NEURAL NETWORK BASED IDENTIFICATION OF A LARGE SEGMENTED SPACE REFLECTOR

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ABSTRACT

This paper presents methods and results on neural network based identification of a multiple segmented telescope system. The neural net identification procedure is the first step toward the development of a neural controller, which will be designed and used for vibration suppression and figure maintenance. Different network structures are developed, tested and evaluated. The networks are trained on input/output data provided by a reduced order model, which has been obtained from a high order finite element model of the structure. After training is completed, the networks are validated as system identifiers, by comparing the neural network response to the system response for various control and disturbance inputs. The identification procedure is performed at the subsystem level and at the overall system level. It is seen that the networks perform very well as system identifiers for all tests.

1. INTRODUCTION

With the need for higher resolutions, the next generation of telescopes will be space based and will require very large mirrors. To circumvent the problems that a large monolithic mirror has (large weight, difficult to manufacture, difficult if not impossible to send to space etc.), segmented mirror telescopes are an effective alternative. A segmented mirror reflector consists of mirror panels, which when formed together become a parabolic primary mirror that magnifies the images from space. A monolithic reflector depends on the mechanical properties of its material to provide the dimensional stability required for good optical performance. A segmented reflector relies on its support structure for stiffness and rigidity and an active control system to maintain alignment of the individual panels.

To study the complex dynamic behavior of large segmented optical systems, NASA has funded a five-year project to design and construct a test-bed in the Control and Structures Research Laboratory (CSRL) at the California State University, Los Angeles. The CSRL test-bed serves as a generic experimental facility capable of performing experiments that simulate the complex dynamics of a large segmented optical system. It is being used as an experimental facility for addressing in an integrated way, problems associated with structural dynamics, control , optics, electronics, actuators and sensor design.

The segmented reflector telescope investigated in this work consists of 6 hexagonal mirror panels arranged in a ring configuration, attached to a supporting truss structure (Fig. 1). Each mirror is 1m from edge to edge, and the focal length of the entire primary mirror is 2.4 m. Interferometric edge sensors and accelerometers are attached to the back of the panels to measure displacement. Each panel has three voice coil actuators, placed equidistantly, for high precision control of each mirror. The large size of the telescope makes the structure flexible to external forces, such as thermal fluctuations and solar disturbances. Control algorithms have to be developed to achieve a telescope figure maintenance within 1μm in a dynamic disturbance environment.

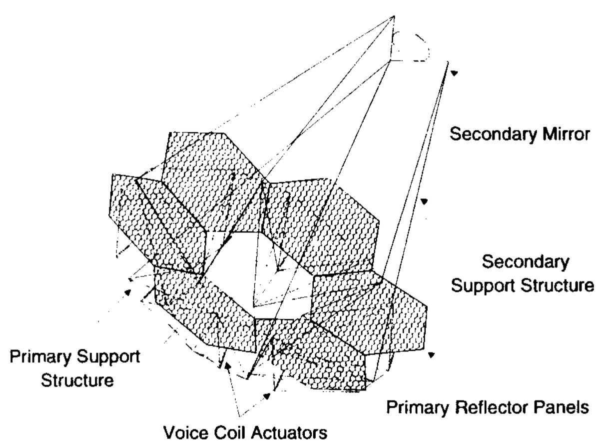

Fig. 1 Segmented telescope concept

This paper presents results on the identification of the segmented reflector telescope, based on neural network methods. The identification procedure is the first step towards the development of a neural controller. Fig. 2

shows the preliminary design for a neural controller working in conjunction with a neural identifier for the vibration suppression and figure maintenance [Yen, 1994]. For the purposes of the present work, a telescope structure was designed and modeled at CSRL. The design presented here is one of three alternative designs done at CSRL and which are currently being evaluated, [Mirmirani et al., 1995]. The structure was designed to be structurally as simple as possible, and it is comprised almost exclusively of tetrahedrons. For creating the control model, the secondary mirror is modeled as a triangular truss with its mass lumped at three nodes. The primary mirror panels are also modeled as triangular trusses with their mass lumped at three nodes. A finite element model was obtained based on this design, through the program IMOS, developed at the Jet Propulsion Laboratory, [Boussalis et al., 1993]. Subsequently, a model reduction technique (Guyan reduction) was performed. The reduced order model of the overall system has 36 states, consisting of 18 displacement variables and their derivatives. Decentralization on the system is performed by isolating each physical subsystem (mirror panel along with its associated structural members). Each isolated panel is represented by a 6x6 system, and has 3 control inputs and 3 measured outputs (designated as locations 1,2,3 for each panel). Also, a disturbance force is assumed acting on the system.

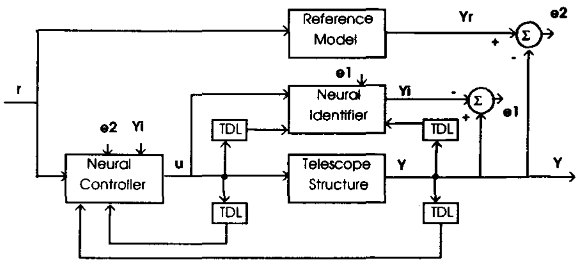

Fig. 2: Control of the structure through neural networks (TDL= tapped delay line)

The neural network identification results are based on the reduced model described above. Several network structures and different training strategies were developed, tested and evaluated. Initially single input / single output subsystems were identified at the panel level. Through this initial approach, familiarity was obtained with the system at hand, the system responses and required training procedures. Next single input / multi-output transfer functions were identified for each subsystem, and subsequently the multi-input/multi-output subsystems representing each isolated panel were modeled by neural nets. Finally, the overall system was identified by a neural network. Feedforward neural networks trained by modified back propagation algorithms were tested and were found to be good representations of the system. The following sections describe the network architectures, training strategies and identification results in detail.

3. NEURAL NETWORK BASED IDENTIFICATION OF STRUCTURES

The identification and control of structural systems based on neural networks has received considerable attention recently. The massive parallelism inherent in neural networks, their learning abilities, their fault-tolerance and their approximating properties make them a good alternative choice for identification of unknown structural systems, even when nonlinearities are present. Some of the previous works on structural identification based on neural networks can be found in [Chassiakos et al., 1991a; 1991b], in [Masri et al., 1992; 1993] and also in [Housner at al., 1995]. Feedforward neural networks have been used by the authors to identify nonlinear internal forces in unknown structures. These networks represent static maps between their inputs and outputs and can be trained by standard back propagation. A static map, however, cannot approximate the dynamics of a dynamical system. Several methods have been proposed for the approximation of dynamical systems by neural networks. In [Chassiakos et al., 1992] neural networks with dynamic neurons have been successfully used to approximate the nonlinear dynamics of a robot manipulator, in continuous time. In [Narendra and Parthasarathy, 1990] the dynamic back propagation method has been used to train these networks. In the present work we follow a discrete-time approach, which enables us to use feedforward networks and train them by back propagation. The delayed outputs of the system are fed back to the network as input, together with delayed system inputs, and the network can be trained by back propagation methods.

The approach taken here consists of the following steps:

- Obtain frequency response characteristics of the system and each subsystem. The frequency response will give a general idea as to what input signals should be chosen for training of the network; it will also provide guidelines as to what order delays may be used to represent the system.
- Identification of a SISO (single input/single output) transfer function on panel 1. This is a relatively easy problem, but it provides us with enough experience as to the type of network, order of delay and training procedures.
- Identification of SIMO (single input/multi-output) transfer functions for each panel (1 input / 3 output transfer functions). This problem is one level of complexity higher. Based on the experience of the previous step and on the frequency response information, appropriate network structures and network sizes are chosen and tested.
- Identification of MIMO (multi-input/multi-output) transfer functions for each panel (3 input / 3 output transfer functions). For this harder problem several network structures were tried and evaluated until

one was eventually chosen. Information from the previous step can be used to decide on the networks for this step. The networks chosen in this step represent the isolated subsystems, and they will be used for a decentralized controller, as subsystem neural identifiers.

- Identification of the overall system.

For all the above steps, the *training phase* is followed by the *validation phase*. The network response is calculated first for the training inputs and subsequently for any arbitrary inputs. The weights are kept at their optimal values and the network is tested as a system identifier.

4. IDENTIFICATION OF SUBSYSTEMS AT THE PANEL LEVEL

4.1 SISO subsystems: Initially the SISO transfer function from input 1 to output 1 on panel 1 was modeled by a neural network. Its frequency response shows that it has a resonant frequency of $\cong$ 2000 *rad/sec*, and that it exhibits second order characteristics with a zero at the origin. Based on this, two delayed outputs *y(k-1), y(k-2)* and one delayed input *u(k-1)* were fed to the input layer of the network at time *t=k*. The training input is chosen as a swept sine signal, with linearly increasing frequency, which passes through the resonant frequency of the structure:

$$u(t) = \sin(\omega(t) * t)$$

and the frequency $\omega(t)$ is given as a function of time by

$$\omega(t) = \omega_0 + (\omega_f - \omega_0)t / t_f$$

where the initial frequency is ω_0=400 *rad/sec*, the final frequency is ω_f = 5000 *rad/sec* and the final time t_f = 0.15 sec .

A two layer network trained by back propagation with momentum and adaptive learning rate is used. Based on time response characteristics, the system outputs were scaled-up by a scaling factor of 400 and fed back to the input layer of the network. During the training phase it took about 500 iterations for the sum of square errors to settle to a small level (Fig. 5 - top). The network was tested with swept sine, step, random and periodic inputs and was seen to be an excellent identifier of the SISO subsystem. Some of the test results are shown in Fig. 5, where the neural net output (dotted line) is compared to the system output (solid line) for swept sine input (Fig. 5b) and for random input (Fig. 5c,d).

4.2 SIMO subsystems: The next step is the identification of single input / multi-output subsystems for each panel. The same swept sine input as in the SISO case was applied to location 1 (Fig. 6 - top). The neural network used has the structure shown in the block diagram of Fig. 3, with 7 inputs and 3 outputs. A two layer network was initially chosen, with 10 hidden nodes, so that the weight matrices W11 and W12 are of dimensions (10x7) and (3x10) respectively.

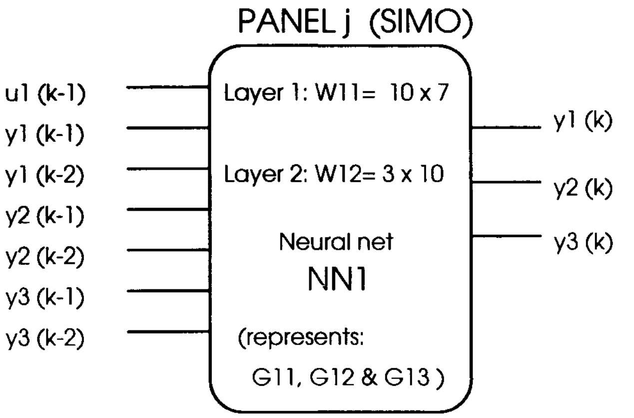

Fig. 3: Neural net for identification of transfer functions G11, G12 and G13

Fig. 6 compares the prediction of the neural network to the system response after training. It is seen that the network is doing an excellent job in reproducing the system. There is a slight difference between network prediction and system response during the initial time in the plots for *y2* and *y3*. This difference is due to the fact that the contribution of outputs *y2* and *y3* to the network input layer is very small as compared to the contribution of *y1*. One way to increase this contribution is to use higher scaling factors for *y2* and *y3*. This approach was tried and it proved to be very successful. It was not used though, because of the desire to keep uniform scaling. Uniform scaling will be necessary for the identification of the MIMO subsystem and of the overall system. The network was validated by testing it with a random input and a unit step input applied to location 1. The results were very good, even though the network was never trained on these particular inputs.

During identification of the SIMO subsystem, several different training strategies and network structures were tested. The results, however, did not show much of a difference from the results of the network described above. Some of these strategies are given next:

- since the model is a linear system, the network nonlinearities (sigmoid functions, such as hyperbolic tangent) were replaced by linear functions, and the network was retrained and tested again.
- tests were performed that forced the bias vectors to be kept constant equal to zero during training.
- different order delays were tried for the input and output, since the transfer functions G12 and G13 exhibit complex zeros at $\omega\cong$ 1000 *rad/sec,* and higher order phase characteristics. This increased the complexity of the network without any visible increase in performance.

Since these different strategies did not produce significant changes in performance, it was decided to keep the network structure as described initially in this section.

4.3 Identification of MIMO subsystems: For the identification of the full multi-input/multi-output subsystem representing each panel, it was decided to use the trained networks obtained in the previous section. The initial idea was to use the three separate networks corresponding to each panel: for panel j (j=1,...6) network NN1 represents the SIMO transfer functions G11, G12 and G13 from input 1 to the three outputs; network NN2 represents the SIMO transfer functions G21, G22 and G23 from input 2; and network NN3 represents the SIMO transfer functions G31, G32 and G33 from input 3. Since these networks were already trained in the previoius section, it was decided to keep them separate and use their optimal weights as initial weights for training of the MIMO subsystems. This network structure uses a combination of the trained networks NN1, NN2, NN3 and two additional unmodifiable layers, one at the input and one at the output. The input unmodifiable layer is implemented by a matrix W0, which is a fixed matrix. It does not get updated during training, and its role is to distribute the inputs u1, u2 and u3 to the networks NN1, NN2 and NN3 respectively. Similarly, the output unmodifiable layer is implemented by a fixed W3, which is used to sum up the corresponding outputs of each distinct network. The overall network represents the 3-input/3-output transfer function of panel j. Data of input/output pairs are generated from the state space representation of the panel

$$\dot{x} = Ax + Bu + B_f F$$

$$y = Cx + Du$$

where B and B_f represent the control influence and disturbance influence matrices respectively.

- *training initialization*: Training of this network is performed on NN1, NN2 and NN3 only, whereas W0 and W3 remain fixed. The three networks NN1, NN2 and NN2 are initialized at the optimal values obtained in the previous section, through the SIMO training.
- *training input:* initially the same swept sine as in the previous section was used for all input locations. The comments made in section 4.2 about the relative magnitudes of each output are applicable here as well and for this reason the training input was modified to a swept sine of amplitude varying with time, as shown in Fig. 7 - top. This signal was used as a training input at location 1, whereas at locations 2 and 3 the same signal as introduced, but phase-shifted by 45° and 90°. This new training inputs, result in more data points throughout the input/output space, hence increasing the approximating accuracy of the network.
- *training algorithm:* a modified version of the back propagation algorithm was used, which allows for keeping selected weights of the network fixed, without any updating.

After training was over, it was observed that many of the elements of the trained matrices are close to 0. This is a result of the structure imposed on the network (several interconnections were set to zero), but it also suggests that the network could be trained with a smaller number of weights.

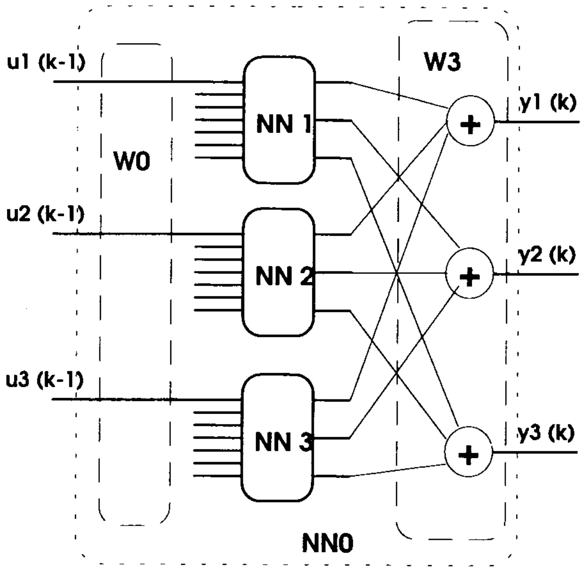

Fig. 4 Neural net for identification of each panel

4.4 Networks of reduced size: The network structure as described above produced very good results. However, based on the last observation, it was decided to try a network of smaller size. The new, smaller network has no fixed weights, and all the parameters are updated by the training algorithm. The training inputs are again swept sine signals of varying amplitude. The same training procedure was repeated for panels 2-6. From frequency response plots of the control input to output transfer functions for each panel, it was determined that the corresponding transfer functions for each panel are similar to each other (i.e. transfer function G12 of panel 1 is very close to G12 of panel 2, etc.). As a result, as soon as the network for panel 1 was trained, the optimal values for this network were used to initialize the weights for the network of panel 2, etc. This strategy resulted in reduced training time for the remaining panels.

4.5 Validation procedure: The trained networks representing each panel are subjected to different control inputs, and their response compared to that of the system. For uniformity of testing, all networks were subjected to the same control inputs:

(a) swept sine input with varying amplitudes, which was also used during training (Fig. 7)

(b) random excitation (Fig. 8)

(c) step input

(d) a periodic input with combined low and high frequency components (Fig. 9)

The results for panel 1 only are shown in Figs. 7-9, where the neural net output (dotted line) is compared to the system output (solid line). Similar results were obtained for the remaining 5 panels, and it is seen that the neural networks perform remarkably well for all subsystems and all inputs tested.

Regarding the weights of the trained networks, some qualitative observations can be made:

- Matrices W1 are very similar to each other for every panel. This is expected, since the MIMO transfer functions for each panel are close to each other and all networks were initialized with the same weights. The same is true for matrices W2 for all panels.
- The bias vectors are close to 0. This is also expected from the linear model used.
- The first three columns of matrix W1 have very small values, for all panels. This suggests that the three control inputs are weighted less in the network than the outputs and that a smaller network could perhaps be trained.

5. IDENTIFICATION OF THE OVERALL SYSTEM

The final step in the identification phase is the identification of the overall system through neural networks. An approach similar to the one described in section 4 was initially considered: using the subsystem neural nets individually and interconnecting them through an additional input layer and an additional output layer. Given, however the experience obtained in section 4 regarding this approach (resulting in large matrices with many zero elements), it was decided to try a completely new network of small dimensions with randomly initialized weights. The network identifies the relation from disturbance input to outputs for the overall system. The disturbance forces act on three points of the structure. A disturbance input determined in [Boussalis et al., 1993] was used for training and is shown in Fig. 10 - top. Fig. 10 compares the system outputs to the neural net prediction, for panel 1 only, when the overall system is subjected to the disturbance input. It is seen that the network has identified the overall system very well. Similar results are obtained for all the remaining panels, when the overall system is subjected to disturbance inputs.

6. CONCLUSIONS

The work presented in this report covers the neural network based identification of a large segmented space telescope. Several neural network structures and training strategies were developed, tested and evaluated. It was shown that two layer networks, whose inputs include delayed versions of the system outputs, can be effective identifiers at the subsystem and at the overall system level. The work currently under progress includes the evaluation of the two additional structural designs developed at CSRL and the preliminary study of neural controllers, incorporating the neural identifiers described in the present paper.

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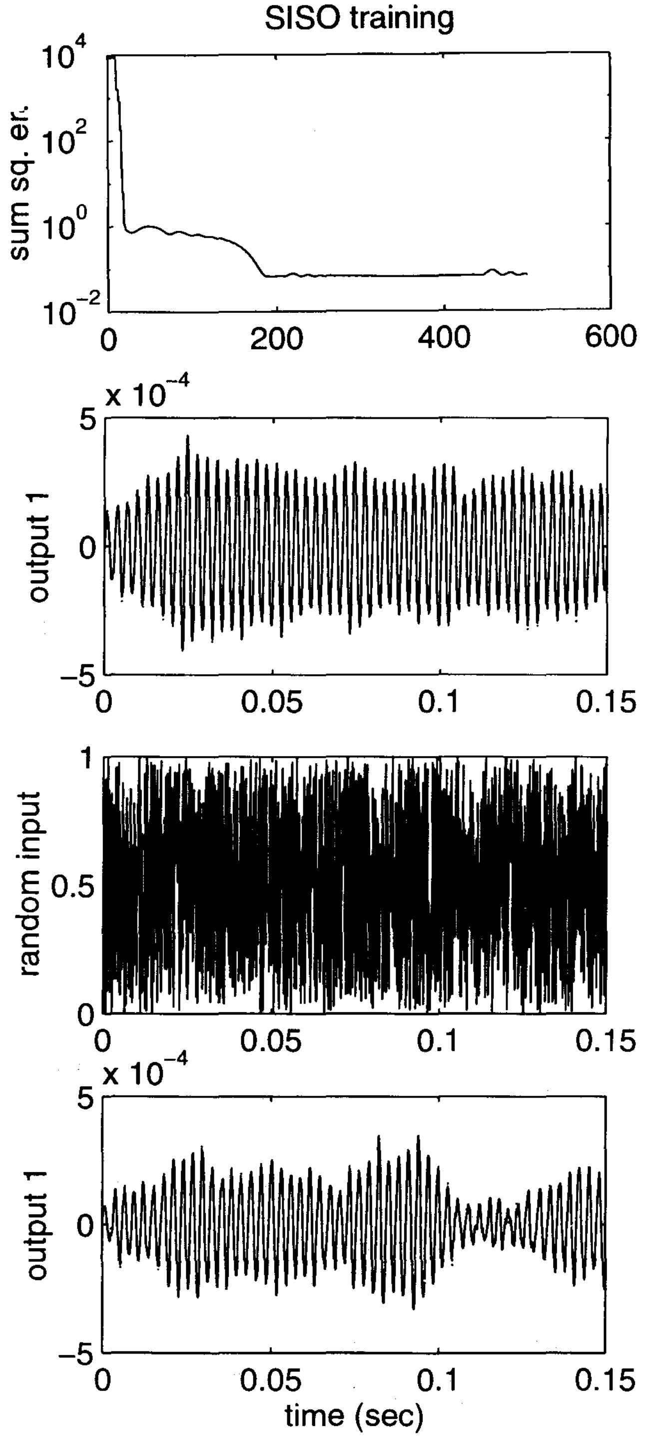

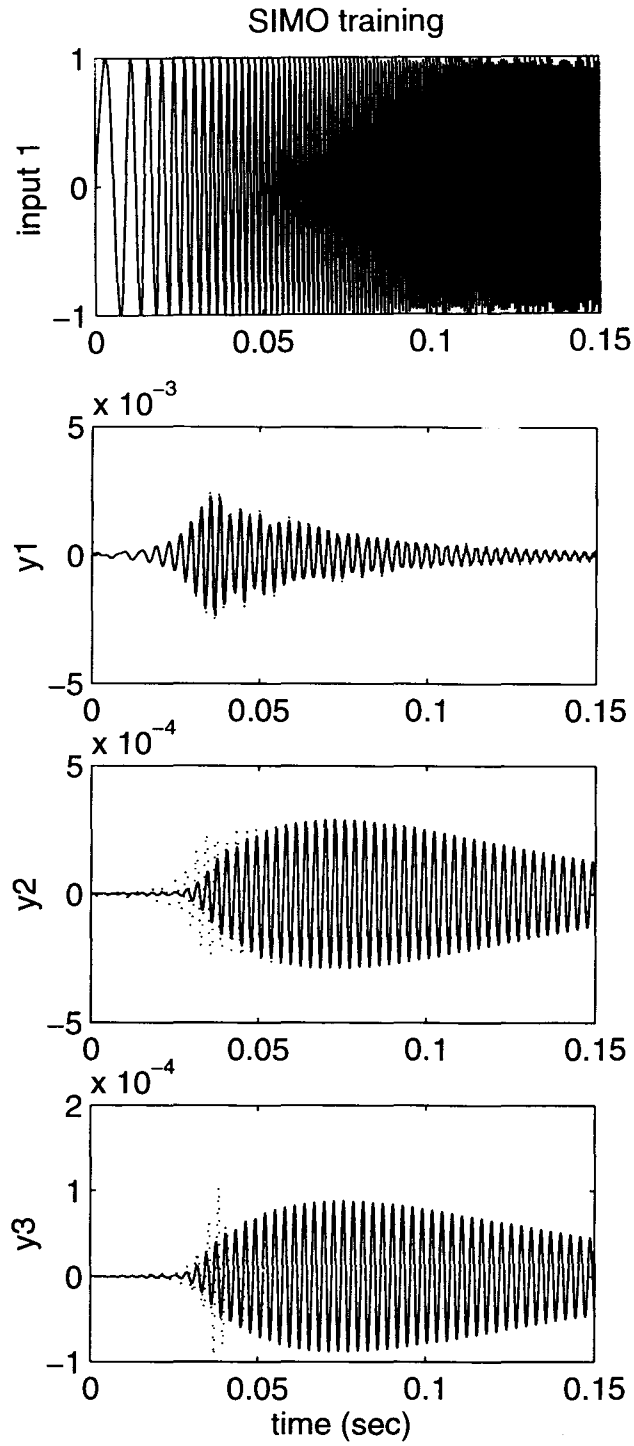

Fig. 5: SISO subsystem (panel 1)
(a) sum squared error vs. number of iterations
(b) neural net prediction (dotted line) vs. system output (solid line) for swept sine input
(c) random testing input
(d) neural net prediction (dotted line) vs. system output (solid line) for random input

Fig. 6: SIMO subsystem (panel 1)
(a) swept sine training input
(b)-(d) neural net prediction (dotted line) vs. system output (solid line) for swept sine input

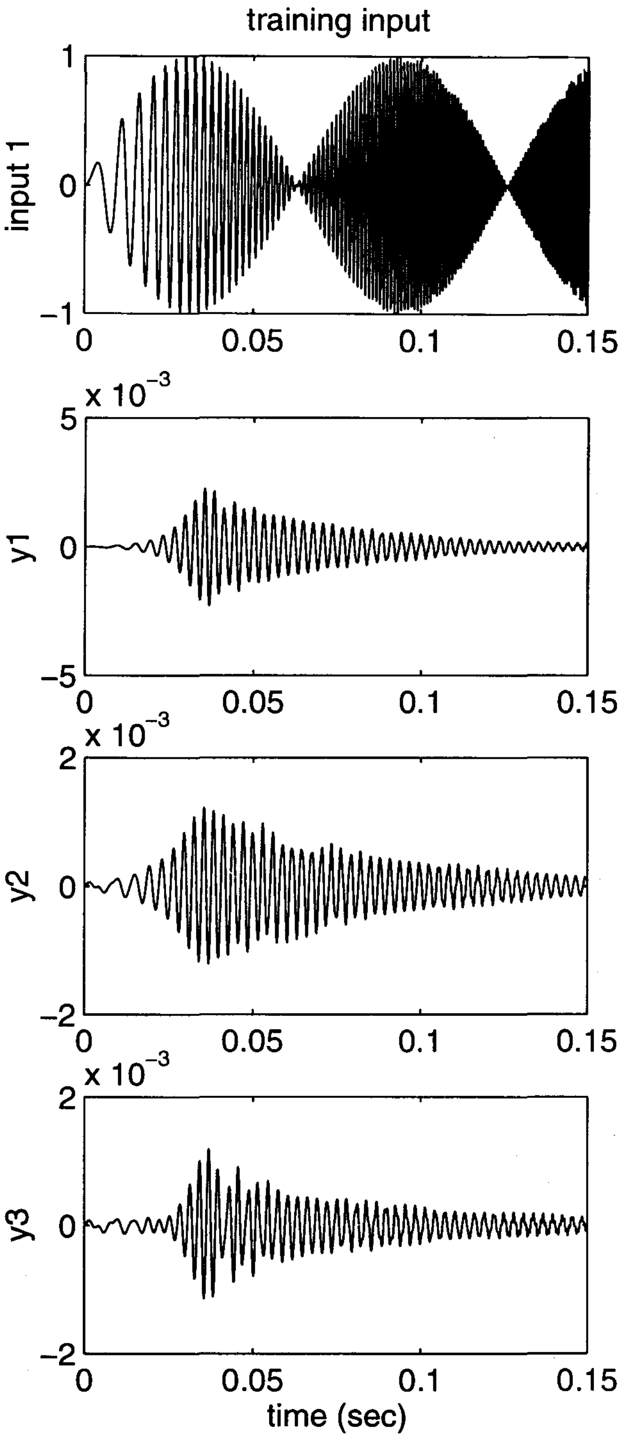

Fig. 7: MIMO subsystem (panel 1)
(a) training input at location 1: swept sine of varying amplitude
(b)-(d) neural net prediction (dotted line) vs. system output (solid line) for training input

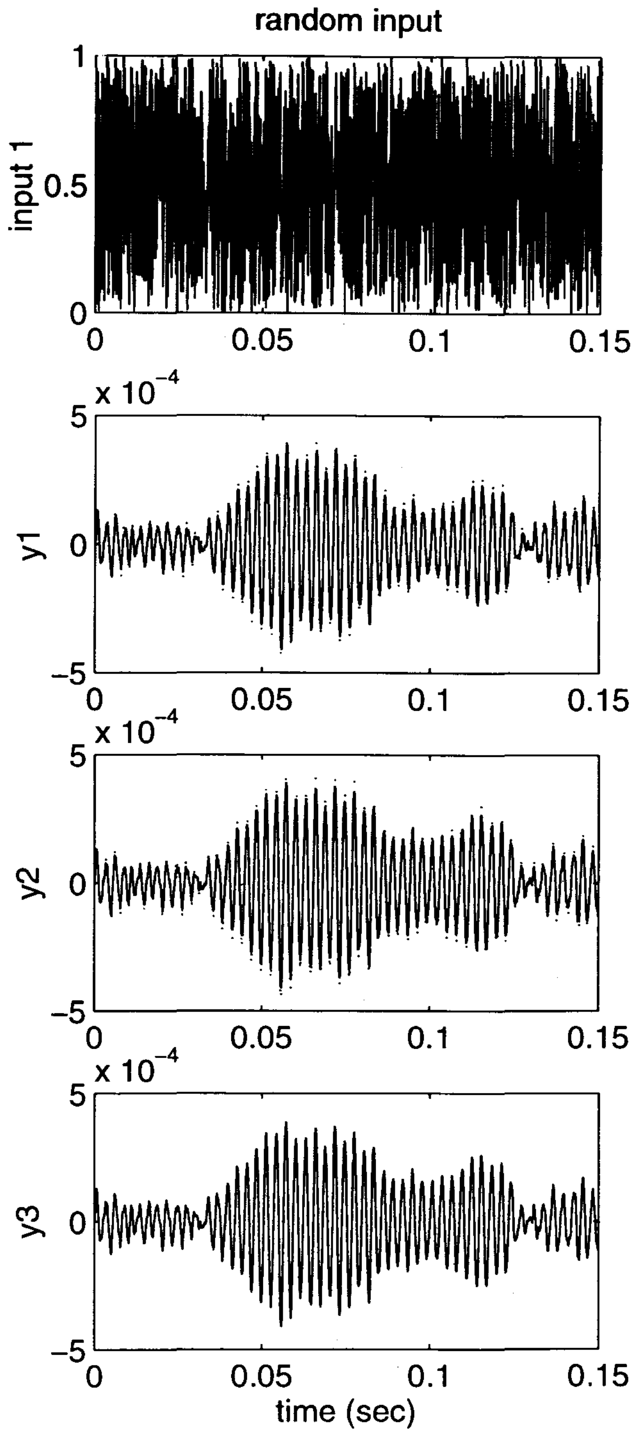

Fig. 8: MIMO subsystem validation (panel 1)
(a) random testing input at location 1
(b)-(d) neural net prediction (dotted line) vs. system output (solid line) for random testing input

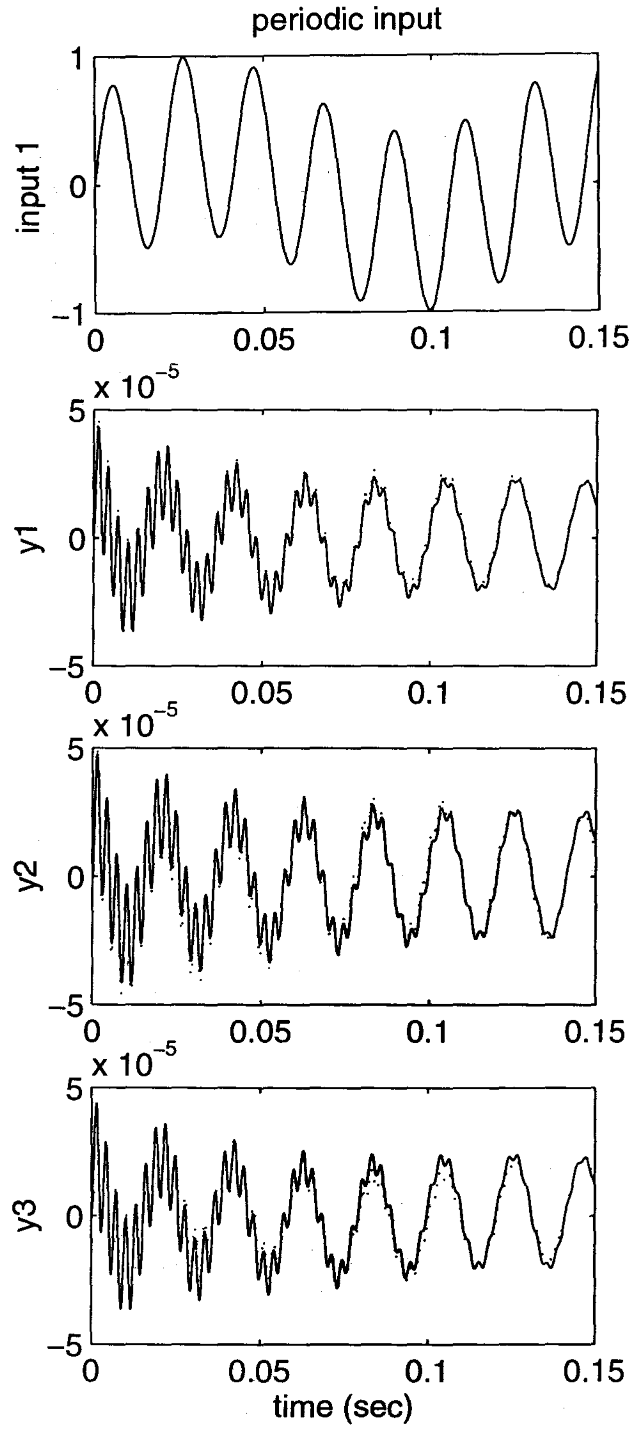

Fig. 9: MIMO subsystem validation (panel 1)
(a) periodic testing input at location 1
(b)-(d) neural net prediction (dotted line) vs. system output (solid line) for periodic testing input

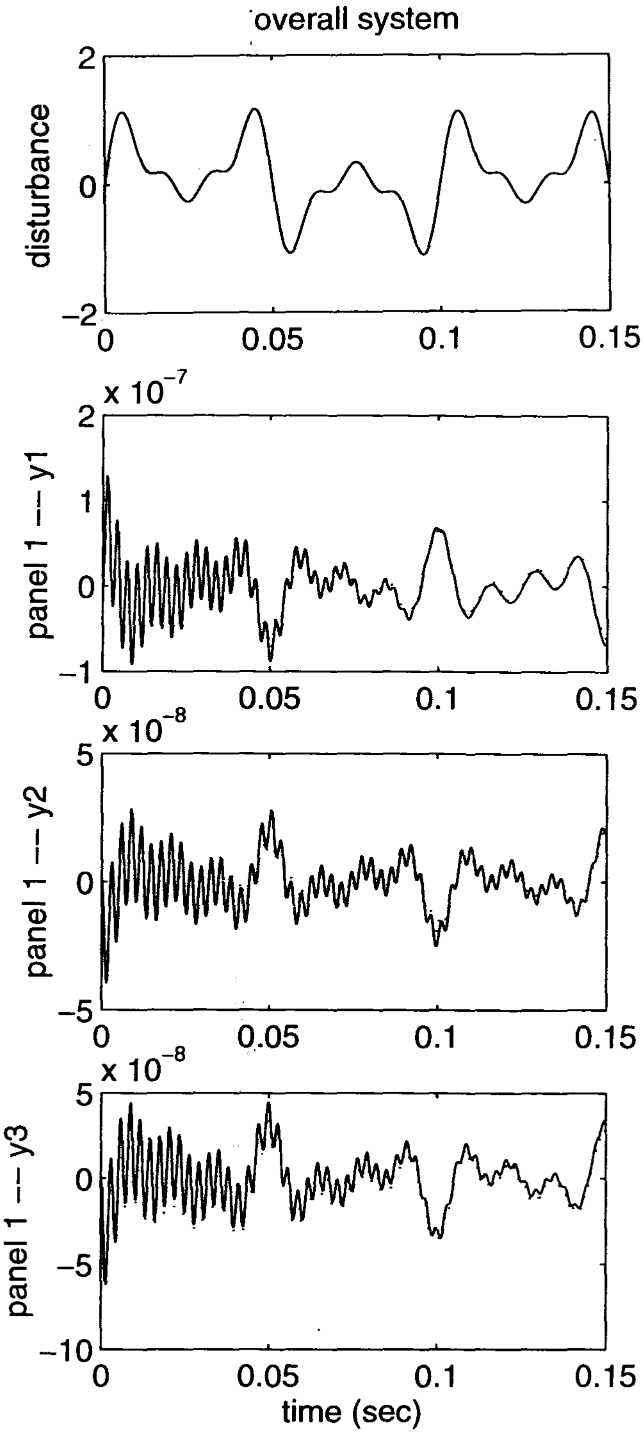

Fig. 10: Overall system identification
(a) disturbance input
(b)-(d) neural net prediction (dotted line) vs. system output (solid line) for disturbance input (only panel 1 outputs shown)