass filter characteristics.

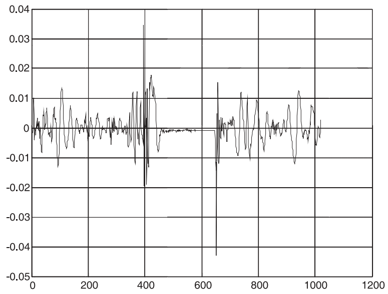


(b) Low-pass filtered training data.

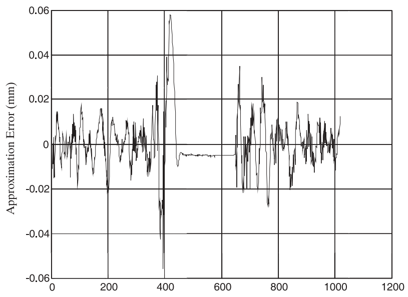
Figure 6. Training data where the carriage velocity is 100 mm/s.



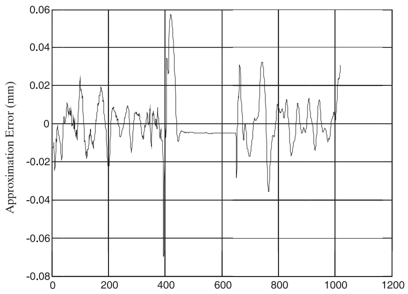
(a) Approximation performance of FNN.



(b) Approximation error of FNN



(c) Approximation error of RBF



(d) Approximation error of RNN

Figure 7. Training performances of ANNs.

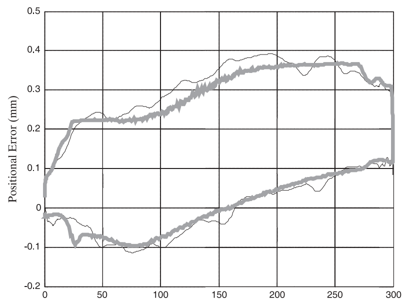
Table 2. ANN training performances.

(in mm)	FFN	RBF	RCN
RMS	0.0052	0.0120	0.0114
Max (Min)	0.0306 (-0.0423)	0.0581 (-0.0561)	0.0517 (-0.0687)
Mean	-1.4860e-006	-5.6860e-015	-1.5877e-007
Data Comp. Ratio	1020/45	1020/50	1020/15

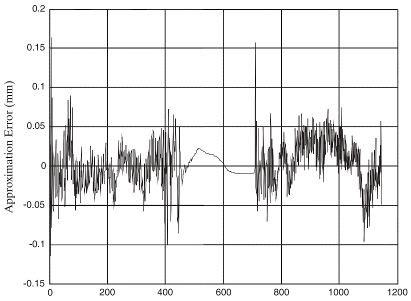
5. Generalization results and discussion

Next, the generalization capabilities of the networks are assessed. The generalization test is conducted with position error data for a carriage velocity of 80 mm/s. The test data is fed to the trained NNs and the estimation results are compared to original data.

The results are illustrated in Figs 8 thru 10. Despite the apparent success of FNN in training phase, its generalization performance is not that impressive if compared to those of others. Hence, the RBF apparently yields better generalization performance.

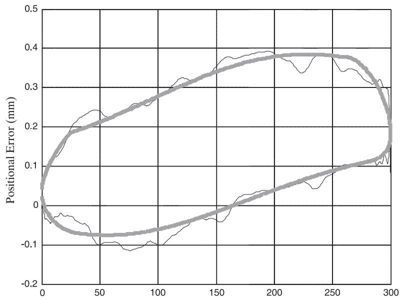


(a) Prediction performance.

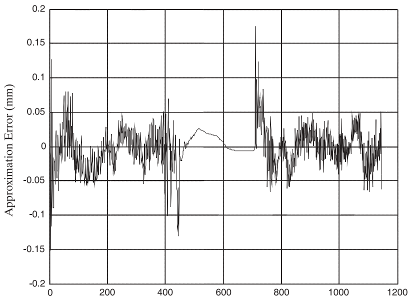


(b) Generalization error.

Figure 8. Generalization capability of FNN when carriage velocity is 80 mm/s.



(a) Prediction performance.

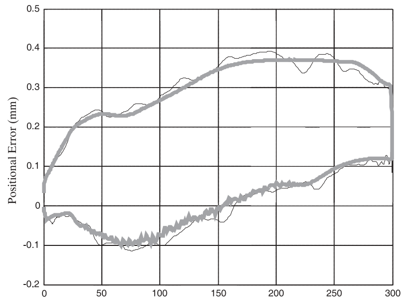


(b) Generalization error.

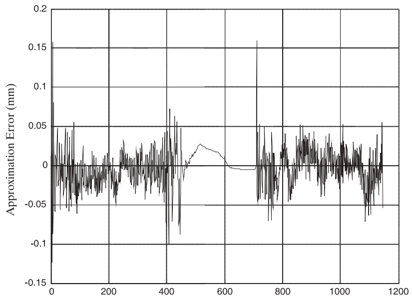
Figure 9. Generalization capability of RBF when carriage velocity is 80 mm/s.

6. Conclusion

In this study, three types of ANNs (FNN, RBF, RNN) are trained to approximate the quasi-static position error pattern of a carriage driven by a timing belt. During the experiments, extensive data is collected in a two-month period under different operating conditions. The collected data is spatially and temporally repeatable in character. Thus ANNs that are implemented to learn the error patterns off-line can be used to estimate the errors in an on-line manner. Consequently, a well-trained ANNs could be employed as a part of a low cost but high performance motion control paradigm.



(a) Prediction performance.



(b) Generalization error.

Figure 10. Generalization capability of RNN when carriage velocity is 80 mm/s.

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