Tracking control of a precision stage with NARX neural network for friction compensation

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Abstract. The objective of this study is to develop a neural network controller for the friction compensation. The purpose models are used as an inverse model of the frictional force and dynamic behaviour of a system. A proportional-integral-derivative (PID) controller and a neural network system architecture are developed for the Nonlinear Autoregressive with Exogenous inputs (NARX) neural network were proposed to control a precision stage. Firstly, a test signal was used to drive the stage then the derived data was used to train a NARX neural network. This neural network model is the inverse dynamic model of the stages and friction force. An architectural approach of NARX showing promising qualities for dynamic system applications, is analysed in this paper. Utilization of this model is as an estimate of the driving force related with the dynamics of the system against displacement, and is then used as a feed-forward controller to compensate for friction errors. Finally, the experimental systems are established and the result shows that the combination of PID and NARX can improve the tracking performance of the precision stage.

1. Introduction

The application of nanotechnology in the system control is crucial. Since it can realize the precision of the system that is increasingly accurate and controllable at the level of positioning model on the various tools. Nanotechnology is also considering to be able to help high resolution into a variety of technologies that are developing gradually. The movement in the vacuum that the machines will use now should be accurate and precise in nanometre scale on the axis of movement. In general, various machines have the same problem in terms of position accuracy, as friction force. Friction is a major nonlinear phenomenon that can detect tracking errors, stick-slip movement etc. This behaviour can distinguish into two operate the regimes: pre sliding and sliding [1]. In stick-slip movement, this mechanism is occurred by the desired movement which increases the energy consumption. The phenomenon may also be unstable [2]. The transformations of stages that have been innovated by several researchers have resulted in various new identification methods and new combinations of methods for friction compensation. Various identification techniques [3]-[6] and friction compensation methods [7]-[10] have also been investigated which can be used for further research. There are various forms of identification in previous research on friction. Such as about disturbance research based on the LuGre [14].

In general, PID is widely used because of its stability [11]. With the step response, PID has undergone evolution [11] - [12], and is a recent adjustment method of step response for different types of damping [13, 14]. In this paper, we use the technique of using natural frequency and damping ratio parameters
which will be described in the next chapter to obtain a plant PID control method with an underdamped step response.

Artificial neural networks have been widely used and developed into various models, this is due to the high adaptive adjustment to model various nonlinear systems and the ease of access to various mathematical problems. The NARX of the recurrent nerve architecture [15, 16], is a recurrent neural model, having a limited feedback architecture scheme that comes only from the output neurons rather than from hidden neurons.

The difference between this NARX model from the conventional recurrent network is that the network model has no computational disadvantages and shows at least commensurate with Turing machines. In addition to having strong computing, NARX networks also have other advantages, such as gradient-drop learning can be effective in NARX networks compared to in other recurring architectures that use "hidden status" [17]. There are many advantages of NARX, but the feasibility of this neural network model has not been fully developed as a primary tool for nonlinear models and univariate time series predictions. In [18] explains how NARX is reduced to a TDNN model for application in time series predictions. So we propose a simple theory based on taken embedding theorem [19] that allows NARX networks with native architectures to be efficiently applied to nonlinear time series predictions.

Based on this, the NARX network architectures are designed by the trial-and-error method to guarantee the good modelling accuracy. The activation functions, weights, and biases of selected network are optimized by differential evolution algorithm. For better prediction, new measured test data, which are not available in the training process, are used to verify the prediction capability of the optimal NARX model. The effect of noise disturbance on the modelling error is also investigated.

2. The system

The modeling system has been proposed in Figure 1. NARX is used to support tracking performance on mechanical systems. In this mechanical system, $u$ is used as input and $y$ is the position output. NARX is used to support tracking control in mechanical systems. In mechanical system, $u$ are used as input and $y$ is position output. To get the desired tracking results, therefore we create a dynamic inverse system using NARX neural network. The combination of PID and NARX represents, that $u$ is the force input, $\hat{u}$ is the necessary force estimated by NARX model, $u_c$ is the output of the feedback PID controller, and $f$ represents the remaining friction disturbance.

3. Inverse neural network dynamics model

This study aims to compensate for friction by looking at the displacement results carried out by underdamped stages where there is a connection between the currents sent through the driver with the desired displacement accuracy. The actuation signal at the input is directly corrected in this inverse system. For the identification procedure, we use parameters from the observed input-output data. First, determine the input and output variables as the basis for the dynamic inverse model. Second is designing the inverse dynamic model. In this case study, we use the NARX model.
3.1. Neural network identification

A recurrent neural network (RNN) is a class of artificial neural networks in which connections between nodes form directional graphs along temporal sequences. One example of RNN is the NARX model. This neural network has several structures which will be described in Chapter 3.2. Based on the PID simulation of the friction that occurs at a stage, the results of the observations made show that the input for the stage is the current $u(n)$ actuation signal and the output of the system displacement is read $x(n)$. The proposed study [20] demonstrated a sufficiently large nonlinear electro vibration in the neural network model for system identification. The inverse model for such a nonlinear system cannot be easily found, so it can be done instead using $x(n)$ as input and $u(n)$ as output. We propose to identify this model using neural networks to maintain structural maintenance.

3.2. NARX neural network architecture

NARX has a feedback connection that covers multiple layers of tissue. By utilizing NARX memory capabilities using predictive time series values or real-time series, NARX will deliver full neural network performance. NARX neural network models include mapping the input/output black box as a whole by a multilayer perceptron that combines time delay unit and output feedback in the input layer. It is an important class of discrete-time nonlinear systems that can be mathematically represented as

$$y(n + 1) = f[y(n), \ldots, y(n - d_y + 1); u(n - k),$$

$$u(n - k - 1), \ldots, u(n - k - d_u + 1)] + e(t),$$

(1)

which $u(n) \in \mathbb{R}$ and $y(n) \in \mathbb{R}$ denote, respectively, the input and output of the model at discrete time step $n$, where $d_u \geq 1$, $d_y \geq 1$ and $d_y \geq d_u$, respectively, described the input-memory orders and output-memory orders. Delay term $k (k \geq 0)$ is the process dead-time. Without lack of generality, we can assume $k=0$ in this paper, thus obtaining the following NARX model:

$$\hat{y}(n) = f[y(n - 1), \ldots, y(n - d_y); u(n), u(n - 1), \ldots, u(n - d_u)] + e(t),$$

(2)

where $e(t)$ is the model error between the target and prediction, the vector form can be expressed as

$$\hat{y}(n + 1) = f[y(n); u(n)] + e(t).$$

(3)

where the vectors $y(n)$ is output and $u(n)$ denote input regressors. Many nonlinear dynamics systems have been analyzed with NARX neural networks [21]. In addition to existing structures such as neural networks in general, this NARX network also has a closed loop structure, which with a feedback loop will connect to the input. To predict future outputs, use past input and output values.

![Block diagram of NARX neural network.](image)

Furthermore, it is necessary to create a neural network structure that will be used for NARX. The first is to determine the number of hidden layers in which the artificial neuron has a 'weight' set of input and a procedure to produce neuron output through the activation function, as well as the number of neurons, in...
each part because this will affect the calculations in the neural network. And also determine the size of the delay in each input sequence.

According to the input variable $u(n)$, the hidden layer output at time $n$ is obtained as

$$H_i(n) = f_1 \left[ \sum_{r=0}^{d_u} w_{ir} u(n-r) + \sum_{r=0}^{d_y} w_{il} y(n-l) + a_i \right]$$

(4)

where $w_{ir}$ is the connection weight between input neuron $u(n-r)$ and hidden neuron $i$th. And $w_{il}$ is the connection weight between output feedback neuron $y(n-l)$ and hidden neuron $i$th; $a_i$ is the bias of the hidden neuron $i$th; and $f_1$ is the hidden layer activation function. For the final equation that from hidden layer output can be given by

$$\hat{y}(n) = f_2 \left[ \sum_{i=1}^{d_h} w_{ji} H_i(n) + b_j \right]$$

(5)

where $w_{ji}$ is connection weight between $j$th predicted output $d_h$ and hidden neuron $i$th; $b_j$ is the bias of the $j$th predicted output; $d_h$ is the number of hidden neurons; and $f_2$ is the output layer activation function.

3.3. Error metric

To evaluate the predicted target results and actual results, two methods of calculating the average error are used, namely Root Square Mean Error (RMSE) and Mean Absolute Error (MAE). Which for the RMSE formula is

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x(n+1) - \hat{x}(n+1))^2}$$

(6)

where $x(n+1)$ is the true value of time series, $\hat{x}(n+1)$ is the predicted value, and $N$ is the how many steps into the future a given network for predict (i.e., Horizon). Furthermore, MAE itself has a formula

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |x(n+1) - \hat{x}(n+1)|$$

(7)

4. Experimental setup and the results of experiment

The experimental results are presented in this section. First, the experimental configuration is described. Then presented the identification results of the stages, in which the parameter values will be explained. Then, compensation for friction is by means of the neural network which is used in the stage system. Finally, the results of the friction compensation with the combination of PID and NARX will be presented.

4.1. Experimental setup

First, the experimental configuration is described. In this study, using stages referred to in figure 3. The feedback control uses dSpace and uses nanometers scale stages connected to coil motor. The motor coil will scroll a linear cross-roller guide path, and in this study only focus is on the Z position control. These nanometer scale stages are in figure 3 and 4 has 16 cm x 24 cm. A voice-coil motor VLR0262-0249-00A (AVM60-25, LTN Servotechnik GmbH) is used because it can move smoothly at low speed values and very small currents, as well as less current input noise. Laser Renishaw RLE10 (RLE, Renishaw) was selected to see the Z-direction displacement, this laser beam is bent upward into the Mz mirror plane. This displacement measurement has a value in the direction of Z with a resolution of 9.8 nm. The real-time controller of the stage is implemented by the dSPACE system (DS1103) with a sampling frequency of 1 kHz. The linear current Trust Automation TA310 Linear Drive functions to drive the linear voice coil motor because it has high stability which is different from the pulse width modulation amplifier.
Figure 5 illustrates the block diagram of the Simulink PID-NARX controller combination proposed for conducting the experiment.

Figure 3. Picture of the stage and the measurement system.

Figure 4. Structure of the stages.

Figure 5. Block diagram of the PID-NARX controller.

4.2. The results of dynamic model
The first step for the tuning of PID controllers is to obtain the plant step response. Several step response tests were conducted. The results of the step tests were summarized in Table I. For obtaining the nominal model of the stage, the average value to be taken is rise time $t_r = 0.0493$, settling time $t_s = 0.1497$, overshoot $= 6.8596$, undershoot $= 0$, and peak time $t_p = 0.1026$. The nominal value of natural frequency and damping ratio are $\zeta = 0.606$ and $\omega_n = 41.121$, respectively.

| Current input (A) | $y_{ss}$ ($\mu$m) | $t_s$ (s) | $t_p$ (s) | $\omega_n$ | $\zeta$ |
|------------------|---------------------|-----------|-----------|------------|---------|
| 0.2              | 347.9               | 0.111     | 0.096     | 48.677     | 0.740   |
| 0.3              | 647.9               | 0.136     | 0.101     | 43.505     | 0.626   |
| 0.4              | 1097                | 0.180     | 0.098     | 38.481     | 0.577   |
| 0.5              | 1169                | 0.213     | 0.101     | 37.636     | 0.551   |
| -0.15            | -372.7              | 0.127     | 0.105     | 43.441     | 0.725   |
Table 1. Step response parameter.

| Current input (A) | \(y_n (\mu m)\) | \(t_e (s)\) | \(t_p (s)\) | \(\omega_n\) | \(\zeta\) |
|------------------|----------------|-------------|-------------|-------------|--------|
| -0.3             | -756.6         | 0.137       | 0.101       | 42.661      | 0.684  |
| -0.4             | -947.7         | 0.240       | 0.097       | 36.269      | 0.450  |
| -0.5             | -1218          | 0.204       | 0.098       | 37.578      | 0.521  |

Using direct trial and error methods at the proposed stages to obtain \(K_p\), \(K_i\) and \(K_d\) values for optimal values. After some trials, the best value is with \(K_p = 0.03605\), one obtain \(K_d = 0.00036\) and \(K_i = 9.695\) The model identified was

\[
G(s) = \frac{3210179.68}{s^2 + 52.07 s + 1609.63}
\]  

(8)

4.3. Identified results of NARX

The architecture determination of the neural network is done by trial and error to determine the best architecture using automatic scripts in MATLAB. NARX neural network axis training was carried out several times to predict the current value that will be made reference for determining the actual position in the experiment. Training period used until 1000 epoch training period in open and closed loop mode. This network structure achieves the lowest error prediction of mean squared error. Predict the mean squared error of \(1.62e-07 \mu m\) in the open loop and \(0.0036 \mu m\) in the closed loop. MSE results from open loop are much better than closed loop. Since in closed loop NARX, delayed target input is replaced by a direct delayed output connection, the output containing errors are fed back to the input.

4.4. Control results

The proposed study was evaluated using sinusoids 0.5, 1 and 2 Hz with amplitudes of 10 and 100 for input in command. Figure 6 shows the comparison between the predicted current output \(\hat{u}\) and the original data \(u\) for test trials, training, and validation of accuracy. Figure 7 shows the platform displacement that occurs using the current input \(u\). Figure 8 shows the control result of the proposed PID controller without NARX to track a 1 Hz sinusoidal an amplitude of 10.

In the results of tracking sinusoidal signals using the PID system without NARX with 1 Hz and an amplitude of 10 \(\mu m\), the maximum error value is 0.2986. By using the RMSE and MAE formula in equation 6 and 7, the value obtained is 0.0966 and 0.0708, respectively.

![Figure 6. Current signal target used in training, testing, validation and the identified results.](image1)

![Figure 7. Displacement of the stages for input data test.](image2)
Figure 8. The results of PID controller (a) and error signal (b) for tracking 1 Hz, 10 μm sinusoidal reference signal.

Figure 9. The results of PID controller with NARX friction compensation (a) and error signal (b) for tracking 1 Hz, 10 μm sinusoidal reference signal.

With NARX neural network friction compensation in figure 9, the maximum tracking error of the controller is reduced to 0.2684 and RMSE to 0.960. Meanwhile, the MAE value obtained is 0.0632. Table 2 shows trace errors for tracking other sinusoidal signals and different amplitude. Obviously, the NARX neural network compensator can improve the performance of the PID controller and the performance of the proposed controller is better than the original PID controller.

| Input | Amplitude | RMSE  | MAE  |
|-------|-----------|-------|------|
|       |           | PID   | PID NARX | PID   | PID NARX |
| 0.5 Hz| 10 μm     | 0.0580| 0.0565   | 0.0430| 0.0411   |
|       | 100 μm    | 0.0923| 0.0868   | 0.0623| 0.0538   |
| 1 Hz  | 10 μm     | 0.0966| 0.0960   | 0.0708| 0.0632   |
|       | 100 μm    | 0.1790| 0.1729   | 0.1078| 0.0933   |
| 2 Hz  | 10 μm     | 0.1829| 0.1933   | 0.1174| 0.1241   |
Table 2. Errors of tracking sinusoidal signals.

| Input | Amplitude | RMSE | MAE |
|-------|-----------|------|-----|
|       | PID NARX  | PID NARX | PID NARX |
| 100 μm | 0.3845 | 0.3585 | 0.2348 | 0.2076 |

Table 2 shows the performance of the sine signal tracking using the error parameters RMSE and MAE. Above shows that at 0.5 Hz input, results in a displacement of 10 and 100 μm explained that the combination of PID NARX generate better value. Similarly, input 1 Hz at 10 and 100 μm displacement which has the result of a combination of PID NARX better. The difference appeared at the 2 Hz input at a 10 μm displacement, where the PID results were better than the NARX PID combinations. This phenomenon occurs because the amplitude factor is too low and the frequency input speed is too fast. Although at the same input, the 100 μm displacement result from PID-NARX is better than PID because the amplitude is not too low. The effect of amplitude will be explained in conclusions and discussion.

5. Conclusions and discussion

In this paper, a neural network precision tracking controller has been proposed. This controller uses a combined method of PID feed-forward controller and NARX neural network feedback controller. The results of the experiment using the combination of these two controls can compensate for the errors and disturbances of the model in nanometres size well. With the NARX neural network controller, it was found that this controller can improve the tracking performance of the PID controller. In the proposed control system, it has been tested with the minimum and maximum amplitudes relevant to the stages. The NARX reference model facilitates a tracking enhancement process which compensates for friction in micro meters. Furthermore, the influence can affect the sensitivity and effectiveness of the controller, which is explained by the MIT rule [22,23]. In [23] according to the MIT rule, it explains that a system that has a very high amplitude will cause the system to become unstable and at a very low amplitude it will reduce the effectiveness of responding to disturbances, several alternative friction compensation control have been suggested to deal with these drawbacks. Evaluation of the stages structures and performance of NARX friction compensation system control structure will be planned for future research.

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