

111-028
4762
10P

A Novel Approach to Noise-Filtering Based on a Gain-Scheduling Neural Network Architecture

T. Troudet
Sverdrup Technology, Inc.
Lewis Research Center Group
Brook Park, Ohio

and

W. Merrill
Lewis Research Center
Cleveland, Ohio

April 1994

(NASA-TM-106563) A NOVEL APPROACH
TO NOISE-FILTERING BASED ON A
GAIN-SCHEDULING NEURAL NETWORK
ARCHITECTURE (NASA, Lewis Research
Center) 10 p

N94-30204

Unclass

G3/08 0004762



National Aeronautics and
Space Administration

A NOVEL APPROACH TO NOISE-FILTERING BASED ON A GAIN-SCHEDULING NEURAL NETWORK ARCHITECTURE

T. Troudet
Sverdrup Technology, Inc.
Lewis Research Center Group
Brook Park, Ohio 44142

W. Merrill
National Aeronautics and Space Administration
Lewis Research Center
Cleveland, Ohio 44135

Abstract.

A Gain-Scheduling Neural Network Architecture is proposed to enhance the noise-filtering efficiency of feedforward neural networks, in terms of both nominal performance and robustness. The synergistic benefits of the proposed architecture are demonstrated and discussed in the context of the noise-filtering of signals that are typically encountered in aerospace control systems. The synthesis of such a gain-scheduled neurofiltering provides the robustness of linear filtering, while preserving the nominal performance advantage of conventional non-linear neurofiltering. Quantitative performance and robustness evaluations are provided for the signal processing of pitch rate responses to typical pilot command inputs for a modern fighter aircraft model.

1. Introduction.

The capability of feedforward neural networks to serve as noise-filters for complex systems with varying characteristics and/or changing modes of operation was recently analyzed for the noise-filtering of signals that are typically encountered in aerospace control and diagnostic systems [1]. For such systems, the nominal dynamics of the signals are a simplified version of the actual dynamics, due to modelling approximations, system uncertainties, and/or changing modes of operation. As a result, the desired neurofilter should not only provide satisfactory signal processing over the nominal dynamic range of the signals, but should also be robust and maintain its performance in the presence of changes in the nominal dynamics of the signals. From that perspective, linear and non-linear feedforward neural networks were trained to filter noise by learning to map sequences of noisy input data onto the exact values of the most recently sampled data [1]. Comparative performance/robustness evaluations indicated that the synthesized non-linear neurofilter performed better than the linear neurofilter within the nominal dynamic range of signals; whereas the linear neurofilter was more robust in the presence of substantial variations in the parameters of the signal generating process. This result pointed to the need for a more global neural architecture with a potential to synergistically combine the complementary benefits of linear neurofiltering and conventional non-linear neurofiltering.

To address that issue, a gain-scheduling neural network (GSNN) architecture is proposed to find the optimal combination of linear and non-linear neurofiltering that provides the best signal estimates from input sequences of noisy data. The system functionality of the gain-scheduled neurofilter is briefly introduced in section 2, while section 3 describes the gain-scheduling training architecture itself. In Section 4, the nominal performance and robustness of the gain-scheduled neural network are compared to those of the linear and non-linear neurofilters separately, while Section 5 discusses possible extensions towards performance/robustness enhancement, non-linear adaptive neurofiltering, and neurosmoothing.

2. System Functionality of the Neurofilter.

The system functionality of the neurofilter is illustrated in Fig.1 in the context of an aerospace control system application. The signals to be filtered are the simulated pitch-rate responses to both pitch rate and velocity commands. The closed-loop system includes a *non-linear* neurocontroller designed in Refs.[2-3] to provide independent control of pitch-rate/airspeed for a state-space representation of a modern fighter aircraft [4]. The plant model consists of an integrated airframe/propulsion linear model, a fuel flow actuator modelled as a linear second order system with position and rate limits, and a thrust vectoring actuator modelled as a linear first order system with position and rate limits. As a result, the signal generating process represented by the closed-loop control system of Fig.1 contains nonlinearities due to the actuator position/rate limits, and the nonlinear structure of the neurocontroller. For the purpose of this study, the

¹Sverdrup Technology, Inc., 2001 Aerospace Parkway, Brook Park, Ohio, 44142.

noise source has been placed outside of the control loop so that a clean baseline signal would be available for comparison. The purpose of the trained neurofilter is to provide an estimate of the actual data values that have been corrupted by noise in order to enhance any subsequent processing by *out-of-the-loop* peripheral modules such as failure-detectors and failure-identifiers (e.g. Ref.[5]), off-line/on-line system-identifiers (e.g. Ref.[6]), damage estimators (e.g. Ref.[7]), etc.

In this simulation, the information needed to synthesize the neurofilter is provided by closed-loop pitch rate responses to input commands $\bar{z}_{SEL}(t) = (q_{SEL}(t), v_{SEL}(t))$, where $q_{SEL}(t)$ is the pitch rate command input, and $v_{SEL}(t)$ is the velocity command input. The pitch rate command input $q_{SEL}(t)$ is a doublet randomly centered at a time t_c between 2.5s and 5s such that $q_{SEL}(t \leq t_c) = Q_0$, $q_{SEL}(t_c < t \leq 2t_c) = -Q_0$, and $q_{SEL}(2t_c < t) = 0$, as indicated in Fig.2a. The concurrent velocity command input is the step function $v_{SEL}(t \leq 0) = 0$ and $v_{SEL}(0 < t) = V_0$, as indicated in Fig.2b. These commanded inputs $q_{SEL}(t)$ and $v_{SEL}(t)$, which represent the frequency-content of typical pilot command inputs, were subsequently filtered through a *prefilter-for-command-shaping* (Fig.1) in order to generate the commanded trajectories $\bar{z}_c(t) = (q_c(t), v_c(t))$ that are to be tracked by the closed-loop control system. The commanded pitch rate response $q_c(t)$ and the commanded velocity response $v_c(t)$ corresponding to a doublet pitch rate command input $q_{SEL}(t)$ and a step velocity command input $v_{SEL}(t)$ are represented in the diagrams of Fig.2. The maximum intensities $|Q_0|$ and $|V_0|$ of the randomly selected input commands were bounded by $Q_{max} = 3deg/sec$ (corresponding to 0.5 inches of pilot stick deflection), and $V_{max} = 20ft/s$. The pitch rate responses to such randomly generated pilot command inputs were sampled every $\Delta = 10ms$ over $T = 14s$, and they were corrupted with additive gaussian white noise with a standard deviation $\sigma_{training} = 0.3deg/sec$ before being passed to the training architecture of the neurofilter.

3. Gain-Scheduling Training Architecture.

The proposed neurofilter consists of a linear neural network and a non-linear neural network with optimized internal configurations, and whose outputs are modulated by a gain-scheduling feedforward neural network. The optimized linear neural network and the optimized non-linear neural network used in this simulation were trained in Ref.[1] with the training architecture shown in Fig.3. During training, the inputs of these two neurofilters consisted of sequences of the fifty most recently sampled noisy data, and the target values were the exact values of the last sampled data. In Fig.3, the notation $F^A(p, h, 1)$ represents a feedforward neural network with p input units, a single hidden layer of h sigmoidal neurons, and a single linear output neuron. Both linear and non-linear neurofilters were trained to minimize the error $(\hat{q} - q)^2(t)$ between the filter output $\hat{q}(t)$ and the exact value $q(t)$ of the pitch rate signal generated as in Section 2. The optimized network configurations of these two types of neurofilters were $F^A(50, 30, 1)$ for the non-linear neurofiltering (i.e. 50 inputs, 30 hidden sigmoidal neurons, and 1 linear output neuron), and $F^A(50, 1)$ for the linear neurofiltering (i.e. 50 inputs, and 1 linear output neuron).

As shown in Fig.4, the "fusion" of the optimized linear and non-linear neurofilters is achieved by training a gain-scheduling neural network to minimize the error $(\hat{q}_{GSNN} - q)^2(t)$ between the *Gain-Scheduled Neural Network* output $\hat{q}_{GSNN}(t)$ and the exact value $q(t)$ of the pitch rate signal generated as in Section 2. As indicated in Fig.4, the gain-scheduled neurofilter estimate $\hat{q}(t)_{GSNN}$ is an adaptive combination of the non-linear neurofilter estimate $\hat{q}(t)_{non-linear}$, and the linear neurofilter estimate $\hat{q}(t)_{linear}$:

$$\hat{q}_{GSNN}(t) = g(t) \times \hat{q}(t)_{non-linear} + (1 - g(t)) \times \hat{q}(t)_{linear} \quad (1)$$

where the gain $g(t)$ is the output of the non-linear gain-scheduling neural network. The role of the gain-scheduling neural network is therefore to find the optimal combination of linear and non-linear neurofiltering that extracts the best signal estimates from input sequences of noise-corrupted data. In order to facilitate this "classification", the inputs of the gain-scheduling neural network were chosen to be filter estimates of the exact signal values instead of the original noisy data values. These filter estimates were furthermore chosen to be the computed outputs of the linear neurofilter, in light of the robustness advantage that linear filtering has over conventional non-linear neurofiltering. The configuration of the gain-scheduling neural network chosen in this application consisted of twenty five input units, ten hidden sigmoidal neurons, and a linear output neuron with the thresholding activation function $y(x)$:

$$y(x < 0) = 0; y(0 \leq x \leq 1) = x; y(1 < x) = 1, \quad (2)$$

and training was performed with the backpropagation algorithm [8-9].

4. Comparative Nominal Performance and Robustness Evaluations.

The ability of the linear, non-linear, and gain-scheduled neurofilters to remove the noise from the pitch rate response to a given pilot commanded input "c" is measured by the ratio R_c

$$R_c = \frac{\sqrt{\sum_{k=0}^{T/\Delta} (\hat{q}(t_k) - q(t_k))^2}}{\sqrt{\sum_{k=0}^{T/\Delta} \hat{n}(t_k)^2}}, \quad (3)$$

T being the duration of the pilot command input, and Δ the sampling time of the vehicle outputs. In Eq.(3), $q(t_k)$ is the exact pitch rate response, $\hat{n}(t_k)$ is the white noise fluctuation added to $q(t_k)$, and $\hat{q}(t_k)$ is the filter output corresponding to an input sequence of p sampled noisy data, i.e. $\{q(t_{k-i}) + \hat{n}(t_{k-i}), \min(k, p) \geq i \geq 0\}$.

To compare the performances of the aforementioned neurofilters, two measures " R " and " r " based on Eq.(3) are introduced [1]. The R -measure is a statistical average of R_c calculated over the whole dynamic range of pilot command inputs as characterized in Section 2 by (Q_0, V_0, t_c) where Q_0 , V_0 , and t_c are uniformly distributed over $[-Q_{max}, +Q_{max}]$, $[-V_{max}, +V_{max}]$, and $[2.5s, 5s]$ respectively. The r -measure is the value of R_c for a most demanding case of pilot command input corresponding to the pitch rate doublet $Q_{SEL}(t \leq 5sec) = Q_{max}$, $Q_{SEL}(5sec < t \leq 10sec) = -Q_{max}$, $Q_{SEL}(10sec < t) = 0$; and the velocity step $V_{SEL}(t < 0) = 0$ and $V_{SEL}(0 < t) = V_{max}$. The R -measure grades the average efficiency of a neurofilter in removing the noise over an exhaustive set of pilot command inputs, whereas the r -measure estimates the filtering efficiency for one of the worst cases of pilot command inputs. To test the ability of the neurofilters to operate at noise levels other than that used in training, the R - and r -measures were evaluated with gaussian white noise of various standard deviations ranging from $\sigma_{min} = 0$ to $\sigma_{max} = 1deg/sec$. The values of the R - and r -measures corresponding to the nominal dynamic range of the signals are plotted in Figs.5a & 6a respectively. The results show that the gain-scheduled neurofilter outperforms both the optimized linear filter and the optimized non-linear neurofilter, not only at the noise level used in training, but also at all noise levels between $\sigma_{min} = 0$ and $\sigma_{max} = 1deg/sec$.

To further compare the robustness of the gain-scheduled neurofilter with the robustness of the optimized linear neurofilter and non-linear neurofilter respectively, the R - and r -measures were also evaluated on a test set extending beyond the nominal dynamic range of the signals (used for training) and generated as follows. The matrix elements of the A , B , and C matrices of the vehicle model [4] were randomly varied within $\pm 50\%$ of their nominal values, with the sole requirement that the stability of the closed-loop system be preserved [2]. Due to the severity of the deviations of the A , B , C matrices from their nominal values, the closed-loop system responses to typical pilot command inputs presented significant deviations from the nominal responses. The statistical evaluations of " R " and " r " are plotted in Figs.5b & 6b respectively for a typical set of A , B , and C s leading to large variations of the vehicle model. The results show that the gain-scheduled neurofilter still outperforms the optimized linear filter and the optimized non-linear neurofilter at all noise levels. This is graphically illustrated in Fig.7 by the filtering of the pitch rate response to the most demanding pilot command input of the vehicle model with the same set of off-nominal A , B , and C matrices as that used for the evaluations of the R - and r -measures plotted in Figs.5b & 6b respectively. As shown by the plots of Fig.7a, 7b & 7c, additive gaussian white noise is more efficiently removed from the noisy closed-loop signals by the gain-scheduled neurofilter (7c) than by the optimized linear neurofilter (7a) or the optimized non-linear neurofilter (7b) separately. The synergistic benefits of the newly proposed gain-scheduling architecture are even more apparent when comparing Figs.7a, 7b & 7c in light of the plot of the gain-scheduling neural network output (identical to the output gain of the non-linear neurofilter) shown in Fig.7d. This comparison indicates that the gain-scheduled neurofiltering presents the characteristics of linear neurofiltering around 1 sec and 6 sec, i.e. when the pitch rate estimates of the linear neurofilter are better than those of the non-linear neurofilter. More specifically, Fig.7d also indicates that, around 1 sec, the gain-scheduled neurofilter estimate consists of about 80 % of linear neurofilter estimate, and about 20 % of non-linear neurofilter estimate. Around 6sec, the gain-scheduled neurofilter estimate is 100 % of the linear neurofilter estimate. Otherwise, the gain-scheduled neurofilter estimate is for the most given by the non-linear neurofilter estimate, e.g. above 12 sec where it is 100 % of the non-linear neurofilter estimate.

5. Conclusion.

A Gain-Scheduling Neural Network Architecture has been proposed to enhance the robustness of feedforward neurofilters, and was analyzed in the context of the noise-filtering of pitch rate responses to pilot command inputs for a modern fighter aircraft model. The proposed architecture consists of an optimized linear feedforward neurofilter, an optimized non-linear feedforward neurofilter, and a gain-scheduling feedforward neural network which is trained with backpropagation to synergistically combine the complementary benefits of the linear and non-linear neurofilters. The resulting gain-scheduled neurofilter consistently performed better than each neurofilter separately, within the nominal as well as off-nominal dynamic range of the simulated signals.

Future areas of research would include possible extensions of the functionality and scope of the proposed gain-scheduling neural network architecture. Of particular interest would be the possibility of further enhancing neurofiltering through the gain-scheduling of a collection of linear filters that would have been separately optimized on the disjoint elements of a partition of the space of the input signals. The synthesis of the multi-output gain-scheduler(s) required for the fusion of such optimized linear neurofilters could benefit from the robustness of genetic algorithms or even fuzzy rule-based scheduling, or from training algorithms like those developed for the hierarchical mixing of expert neural networks [10].

Of additional interest would be the possibility to extend the proposed architecture to achieve *non-linear adaptive neurofiltering* through the synergy of supervised and unsupervised training schemes, and by taking advantage of the on-line learning capabilities of neural networks. An important practical issue to be addressed in that regard would be whether neural networks can be trained in unsupervised training modes to efficiently gain-schedule the supervised training of a partition of individual neurofilters of the type proposed in Ref.[11].

Of further interest would be the possibility to extend the proposed architecture to the smoothing of noisy signals by training a neural network to gain-schedule optimized linear and non-linear *neurosmoothers* that would have been previously trained to map sequences of p successively sampled noisy data onto the exact values of any of the previous $(p-1)$ samples input to the network. Such gain-scheduled *neurosmoothers* would be expected to provide better signal estimates than their *neurofilter* counterparts in view of the additional information provided [11-12], yet at the expense of the time corresponding to the delay needed for the signals to be available. How to reach the best compromise between "accuracy" and "time" would therefore depend upon the computational requirements and characteristics of the specific post-processing to be performed on the signals.

Finally, future comparative analysis with other traditional techniques, such as Extended Kalman Filtering [13], could also provide insight on how to improve the performance and broaden the applicability of the proposed Gain-Scheduling Neural Network approach.

References.

- [1] Troudet, T., and Merrill, W., "A Comparative Robustness Evaluation of Feedforward Neurofilters", *32nd AIAA Aerospace Sciences Meeting*, Reno, NV, January 1994.
- [2] Troudet, T., "Robustness Enhancement of Neurocontroller and State Estimator", *World Congress on Neural Networks*, Vol. III, pp. 163-167, Portland, July 1993.
- [3] Troudet, T., Garg, S., and Merrill, W., "Design and Evaluation of a Robust Neurocontroller for a Multivariable Aircraft Control Problem", *Int. Joint Conf. on Neural Networks*, Baltimore, MD, June 1992.
- [4] Garg, S., Mattern, D.L., and Bullard, R.E., "Integrated Flight/Propulsion Control System Design Based on a Centralized Approach", *Journal of Guidance, Control and Dynamics*, Vol.14, No.1, 1991.
- [5] Duyar, A., and Merrill, W., "Fault Diagnosis of the Space Shuttle Main Engine", *Journal of Guidance, Control, and Dynamics*, Vol.15, No.2, pp.384-389, 1992.
- [6] Troudet, T., and Merrill, W., "Neuromorphic Learning of Continuous-Valued Mappings from Noise-Corrupted Data", *IEEE Trans. on Neural Networks*, Vol.2, No.2, pp.294-301, 1991.
- [7] Troudet, T., and Merrill, W., "A Real Time Neural Net Estimator of Fatigue Life", *Inter. Joint Conf. On Neural Networks*, Vol.2, pp.59-64, San Diego, 1990.
- [8] Werbos, P., "Beyond Regression: New Tools for Prediction and Analysis in the Behavioral Sciences", *Thesis in Applied Mathematics*, Harvard University (August, 1974).
- [9] Rumelhart, D., Hinton, G., and Williams R., "Learning Internal Representations by Error Propagation", *Parallel Distributed Processing: Explorations in the Microstructures of Cognition*, ed. by D. Rumelhart, J. McClelland, et al., Vol.I, pp.318-362, MIT Press, 1986.
- [10] Jordan, M. I., and Jacobs, R. A., "Hierarchical Mixtures of Experts and the EM Algorithm", *MIT Preprint*, Submitted to *Neural Computation*; and References therein.

- [11] Klimasauskas, C., "Neural Nets and Noise Filtering", *Dr. Dobb's Journal*, p.32, Jan. 1989.
 [12] Anderson, B., and Montgomery, D., "A Method for Noise-Filtering with Feed-forward Neural Networks: Analysis and Comparison with Low-pass and Optimal Filtering", *Int. Joint Conf. on Neural Networks*, Vol.I, pp.209-214, San Diego, 1990.
 [13] Gelb, A., "Applied Optimal Estimation", *The MIT Press*, 1974.

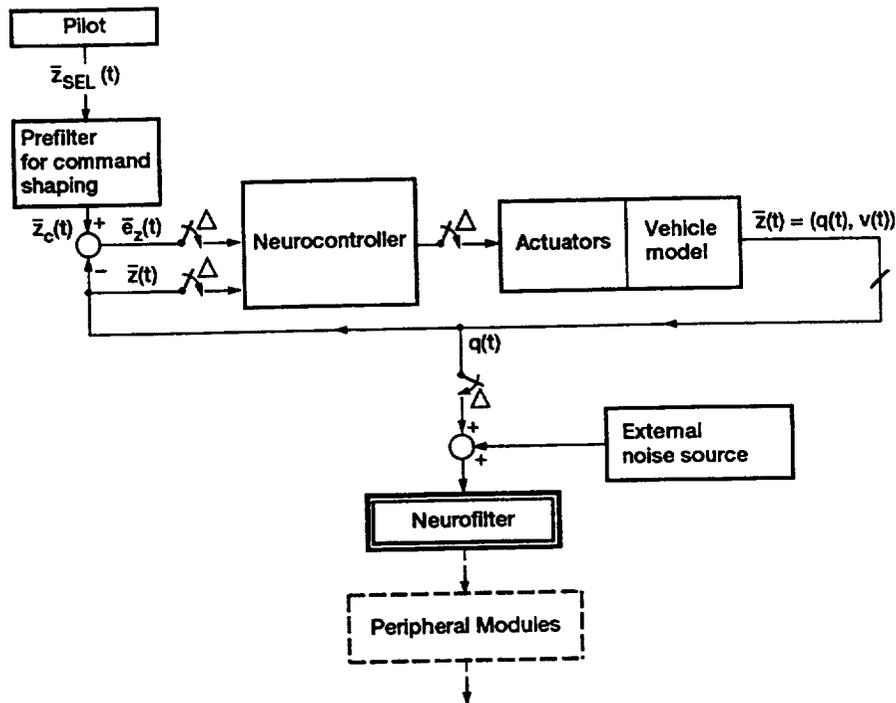
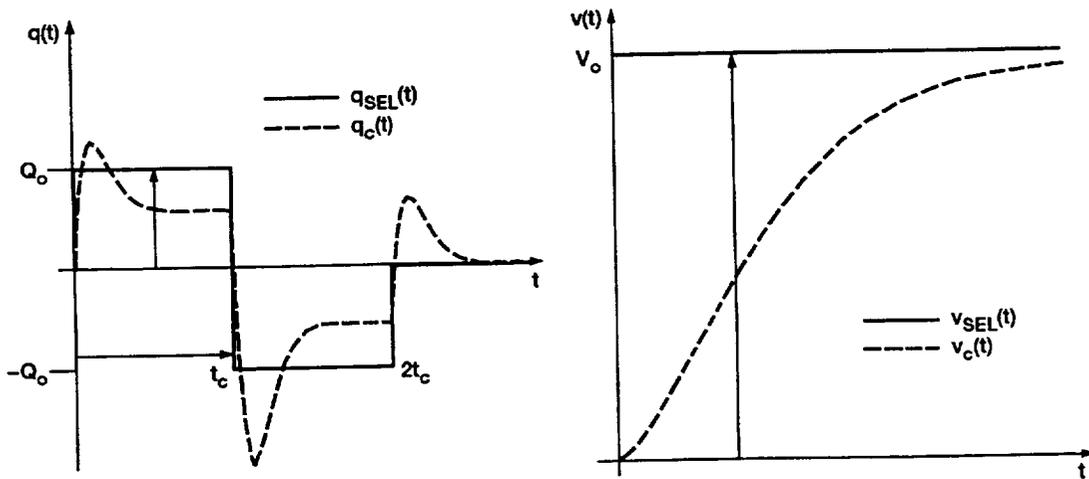


Figure 1.—Functional system diagram of the trained neurofilter.



(a) Doublet pitch-rate centered at time $t = t_c$.

(b) Step velocity.

Figure 2.—Pilot command input, $\bar{z}_{SEL}(t) = (q_{SEL}(t), v_{SEL}(t))$, and commanded trajectory $\bar{z}_c(t) = (q_c(t), v_c(t))$.

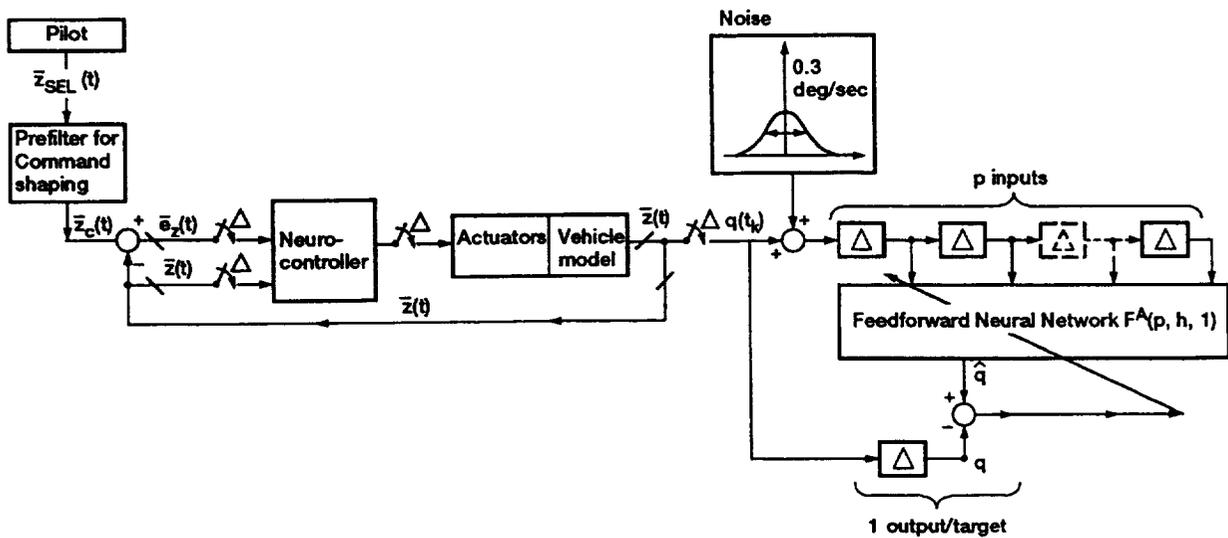


Figure 3.—Training architecture of asymmetric neurofilters $F^A(p, h, 1)$ with p input units, one linear output, and a single hidden layer of h sigmoidal neurons.

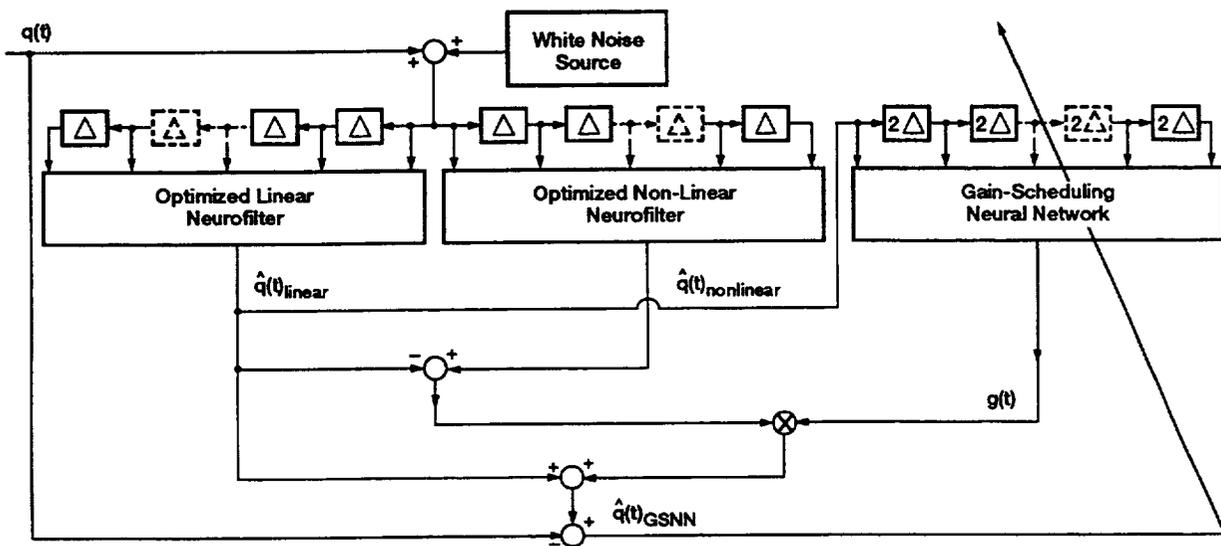


Figure 4.—Training architecture of the gain-scheduling neural network.

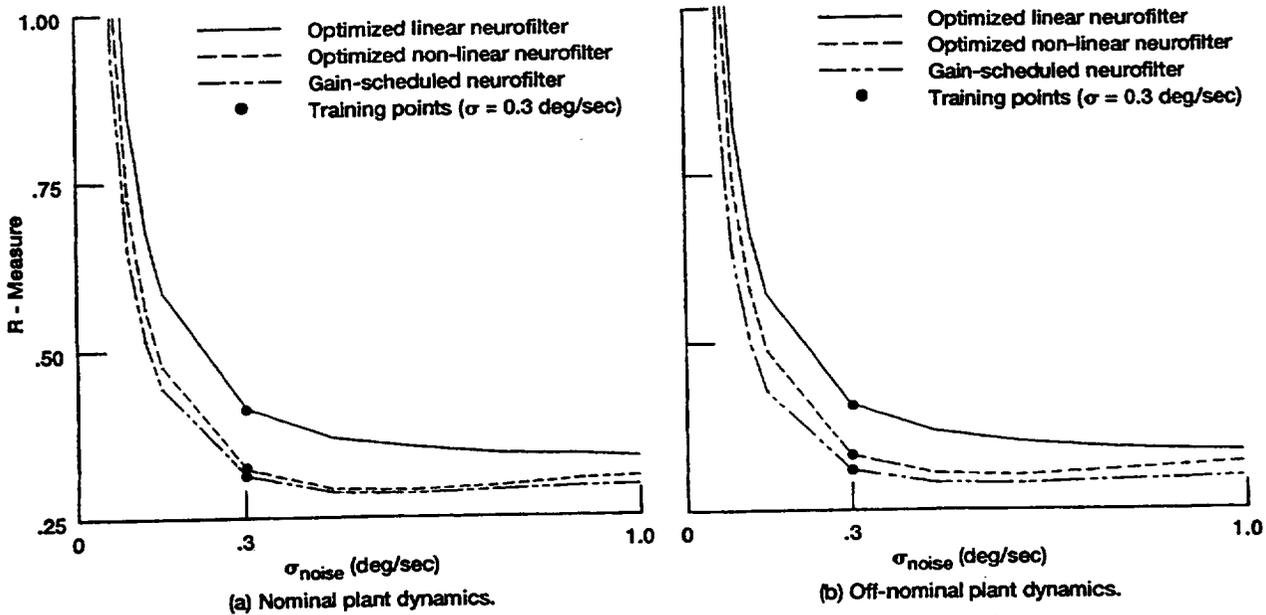


Figure 5.—Noise filtering efficiency averaged over the entire set of pilot command inputs.

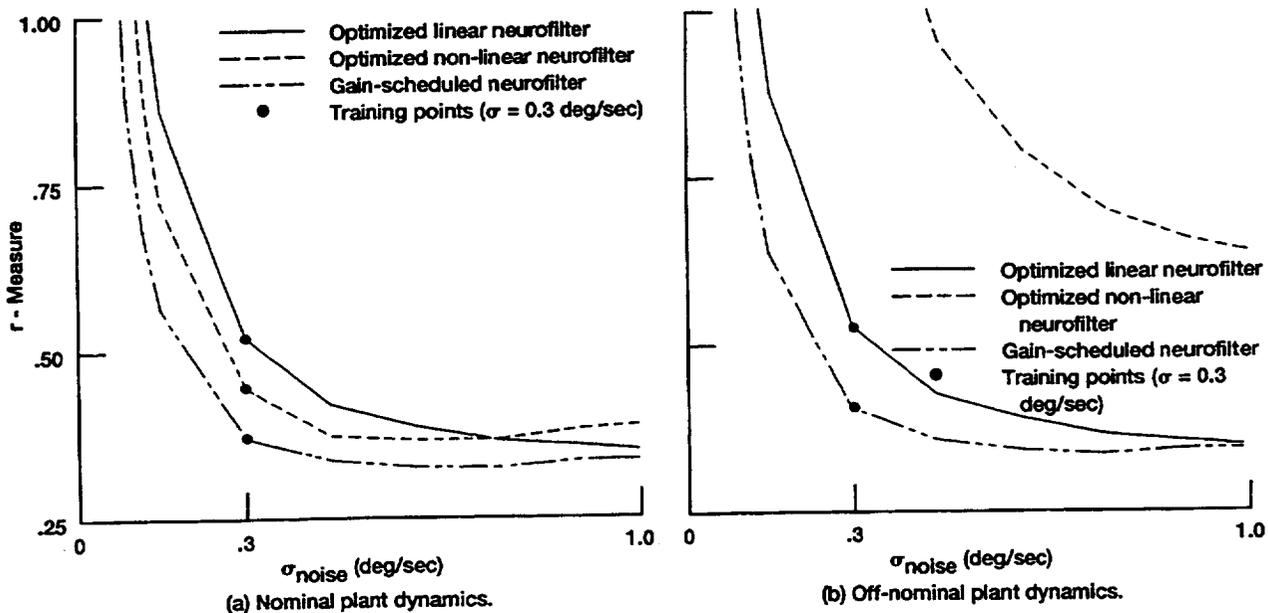
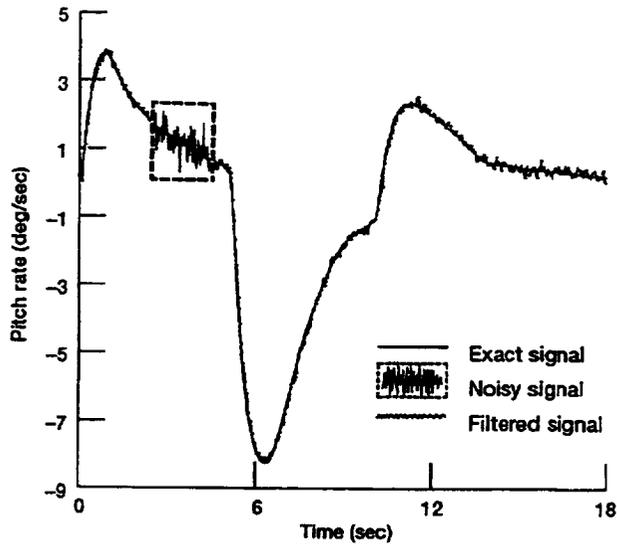
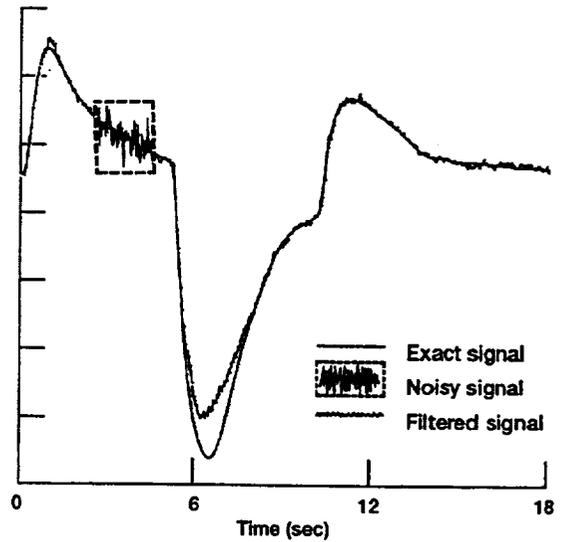


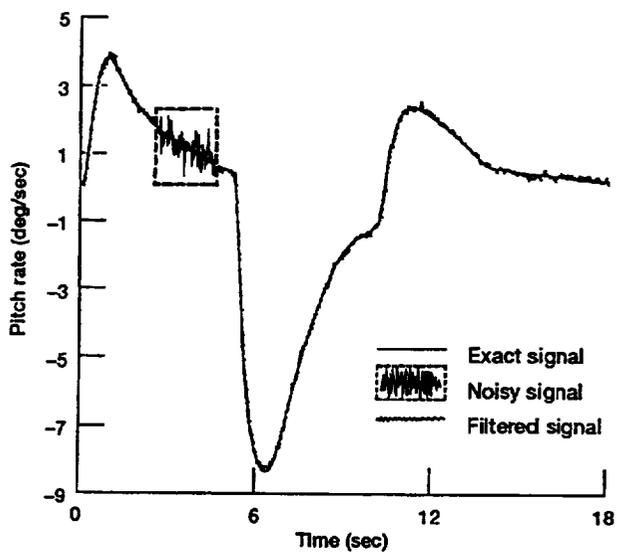
Figure 6.—Noise filtering efficiency averaged over the most demanding case of pilot command input.



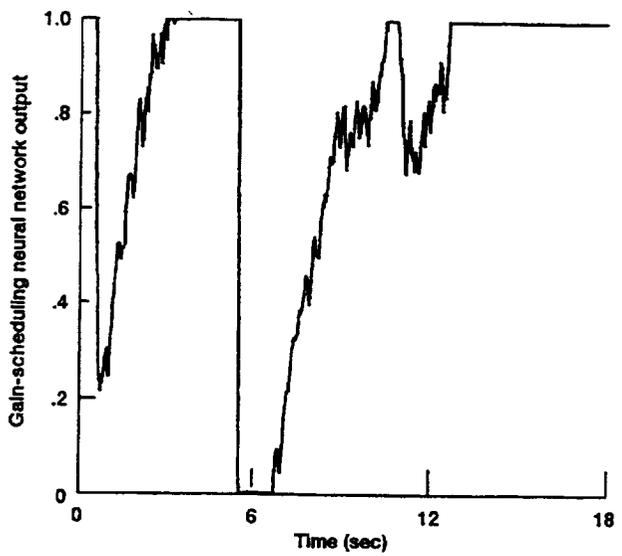
(a) Optimized linear neurofilter.



(b) Optimized non-linear neurofilter.



(c) Gain-scheduled neurofilter.



(d) Gain-scheduling neural network.

Figure 7.—Filtering of the pitch rate response to the most demanding pilot command input with off-nominal plant dynamics.

REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington Headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188), Washington, DC 20503.

1. AGENCY USE ONLY (<i>Leave blank</i>)	2. REPORT DATE April 1994	3. REPORT TYPE AND DATES COVERED Technical Memorandum	
4. TITLE AND SUBTITLE A Novel Approach to Noise-Filtering Based on a Gain-Scheduling Neural Network Architecture		5. FUNDING NUMBERS WU-584-03-11	
6. AUTHOR(S) T. Troudet and W. Merrill			
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) National Aeronautics and Space Administration Lewis Research Center Cleveland, Ohio 44135-3191		8. PERFORMING ORGANIZATION REPORT NUMBER E-8739	
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES) National Aeronautics and Space Administration Washington, D.C. 20546-0001		10. SPONSORING/MONITORING AGENCY REPORT NUMBER NASA TM-106563	
11. SUPPLEMENTARY NOTES T. Troudet, Sverdrup Technology, Inc., Lewis Research Center Group, Brook Park, Ohio 44142 (work funded by NASA Contract NAS3-25266), presently at nyma, Inc., Engineering Services Division, 2001 Aerospace Parkway, Brook Park, Ohio 44142 ; and W. Merrill, NASA Lewis Research Center. Responsible person, T. Troudet. organization code 2550, (216) 433-8524.			
12a. DISTRIBUTION/AVAILABILITY STATEMENT Unclassified - Unlimited Subject Category 08		12b. DISTRIBUTION CODE	
13. ABSTRACT (<i>Maximum 200 words</i>) A Gain-Scheduling Neural Network Architecture is proposed to enhance the noise-filtering efficiency of feedforward neural networks, in terms of both nominal performance and robustness. The synergistic benefits of the proposed architecture are demonstrated and discussed in the context of the noise-filtering of signals that are typically encountered in aerospace control systems. The synthesis of such a gain-scheduled neurofiltering provides the robustness of linear filtering, while preserving the nominal performance advantage of conventional non-linear neurofiltering. Quantitative performance and robustness evaluations are provided for the signal processing of pitch rate responses to typical pilot command inputs for a modern fighter aircraft model.			
14. SUBJECT TERMS Signal processing; Neural networks; Noise filtering; Robustness; Linear filtering; Non-linear filtering		15. NUMBER OF PAGES 10	
		16. PRICE CODE A02	
17. SECURITY CLASSIFICATION OF REPORT Unclassified	18. SECURITY CLASSIFICATION OF THIS PAGE Unclassified	19. SECURITY CLASSIFICATION OF ABSTRACT Unclassified	20. LIMITATION OF ABSTRACT

