Applied Mathematics & Information Sciences
An International Journal

http://dx.doi.org/10.12785/amis/091L15

Improving Neural Network based Vibration Control for Smart Structures by Adding Repetitive Control

Chi-Ying Lin and Chih-Ming Chang*

Department of Mechanical Engineering, National Taiwan University of Science and Technology, Taipei, Taiwan

Received: 16 Nov. 2013, Revised: 17 Mar. 2014, Accepted: 18 Mar. 2014
Published online: 1 Feb. 2015

Abstract: Neural networks (NN) has been a popular vibration control method because of its robustness and practicability to reject broad band disturbances for complex systems such as smart structures. However, the benign characteristic of NN, suppressing a wide range frequency of disturbances, may also limit its control performance at specific frequencies and inevitably cause non-minimum output responses in particular under persistent excitation. To alleviate this limitation and improve the performance of NN based control methods, this paper presents a hybrid control strategy comprising a neural controller and a repetitive controller for active vibration control of smart structures. The neural controller is a fundamental controller which applies back-propagation networks for performance evaluation. To add repetitive control into the existing NN control system, the work transforms a feedback controller to a feedforward control problem with the solutions of a bezout identity embedded with known internal models of injecting disturbances. The presented hybrid control provides a synergetic effect and aims for better suppression performance subject to complicated disturbances in stringent environments. Experimental results on a flexible beam demonstrate the effectiveness of the proposed control method.

Keywords: Neural Networks, Repetitive Control, Active Vibration Control, Smart Structures

1 Introduction

In the past two decades neural networks (NN) has been recognized as an effective technique for active vibration control applications [1,2,3,4] due to its robustness to dynamic parameters variation and adaptability to broad band disturbances rejection [4]. For smart structures applications, NN is commonly realized in particular along with func-tional materials made sensors and actuators [5] Ibecause the demands of lightness and compactness are continuously increasing from industries.

Among the available functional materials, piezoelectric materials are the most popular ones because they provide fast response and fine resolution. As a result, a great number of re-search concerning the use of NN and piezoelectric actuators on various kinds of structures for active vibration control has been widely reported, ranging from simulation study [4,6,7,8] to experimental investigation [1,9,10,11,12,13]. Most of the research has been concentrated on developing various NN models and controllers and emphasized on the vibration control performance by injecting complicated board band disturbances including band-limited white noises [9,11, 12]. NN is considered as a robust control method and particularly suitable for suppressing vibration responses with respect to unknown excitation or time varying environments. From practical point of view, this is not a surprising result because the mechanism of NN basically aims to minimize the mean square value of the error between desired input and target output [14], or equivalently the measured output in most active vibration control studies. This benign property explains why NN based methods effectively address uncertain situations and surpass other classical methods with smaller amplitude and smoother shape characteristics frequently discussed in frequency domain anal-ysis, showing the ability of rejecting distur-bances comprising a wide range of frequencies.

However, although useful in smart structures technology, the NN based vibration control tech-niques still have limitations and need further investigation. Considering the well-known Bode integral constraint [15] the increased robustness of NN may simultaneously constrain the control performance and cause periodic and non-minimum output responses especially when dealing with deterministic signals [1,11,12,16]. Although these repeatable errors could be reduced with the aid of

* Corresponding author e-mail: chiying@mail.ntust.edu.tw

carefully adjusting the learning parameters in NN, it is inconvenient to perform such an exhaustive tuning task which makes limited performance improvement and remains non-convergent steady state errors.

To release this performance constraint and improve the vibration suppression more efficiently, this paper presents an enhanced NN control method that includes a repetitive controller based on a hybrid control structure [17]. Following the internal model principle [18] the added repetitive control can effectively eliminate the periodic errors coming from the persistent excitation near resonant frequencies. Besides improving the performance of rejecting periodic disturbances, the hybrid control provides a synergetic effect and aims for better vibration control subject to complicated distur-bances in stringent environments. The work first introduces a neural controller applying back propagation networks as a fundamental controller for performance evaluation. The study then experimentally verifies the performance and effectiveness of the proposed hybrid NN controller on a flexible beam for better active vibration control.

2 Hybrid Neural Network and Repetitive Controller Design

Figure 1 shows the schematic diagram of the proposed hybrid neural network and repetitive controller, where v and u represent the system output and control input, respectively. The control goal of this study is to further improve the vibration suppression performance of neural network controller C_1 with the aid of adding repetitive controller C_2. For this hybrid control system, C_1 could be any standard feedback controller besides neural network controller and C_2 is another feedback controller which includes a positive feedback loop cascaded by a plant model $\hat{G}$. Using this specific control structure, one can embed the repetitive controller into an existing feedback control system because finding C_2 hen becomes a typical feedforward control problem as explained in the following sections.

2.1 Neural Network Controller Design

The neural network applied in this study is a back propagation algorithm [14] which can propagate the input signals through weighted operation and activation functions (neurons) in hidden layers and pass them to the output layer. If the difference between the network outputs and the desired values exists, the networks will propagate the signals back to the hidden layers and iteratively adjust the weights and biases until the difference reduces to an acceptable range. Figure 2 shows the schematic diagram of a typical back-propagation neural network, in which x_i, H_j and y_k represent the input signal, activation function, and output signal, respectively.

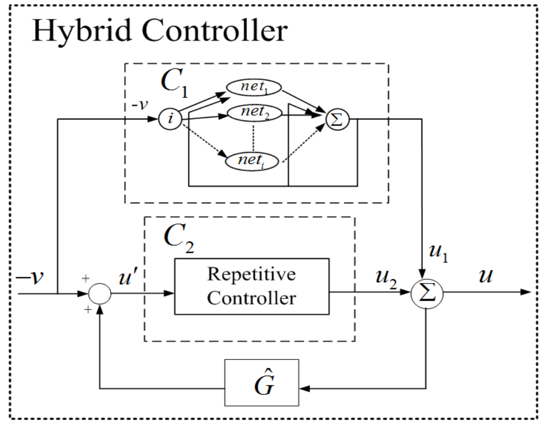

Figure 1 Schematic diagram for the hybrid controller

The mathematical representation relating to the network in Figure 2 can be explained as follows:

$$y_k^n = H_j(net_j^n), \quad net_j^n = \sum_i w_{ij}^n x_i^{n-1} + b_j^n, \tag{1}$$

where n and j denote the number of interested layer and neuron, respectively, w_{ij} and b_j represent the weight and bias corresponding to the j^{th} neuron, and net_j^n indicates the sum of weighted outputs from the $(n-1)^{th}$ layer. The activation function H in equation (1) is a hyperbolic function presented as

$$H_j(net_j^n) = tanh(net_j^n). \tag{2}$$

To reduce the error between network output y_k and the desired value d_k, define a cost function E as

$$E = \frac{1}{2}\sum_k (d_k - y_k)^2. \tag{3}$$

By using a steepest descent method and minimizing the above cost function, the update formula for weights w_{ij} can be determined as

$$w_{ij}(p+1) = w_{ij}(p) - \eta \frac{\partial E}{\partial w_{ij}}. \tag{4}$$

In equation (4) $w_{ij}(p)$ and $w_{ij}(p+1)$ represent the weight at current and next time step, respectively. η is a tuning parameter which determines the learning rate. The real-time update of weights reduces the error and achieves the desired control performance when the neurons persistently receive signals for training purpose. The training process is repeated and stopped until the error is within an allowed small range.

2.2 Repetitive Controller Design

A repetitive controller is a feedback controller that includes an internal model of input signals. This type of

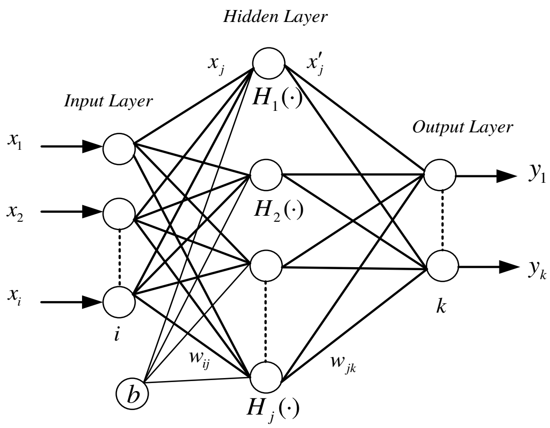

Figure 2 Schematic diagram for the hybrid controller

controller can eliminate periodic disturbances based on the internal model principle [18]. Researchers have developed various repetitive controllers for many control applications, including prototype repetitive control [19], robust repetitive control [20], and the internal model control approach mentioned in [21]. The applied repetitive controller in this study is similar to the technique presented in [21], but excludes an adaptive controller component. The transfer function from exogenous input d to system output y can be derived as follows:

$$y = \frac{1-\hat{G}C}{1-\hat{G}C+GC}d, \tag{5}$$

where $\hat{G}$ is the plant model of G and can be obtained using a finite element model [5] or system identification methods [22]. Assuming that the system plant is stable and the identified plant model is sufficiently accurate, meaning that $\hat{G} \approx G$, equation (5) then becomes

$$y = (1-\hat{G}C)d. \tag{6}$$

The original feedback control problem has been transformed to a feed-forward control problem. Thus, the control goal here is to minimize the tracking error with cost a function $J = (1-\hat{G}C)$. The simplest solution to this control problem is to find a stable plant inverse of $\hat{G}$ [23]. Several performance indexes, such as 2-norm or infinity-norm, can be used for different optimal control problems [24]. For practical applications, consider the case when the system input contains some specific internal models D, which is usually known a priori. To control the vibration of flexible structures, an important goal is to minimize the significant structural res-ponses under persistent excitation at or near resonant frequencies. Therefore, it is natural to choose a periodic signal generator $D = 1 - z^{-N}$, whose period N corresponds to the fundamental frequency and resonant modes in the repetitive controller design. Let

$$1-\hat{G}C = RD \quad or \quad \hat{G}C + RD = 1, \tag{7}$$

where R is a part of the controller C and needs to be designed later. The equation above can be recognized as the famous "Bezout Identity" [25] with the assumption that $\hat{G}$ and D are coprime.

Next, consider a single input, single output (SISO) plant model $\hat{G}$ and factorize c into two parts $\hat{G} = G_o G_i$, in which G_o is minimum phase and G_i is non-minimum phase, respectively. Suppose

$$\begin{aligned} \hat{G} &= \frac{B}{A} = \frac{B^+B^-}{A} = G_o G_i, \\ G_o &= \frac{B^+}{A}, \quad G_i = B^-, \end{aligned} \tag{8}$$

where A and B represent the denominator and numerator of $\hat{G}$, and B^+ and B^- indicate the stable and unstable parts of B, respectively. Substituting equation (8) into equation (7), one can obtain

$$\begin{aligned} RD + \tilde{C} &= 1, \\ \tilde{C} &= CG_o. \end{aligned} \tag{9}$$

From the plant inversion idea presented in [23] one solution pair R', C' to solve equation (9) is given as follows:

$$\begin{aligned} R' &= \frac{1}{1-(1-\gamma G_i^* G_i)qz^{-N}}, \\ \tilde{C} &= \frac{\gamma G_i^* qz^{-N}}{1-(1-\gamma G_i^* G_i)qz^{-N}}, \\ C' &= \tilde{C}G_o^{-1}, \end{aligned} \tag{10}$$

where γ is a learning gain for performance tuning, $G_i^*(z^{-1}) = G_i(z)$, and q is a zero phase low pass filter to suppress the instability caused by the high gain feedback at undesired frequency ranges. Note that this q filter is embedded within the selected internal model as $D = 1 - q(z,z^{-1})z^{-N}$. Refer to [21] for a detailed performance analysis of the design parameters in equation (10).

3 Experimental Setup

This study used an aluminum flexible beam for active vibration control experiments. Table 1 lists the beam properties. A piezoelectric patch actuator (Model No. SB4020008 from Piezo actuator$^{\text{TM}}$) and a PVDF sensor (Model No. LDT0-028K/L from MEAS) were surface bonded to the fixed end of the cantilever beam as a pair of collocated piezoelectric actuator-sensor patches. Table 2 summarizes the properties of the piezoelectric patches.

Table 1 Beam properties

Symbol	Quantity	Unit	Cantilever Beam
L	Beam length	mm	500
h	Beam thickness	mm	1.76
W	Beam width	mm	25.45
ρ	Beam density	Kg/m^3	2700
E	Young's modulus	N/m^2	7.1×10^{10}

Table 2 PZT patches properties

Symbol	Quantity	Unit	PZT actuator	PVDF sensor
L_{px}	Length	mm	40	25
h_p	Thickness	mm	0.8	0.2
L_{py}	Width	mm	20	13
ρ_p	Density	Kg/m^3	7.4×10^3	1.78×10^3
g_{31}	Stress constant	Vm/N	-8.2×10^{-3}	0.216
d_{31}	Stress constant	C/N	-3.2×10^{-1}	2.3×10^{-11}
E	Young's modulus	N/m^2	7.1×10^{10}	0.2×10^{10}

Figure 3 presents the experimental setup for real-time vibration control experiment. A third PZT patch used to excite resonant mode was attached to the free end of the beam. A twenty-times voltage amplifier (VP7206 made by PiezoMaster) was used to supply enough voltage input to actuate the PZT actuator and suppress the structural vibration. A sensor amplifier (Piezo film lab amplifier made by MEAS) with a 30 mV r.m.s. noise level and an 0.1 Hz $\sim$ 10 Hz band-pass filter setup was adopted to filter out unwanted noises and obtain useful measurement for feedback control. This study is primarily concerned with the suppression of beam's first mode, whose resonant frequency is approximately 6 Hz. The proposed hybrid control algorithms were implemented using MATLAB Simulink, and the data was acquired by a 16-bit A/D and 12-bit D/A DAQ board (PCIM-DAS1602/16) at a 3 kHz sampling rate.

4 Experimental Results and Discussion

Because of the applied repetitive control, a mathematical model is still needed to facilitate the proposed controller design. This section first presents system identification results and then moves to the discussion of vibration control experimental results on a flexible cantilever beam.

4.1 Neural Network Controller Design

As shown in the literature and also in experi-ments, the first mode of the flexible beam mainly dominates its

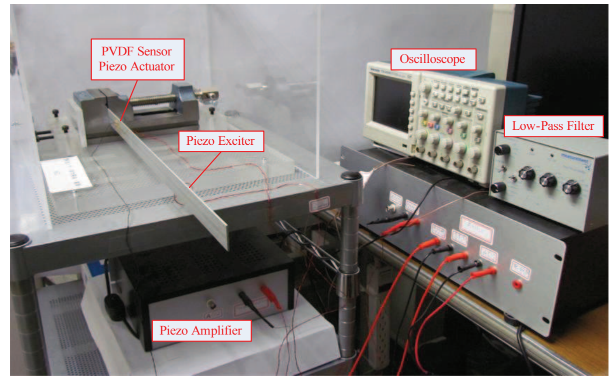

Figure 3 Photograph of the experimental setup

vibration response and thus becomes the major concern in this study. To obtain a mathematical model for the repetitive controller design, system identification technique was performed by injecting a time series of random binary signal and recording the sensor output as input and output data. The random frequency range was from 0 $\sim$ 15 Hz sampled at 3 kHz for 10 seconds. Using the system identification toolbox "ident" in Matlab and filtering out high frequency dynamics one can fit a discretized second order model. Figure 4 presents the identification results.

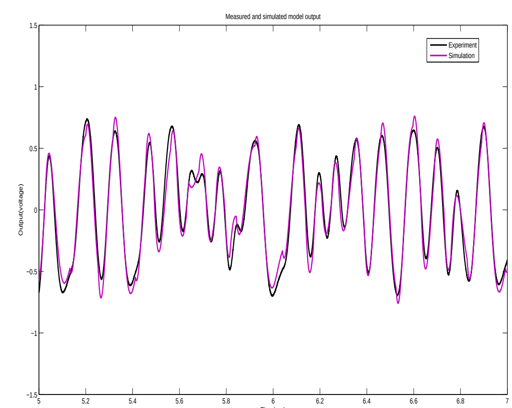

Figure 4 Measured and simulated model output

4.2 Vibration Control Results and Discussion

For the training of neural network controller, the work applied a network which consists of one hidden layer with four neurons and one output neuron for NN control input.

The neurons in the hidden layer and output layer use a sigmoid function and a linear function, respectively. Considering the case that the dis-turbance is measureable, the three inputs are excitation signals, its one step delay, and error signal. After the training and fine tuning process the weights in the network are fixed for controller implementation.

To further demonstrate the effectiveness of the proposed method, this study designed two sets of disturbance sources for vibration suppression experiment, including (1) combination of sine wave and impulse disturbances; and (2) combination of sine wave and band-limited white noise disturbances. The following compares the vibration suppression performance of three controllers: NN control, repetitive control, and hybrid NN/repetitive control.

1) Vibration Suppression Result for Impulse and Sine Wave Disturbances

In the first experiment, the study gives sine wave disturbance in the first 10 seconds and then adds impulse disturbance by hitting the end of the beam. Besides performance evaluation, one purpose of injecting this kind of disturbance is to test the robustness of the proposed method subject to an unexpected input particularly under persistent excitation.

Figure 5 illustrates the frequency responses of the uncontrolled and controlled output using fast Fourier transform (FFT). It is obvious from figure 5 that for no control case there exist two peaks coming from impulse and sinusoidal input excitation, respectively. Table 3 lists the amplitude reduction results for these two peaks. As can be seen, applying NN control alone achieves about 39% at first mode and 81% at 6 Hz vibration suppression, respectively. Using repetitive control further reduces the am-plitude peak at 6 Hz by 87% but pops up the peak at the first mode. Figure 6 shows the time responses of the controlled output by using three different controllers. Clearly, applying either NN control or RC control suppresses the oscillating outputs well, reaching a steady state less than 7 seconds. It is found that trained neural networks reduce the maximum absolute value of the output time data but cause a relatively larger steady state value comparing to the RC control case. Next, the influences of using the proposed hybrid control method are justified through injecting an impulse input right after 10 seconds. As shown, an apparent transience occurs in particular in the RC control case (figure 6(b)). The above results indicate that RC control is effective in rejecting periodic-like signals but is unable to suppress the vibration response caused by impulse inputs. However, if we add the RC control into an existing NN control system, the resultant control further improves the overall suppression performance and reserves the advantages of each control, shown in figure 6(c).

2) Vibration Suppression Result for Sine Wave and Band-Limited White Noise Disturbances

Table 3 Amplitude reduction results for the first mode and 6 Hz subject to impulse and sine wave disturbances

Amplitude (reduction)	No control	NN control	RC control	RC+NN control
At first mode	0.23	0.14(39%)	0.24(−4%)	0.09(61%)
At 6 Hz	0.47	0.09(81%)	0.06(87%)	0.02(96%)

In the previous experiment we have shown the effectiveness and robustness of using the enhanced NN control by adding repetitive control to suppress the vibration response subject to sinusoidal and impulse disturbances. To demonstrate the practicality of this method this study also gives another set of disturbances by combining band-limited white noises ($0 \sim 0.5$ Hz) with a 6 Hz sine wave for performance evaluation. This is a case commonly seen in many applications because random distur-bances always exist in real environment and applied experimental hardware.

Figure 7 shows the time responses of the controlled output using three control methods. Because of its learning properties under complicated environments, the result in figure 7(a) indicates that NN control smoothes the output with a fast converging speed (in 7 seconds) and reaches the steady state with over 50% reduction. On the other hand, the transient time in RC control case (figure 7(b)) is twice longer than in NN control case. Be-cause the main components of the injected disturbances are periodic signals, the RC control iteratively adjusts its control input based on a known internal model and achieves an asymptotic output contaminated by the random disturbances. It is found that applying the proposed hybrid NN/RC control still improves the control performance and alleviates this undesired effect in particular for the transient part as shown in figure 7(c).

5 Conclusion

To improve the performance and practicability of NN based vibration control in smart structures technology, this paper presents a hybrid control design method by adding a repetitive controller into the existing NN control system. The experimental results conducted by injecting different combinations of sine wave, impulse, and band-limited white noises show excellent performance and effectiveness of the presented method. It is found that adding repetitive control effectively improves the overall performance both in transient and steady state responses in particular under per-sistent excitation. The enhanced NN control rejects complicated disturbances well and at-tains better vibration reduction comparing to applying NN control alone.

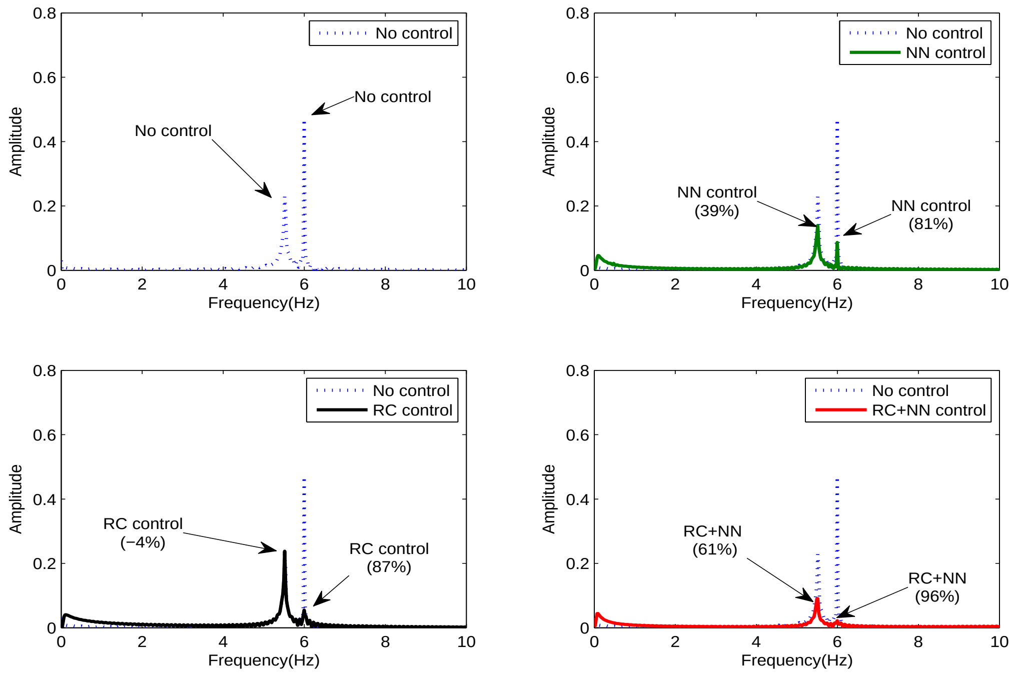

Figure 5 Frequency responses of the controlled output by FFT for impulse and sine wave disturbances

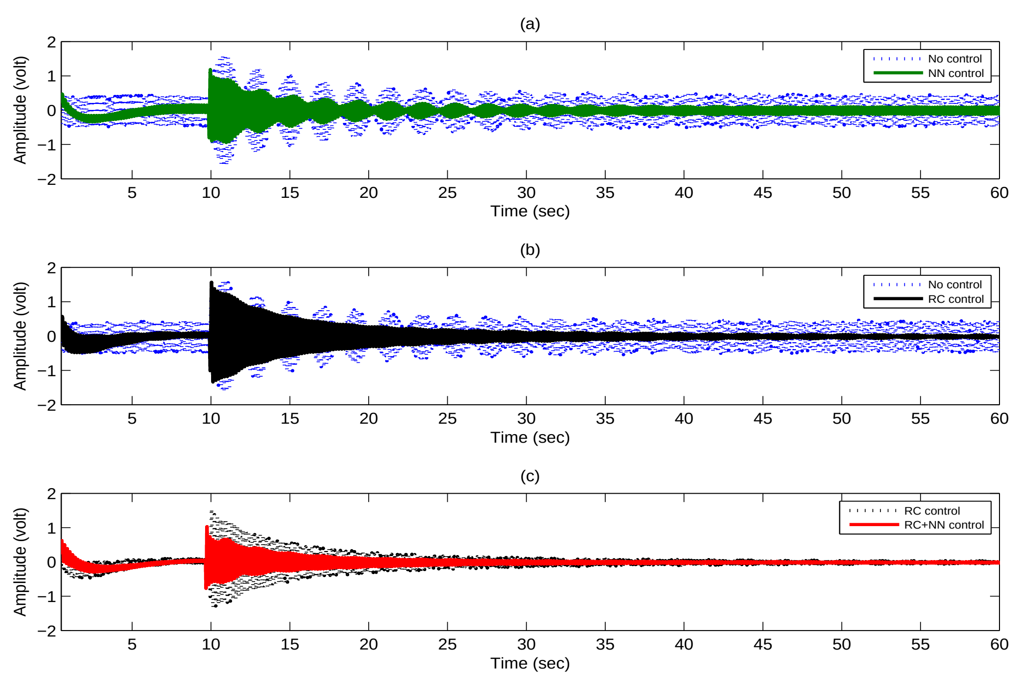

Figure 6 Time response of the controlled output for sine wave and impulse disturbances: (a) NN control; (b) RC control; (c) Hybrid NN/RC control

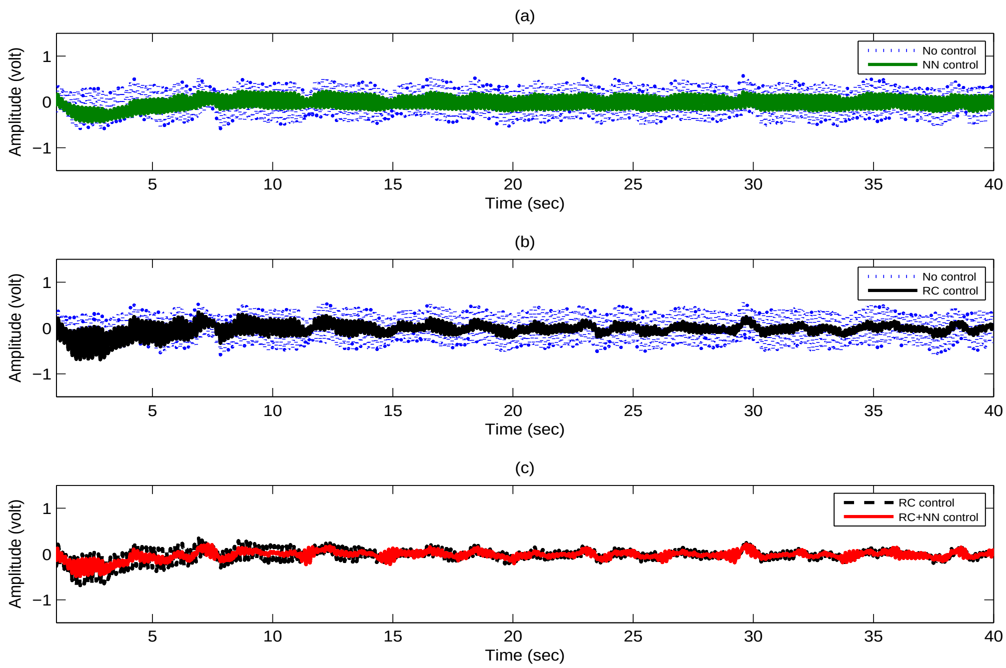

Figure 7 Time response of the controlled output for sine wave and impulse disturbances: (a) NN control; (b) RC control; (c) Hybrid NN/RC control

Acknowledgement

This work was partially supported by National Science Council, Taiwan, R.O.C., under grant number NSC 99-2221-E-011-096.

References

[1] S. D. Snyder and N. Tanaka, Active Control of Vibration Using a Neural Network, IEEE Transactions on Neural Networks. (1995), **6**, 819-828.
[2] Y. M. Song, C. Zhang, and Y. Q. Yu, Neural Networks Based Active Vibration Control of Flexible Linkage Mechanisms, Journal of Mechanical Design. (2001), **123**, 266-271.
[3] S. Yildirim, Vibration Control of Suspension Systems Using a Proposed Neural Network, Journal of Sound and Vibration. (2004), **277**, 1059-1069.
[4] A. Madkour, M. A. Hossain, K. P. Dahal, and H. Yu, Intelligent Learning Algorithms for Active Vibration Control, IEEE Transactions on Systems, Man, and Cy-bernetics Part C: Applications and Reviews. (2007), **37**, 1022-1033.
[5] A. Premount, Vibration Control of Active Structures: an Introduction, Springer (2002).
[6] Y. K. Wen, J. Ghaboussi, P. Venini, and K. Nikzad, Control of Structures Using Neural Networks, Smart Materials and Structures. (1995), **4**.
[7] M. T. Valoor, K. Chandrashekhara, and S. Agarwasl, Active Vibration Control of Smart Composite Plates Using Self-Adaptive Neuro-Controller, Smart Materials and Structures. (2000), **9**.
[8] M. T. Valoor, K. Chandrashekhara, and S. Agarwasl, Self-Adaptive Vibration Control of Smart Composite Beams Using Recurrent Neural Architecture, International Journal of Solids and Structures. (2001), **38**, 7857-7874.
[9] L. Davis, D. Hyland, G. Yen, and A. Das, Adaptive Neural Control for Space Structure Vibration Suppression, Smart Materials and Structures. (1999), **8**.
[10] S. H. Youn, J. H. Han, and I. Lee, Neuro Adaptive Vibration Control of Composite Beams Subject to Sudden Delamination, Journal of Sound and Vibration. (2000), **238**, 215-231.
[11] R. Jha and J. Rower, Experimental Investigation of Active Vibration Control Using Neural Networks and Piezoelectric Actuators, Smart Materials and Structures. (2002), **11**,
[12] R. Jha and C. He, Neural-Network-Based Adaptive Predictive Control for Vibration Suppression of Smart Structures, Smart Materials and Structures. (2002), **11**.
[13] D. H. Kim, J. H. Han, D. H. Kim, and I. Lee, Vibration Control of Structures With Interferometric Sensor Non-Linearity, Smart Materials and Structures. (2004), **13**.
[14] S. Haykin, Neural Networks and Learning Machines, Prentice Hall (2008).
[15] G. J. Balas and J. C. Doyle, Robustness and Performance Trade-offs in Control Design for Flexible Struc-tures, IEEE

Transactions on Control Systems Technology. (1994), **2**, 352-361.
[16] H. L. Ji, J. H. Qiu, Y. P. Wu, J. Cheng, and M. N. Ichchou, Novel Approach of Self-Sensing Actuation for Active Vibration Control, Journal of Intelligent Material Systems and Structures. (2011), **22**, 449-459.
[17] C. Y. Lin and C. M. Chang, Vibration Control of Active Structures Using Hybrid PD/Repetitive Control, IEEE International Conference on Mechatronics and Automation. (2011), 926-931.
[18] B. A. Francis and W. M. Wonham, The Internal Model Principle of Control Theory, Automatica. (1976), **12**, 457-465.
[19] M. Tomizuka, T. C. Tsao, and K. K. Chew, Analysis and S1976ynthesis of Discrete-Time Repetitive Controllers, Journal of Dynamic Systems, Measurement, and Control. (1989), **111**, 353-358.
[20] J. Li and T. C. Tsao, Robust performance repetitive control systems, Journal of Dynamic Systems, Measurement, and Control. (2001), **123**, 330-337.
[21] C. Y. Lin and T. C. Tsao, Adaptive Control with Internal Model or High Performance Precision Motion Control, ASME International Mechanical Engineering Congress and Exposition, Settle, WA, USA, 1021-1029 (2007).
[22] L. Ljung and E. J. Ljung, System Identification: Theory for The User, Prentice-Hall NJ (1987).
[23] M. Tomizuka, Zero Phase Error Tracking Algorithm for Digital Control, Journal of Dynamic Systems, Measurement, and Control. (1987), **109**, 65-69.
[24] T. C. Tsao, Optimal Feed-Forward Digital Tracking Controller Design, Journal of Dynamic Systems, Measurement, and Control. (1994), **116**, 583-592.
[25] S. Skogestad and I. Postlethwaite, Multivariable Feed-back Control: Analysis and Design, Wiley (1996).

Chi-Ying Lin received the Ph.D. degree in mechanical engineering from University of California, Los Angeles, USA, in 2008. He is currently an associate professor in the Department of Mechanical Engineering, National Taiwan University of Science and Technology, Taiwan. His research interests include design and control of precision positioning systems, active vibration control, intelligent robots, and mechatronics.

Chih-Ming Chang received the Master degree in mechanical engineering from National Taiwan University of Science and Tech-nology, Taipei, Taiwan, in 2011. He is currently serving his compulsory military service. His research interests include active vibration control of smart structures.