12-10-93
E-8282

NASA Technical Memorandum 106440
AIAA-94-0397

A Comparative Robustness Evaluation of Feedforward Neurofilters

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Prepared for the
32nd Aerospace Sciences Meeting and Exhibit
sponsored by the American Institute of Aeronautics and Astronautics
Reno, Nevada, January 10–13, 1994

NASA

A COMPARATIVE ROBUSTNESS EVALUATION OF FEEDFORWARD NEUROFILTERS *

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Abstract

A comparative performance and robustness analysis is provided for feedforward neurofilters trained with backpropagation to filter additive white noise. The signals used in this analysis are simulated pitch rate responses to typical pilot command inputs for a modern fighter aircraft model. Various configurations of non-linear and linear neurofilters are trained to estimate exact signal values from input sequences of noisy sampled signal values. In this application, non-linear neurofiltering is found to be more efficient than linear neurofiltering in removing the noise from responses of the nominal vehicle model, whereas linear neurofiltering is found to be more robust in the presence of changes in the vehicle dynamics. The possibility of enhancing neurofiltering through hybrid architectures based on linear and non-linear neuroprocessing is therefore suggested as a way of taking advantage of the robustness of linear neurofiltering, while maintaining the nominal performance advantage of non-linear neurofiltering.

1. Introduction.

Neural networks are being used throughout the engineering community to solve a broad range of problems by acquiring knowledge of the application at hand from extensive training data. Their trainability sets them apart from traditional computing techniques in that they are not so much programmed as they are trained with data. In addition, their ever growing massive parallelism made possible through steady advances in analog VLSI is opening the way to new engineering perspectives. The benefit of such adaptability, fast processing, and ease-of-implementation has already been shown in a broad range of engineering disciplines, from optimization and pattern recognition, through signal processing, to the field of control.

In the area of signal processing, computer simulations reported in the literature indicate that feedforward neural networks can be trained to filter signals that have been corrupted by noise [1-3], or to extract input/output mappings from noise-corrupted data [4]. In these applications however, the evaluations of the synthesized neurofilters have been mostly limited to the nominal dynamic range of the signals. Moreover, little is known about the *relative* efficiency of the various neurofiltering techniques so far proposed in the literature. The objective of this paper is to provide a certain measure of comparison for the performance and robustness of these known neurofilters, where "robustness" is defined as the ability to maintain performance in the presence of changes in the nominal dynamics of the signals due to modelling uncertainties or system degradations. Since the nominal dynamics of the signals are only a simplified version of the actual dynamics, an important issue in the applicability of feedforward nets to serve as noise-filters is indeed that of robustness.

Towards that goal, the nominal performance and the robustness of non-linear and linear neurofilters are analyzed in the context of the noise-filtering of signals that are typically encountered in aerospace control systems. The signals used in this analysis are pitch rate responses to typical pilot command inputs for the short take-off and landing flight condition of a longitudinal dynamics model of a modern fighter aircraft [5-6].

The paper is organized as follows. Section 2 briefly introduces the systemic functionality of the neurofilters, and sets the foundations for the training architecture described in Section 3. The nominal performance and robustness of the neurofilters as trained in

Section 3 for various network configurations are evaluated in Section 4. A possible improvement of the neurofiltering is suggested in Section 5, and some issues relating to future comparative evaluations with conventional filtering techniques. e.g. Kalman filtering, are raised.

2. Systemic Functionality of the Neurofilters.

The systemic functionality of the neurofilters 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.[5-6] to provide independent control of pitch-rate/airspeed for a state-space representation of a modern fighter aircraft. 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, nonlinearities are present in the signal generating process in the form of actuators position and rate limits, and through the nonlinearities of the neurocontroller. For the purpose of this study, the 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 to enhance any subsequent processing by *out-of-the-loop* peripheral modules such as failure-detectors and failure-identifiers, off-line/on-line system-identifiers, damage estimators [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 $q_{SEL}(t \leq t_c) = Q_0$, $q_{SEL}(2t_c \geq t > t_c) = -Q_0$, and $q_{SEL}(t > 2t_c) = 0$, as indicated in Fig.2a. The concurrent velocity command input is the step function $v_{SEL}(t \leq 0) = 0$ and $v_{SEL}(t > 0) = V_0$, 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 over a period $T = 14s$ to generate the commanded trajectories $\bar{z}_c(t) = (q_c(t), v_c(t))$ as shown in Fig.1. The desired dynamic filtering $(\bar{z}_c(t))$ of the pilot command inputs, $\bar{z}_{SEL}(t)$, is achieved through a linear state-space representation (in terms of system matrices A_m, B_m, and C_m) of the ideal response transfer functions listed in Ref.[8]. 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. Training Architecture.

The feedforward neurofilters that are trained and evaluated in this simulation are of the *symmetric* type as defined in Refs.[1-2], and of the *asymmetric* type as defined in Ref.[3]. In this application, the corresponding training architectures are represented in Fig.3a for the *symmetric* mode, and in Fig.3b for the *asymmetric* mode. For both types of architecture, the weights were updated using the backpropagation algorithm [9]. In Fig.3a, the notation $F^S(p, h_1, h_2, h_3, p)$ represents a feedforward neural network with p input units, three hidden layers of h_1, h_2, and h_3 sigmoidal neurons respectively, and p linear output neurons. In Fig.3b, the notation $F^A(p, h, 1)$ represents a feedforward neural network with p input units, a single layer of h sigmoidal neurons, and a single linear output neuron.

During training, the input of a *symmetric* neurofilter consists of a sequence of noisy sampled data, and the target values coincide with the very input sequence of noisy sampled data, as shown in Fig.3a. In the *symmetric mode*, a non-linear neural network $F^S(p, h_1, h_2, h_3, p)$ is trained to project the sequences of the p *correlated* input data on a subspace of smaller dimension $h_2 < p$, and then back onto the original $p-$*dimensional* space. The mechanism by which the noise is attenuated is conceptually similar to that of linear orthogonal projections [10]. In the presence of non-linear correlations among input data, the compression and decompression onto and from the middle layer can be enhanced by the processing of the first hidden layer and last hidden layer respectively, as indicated in Ref.[2] in the case of time-dependent correlations, and in Ref.[11] in the case of space-dependent correlations. As shown in Fig.3a, the symmetric neurofilter was trained by minimizing the error sums $\Sigma_{k=0}^{(p-1)}[\hat{q} - (q + \hat{n})]^2(t - k\Delta)$ between successive filter estimates $\hat{q}(t)$ and the noisy input data values $q(t) + \hat{n}(t)$, $q(t)$ being the exact pitch rate signal generated as in Section 2, and $\hat{n}(t)$ representing random white noise fluctuations. By construction, a neural network which has been trained in this mode can be used to estimate the value of the most recent sampling, in which case it is operated as a *neurofilter*, or the value of any of the previous $(p-1)$ samples input to the network, in which case it is operated as a *neurosmoother*. This simulation however will be exclusively concerned with neurofiltering.

During training, the input of an *asymmetric* neurofilter consists of a sequence of noisy sampled data, and the target value is the exact value of the last sampled data, as shown in Fig.3b. In the *asymmetric mode*, a non-linear neural network $F^A(p,h,1)$ is trained to map sequences of noisy input values onto the exact value of the most recent input. (It is noted that training a neural network to map noisy input data sequences onto the exact value of one of the previous $(p-1)$ samples would synthesize a *neurosmoother*, as defined above). The asymmetric mode can also be used to synthesize a linear neurofilter by training a network configuration $F^A(p,0,1)$ having an input layer of p units, no hidden layer, and an output layer with a single linear neuron. For every sampled data, linear neurofiltering reduces the noise by some averaging of the randomly distributed fluctuations through a weighted summation over the sequence of the previously sampled noisy data. Both types of linear and non-linear asymmetric 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. A low-pass filter of the type $d\hat{q}/dt = (q(t)-\hat{q}(t))/\tau_f$ was also evaluated in place of the generic neurofilter of Fig.1 after choosing its time-constant τ_f as minimizing the error $(\hat{q}-q)^2(t)$ between the low-pass estimate and the exact value of the pitch rate signal generated as above. This low-pass filter was not expected to have good performance, but was provided for comparison.

4. Nominal Performance and Robustness Evaluations.

The ability of the above filters to remove the noise from the pitch rate response to a given pilot commanded input "c" is measured by the ratio R_c

$$R_c = \frac{\sqrt{\Sigma_{k=0}^{T/\Delta}(\hat{q}(t_k)-q(t_k))^2}}{\sqrt{\Sigma_{k=0}^{T/\Delta}\hat{n}(t_k)^2}} \qquad (1)$$

T being the duration of the pilot command input, and Δ the sampling time of the vehicle outputs. In Eq.(1), $q(t_k)$ 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 evaluate the performance of the various neurofilters, two measures "R" and "r" based on expression (1) are introduced. The R-measure is a statistical average of R_c, Eq.(1), 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 $[2.5s, 5s]$. The r-measure is the value of R_c, Eq.(1), for a most demanding case of pilot command input corresponding to the pitch rate doublet $q_{SEL}(t \leq 5sec) = Q_{max}$, $q_{SEL}(10sec \geq t \geq 5sec) = -Q_{max}$, $q_{SEL}(t > 10sec) = 0$; and the velocity step $v_{SEL}(t<0) = 0$ and $v_{SEL}(t>0) = V_{max}$. 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.4 for the neural network configurations $F^S(25,13,3,13,25)$ referred to as symmetric non-linear neurofilter, $F^A(50,30,1)$ referred to as asymmetric non-linear neurofilter, $F^A(50,0,1)$ referred to as linear neurofilter, and the low-pass filter defined in section 3. The training of the linear and non-linear neurofilters, and the optimization of the low-pass filter, were performed with closed-loop responses of the nominal vehicle model corresponding to the set of pilot command inputs defined in Section 2.

It is noted that, among the p neurons of the output layer of a neural network *trained* in symmetric mode, only the first neuron is needed to achieve the neurofiltering. As a result, the other $(p-1)$ output neurons and their connections from the last hidden layer can be removed from the neurofilter *once it has been synthesized* in the symmetric training mode depicted in Fig.3a.

Figs.4a & 4b indicate that, in this application, the asymmetric non-linear neurofilter performs better than the symmetric non-linear neurofilter, except at very low noise levels. With little surprise, the linear neurofilter is found to outperform the optimized low-pass filter at all noise levels. While the average efficiency of the asymmetric non-linear filter is higher than that of the linear neurofilter, as shown in Fig.4a, the latter filter appears to be more robust in the domain of large amplitude signals and high noise levels, as suggested by Fig.4b. In the absence of noise, the estimates of the neurofilters are very close, yet not identical, to the exact values. Due to this small, but non-zero residual error in the absence of noise, the plots of Figs.4 and Figs.5 exhibit the asymptotic behavior that $R \rightarrow \infty$ and $r \rightarrow \infty$, as $\sigma_{noise} \rightarrow 0$. Likewise for the low-pass filter, since the low-pass estimates only converge to the exact signal values with a time-constant τ_f in the absence of noise. It is also emphasized that the average error between filter estimate and exact value increases with the level of noise.

To further estimate the robustness of the various filters trained as above, the R- and r-measures were 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 were randomly varied within a margin of $\pm 50\%$ of their nominal values, with the sole requirement that the stability of the closed-loop system be preserved [5]. Due to the severity of the deviations of the A, B, and C matrices from their nominal values, the closed-loop system responses to typical pilot command inputs presented significant deviations from the nominal responses, as illustrated by the comparison between the exact pitch rate responses to the most demanding pilot command input of the vehicle model with nominal parameter values (Fig.6) and with the off-nominal parameter values generated as indicated above (Fig.7). Although the closed-loop system can also be varied by modifying a physical parameter, say the weight of the aircraft, the choice of randomly varying the matrix elements of the A, B, and C matrices was adopted herein for its simplicity, and because it provided sufficiently large model variations (i.e. Fig.6/Fig.7).

The resulting statistical evaluations of R and r are plotted in Figs.5a & 5b respectively. As indicated in Figs.5, the asymmetric neurofilter performs better than the symmetric neurofilter, and the linear neurofilter outperforms the optimized low-pass filter at all noise levels. Although the average efficiency of the asymmetric non-linear neurofilter is higher than that of the linear neurofilter at high noise levels (Fig.5a), the former neurofilter deals poorly with the large amplitude and frequency content of the most demanding case of command input (Fig.5b). A natural way to enhance the robustness of backpropagation-trained neural networks vis-a-vis modeling uncertainties or system degradations is to train these networks to achieve the minimization objective(s) in the presence of such uncertainties [5]. Training the non-linear neurofilters with sequences of data having a broader amplitude and frequency content is therefore expected to enhance the non-linear neurofiltering of such signals.

In order to analyze this possibility, both symmetric and asymmetric non-linear neurofilters were retrained with noise-corrupted closed-loop pitch rate responses of the vehicle model for which the matrix elements of the A, B, and C matrices were randomly varied within a margin of $\pm 50\%$ of their nominal values, and this, with a different choice of the A, B, Cs for every randomly generated pilot command input. As a result, the data set used for retraining included closed-loop pitch rate responses corresponding to values of the A, B, and C matrices "centered" around the nominal values $A^{nominal}$, $B^{nominal}$, and $C^{nominal}$, respectively. Within such model variations, and for the proposed training scheme, the non-linear neurofilters were able to maintain their efficiency in removing the noise from closed-loop responses of the vehicle model with the nominal values of the A, B, Cs. Further attempt to enhance robustness by allowing A, B, and Cs variations above the 50% margin led to a loss of nominal performance. As a result, the robustness acquired within the latter 50% margin provided a fair estimate of the maximum robustness that can be induced in the neurofilters through training in the presence of model variations. The simulation results indicated a performance enhancement for both types of non-linear neurofilters, and showed that the retrained asymmetric non-linear neurofilter performed better than the other filters when operating within the nominal dynamic range of the signals. This is illustrated in the set of Figs.6a, 6b, & 6c, which compare the exact pitch rate response (to the most demanding pilot command input of the vehicle model with nominal parameter values) and the estimate of the linear neurofilter, the asymmetric non-linear neurofilter, and the symmetric non-linear neurofilter respectively. Yet, the retrained non-linear neurofilters still could not match the robustness of the linear neurofilter in the domain of very large amplitude signals, as illustrated in Fig.7 by the second transient (i.e. between approximately 5 and 10 sec) of the closed-loop pitch rate response to the most demanding command input with a typical set of A, B, and Cs leading to large variations of the vehicle model. (The dashed boxes in Fig.7 illustrate the noise fluctuations used to train the networks as well as to evaluate them). Whether or not the performance of the non-linear neurofilters as trained in Figs.3 can be enhanced through more efficient supervised training algorithms is an open issue worth to be addressed in future works [12].

As mentioned in Section 2 and illustrated in Fig.1, the white noise source was chosen outside of the control loop, and the neurofilters trained in Fig.3 were used for out-of-the-loop signal processing. Since practical implementations of controllers always lead to the presence of noise (and not necessarily gaussian, nor white) within the control loop, enhancing the controller performance through neurofiltering is an issue that warrant further study. In particular, whether the neurofilter should be embedded within the neurocontroller itself (i.e. by feeding the neurocontroller with input sequences of noisy sampled data values or through the use of feedback internal connections [13]), or should be placed at the front end of the neurocontroller (and trained in synergy with the latter to achieve the control objectives in the presence of noise) is an area of future research.

5. Conclusion.

The ability of feedforward neural networks trained with backpropagation to filter additive gaussian white noise has been analyzed in the context of pitch rate responses to typical pilot command inputs for a modern fighter aircraft. Two types of non-linear neurofilters were analyzed. An asymmetric neurofilter was trained to map sequences of noisy input data onto the exact sampled data; and a symmetric neurofilter was trained to map sequences of noisy input data onto themselves, following a compression/decompression scheme through multiple hidden layers. For the various network configurations and training sequences analyzed in this simulation, the asymmetric neurofilter was found to perform better than the symmetric neurofilter.

The ability of the non-linear neurofilters to maintain their efficiency in the presence of severe system degradations was analyzed and compared with that of a linear neurofilter. Although the performance of the non-linear neurofilters could be enhanced by training these networks with closed-loop responses of the vehicle model with off-nominal parameter values, the newly synthesized neurofilters could not match the robustness of the linear neurofilter. A future avenue of research to be addressed would be therefore that of devising hybrid neural architectures to benefit from the robustness of the linear neurofiltering, while preserving the nominal performance advantage of the non-linear neurofiltering. The potential synergy between such linear and non-linear neural processings is currently being investigated in the context of the present application.

Traditional filtering techniques such as optimal filtering, Kalman filtering, extended Kalman filtering, and others, require estimations of noise-spectrum, parameters of the signal generating process, etc. While still requiring an estimation of the noise spectrum, the asymmetric non-linear neurofilter can be trained from representations of the signal generating process in terms of (experimental and/or model-generated) input/output data. The symmetric neurofilter can even be trained from noise-corrupted representations of the signal generating process in terms of noisy experimental input/output data, without requiring any noise spectrum estimation. Of particular interest would be therefore further comparative evaluations of these various filtering techniques on the basis of their robustness, their knowledge requirement, and the information available.

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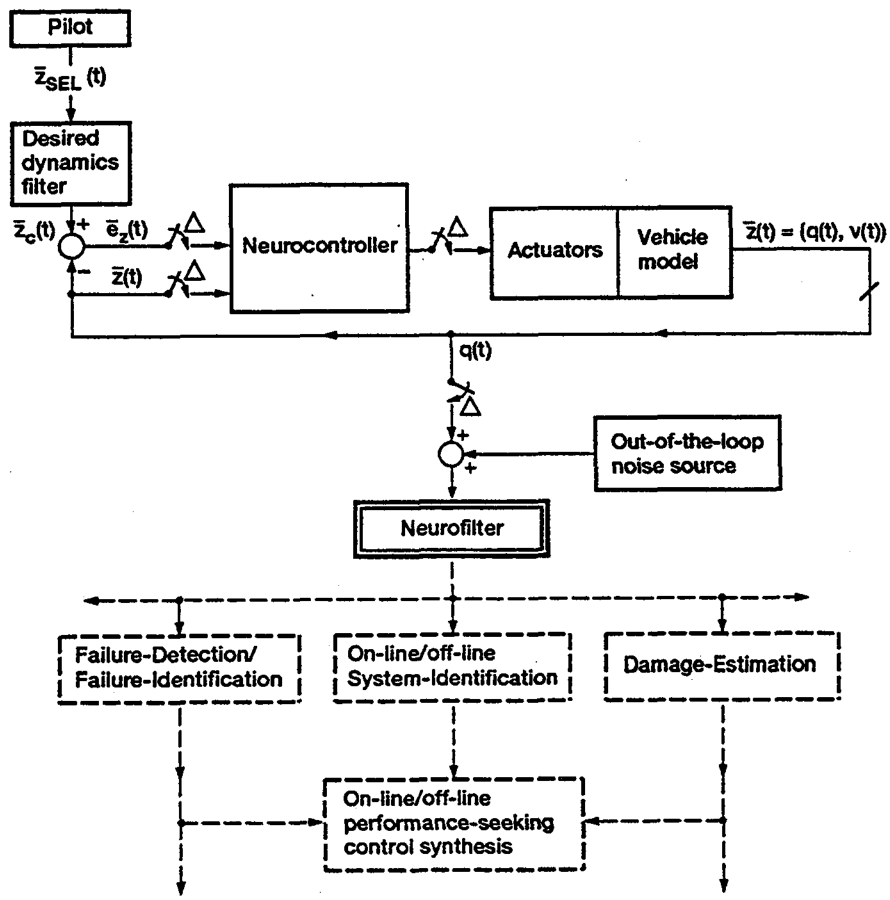
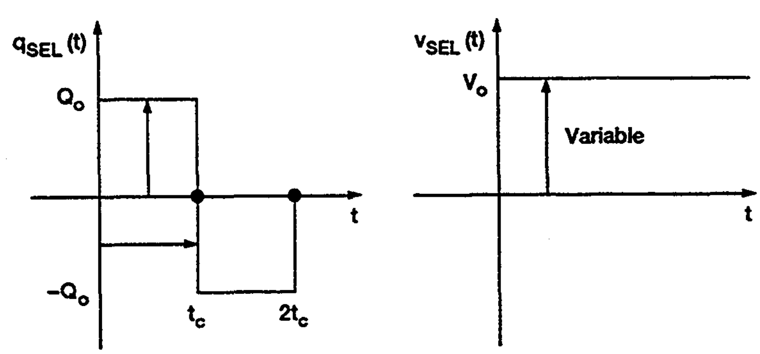


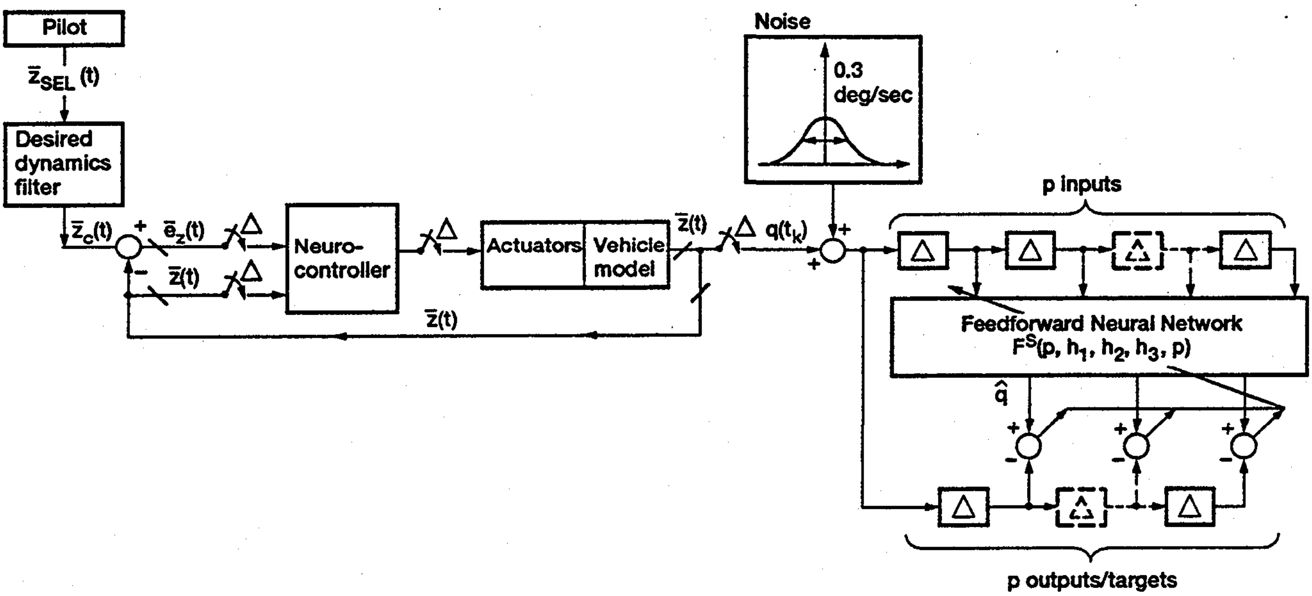
Figure 1.—Systemic functionality of the trained neurofilter.



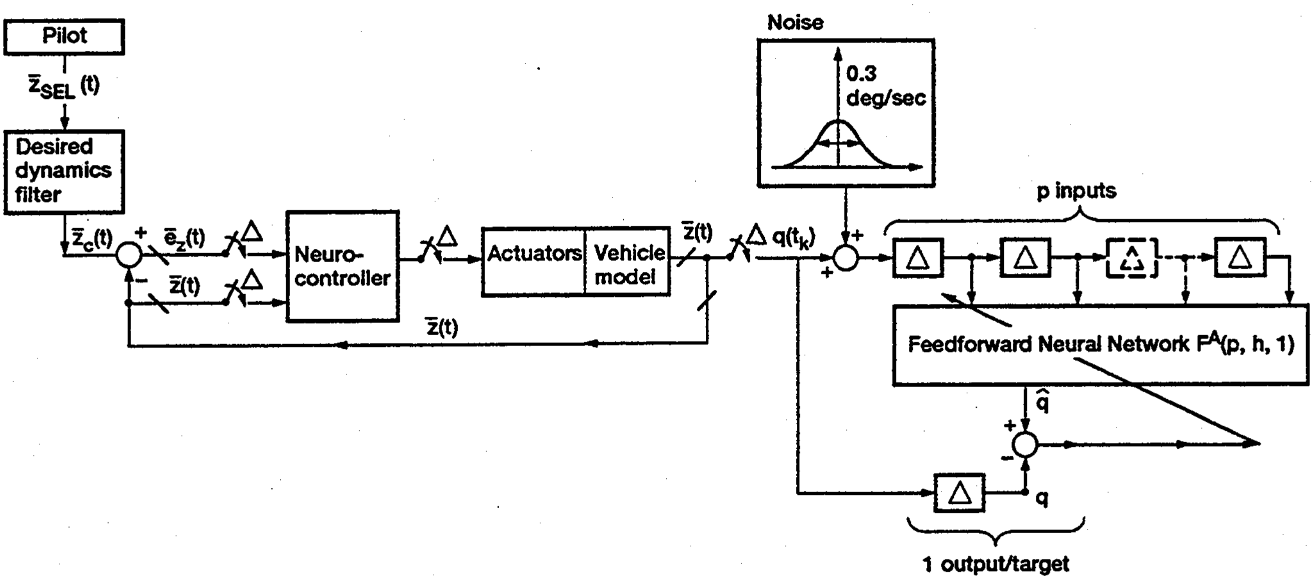
(a) Doublet pitch-rate centered at time $t = t_c$.

(b) Step velocity.

Figure 2.—Pilot command input, $\bar{z}_{SEL}$ (t) = (q_{SEL} (t), v_{SEL} (t)).

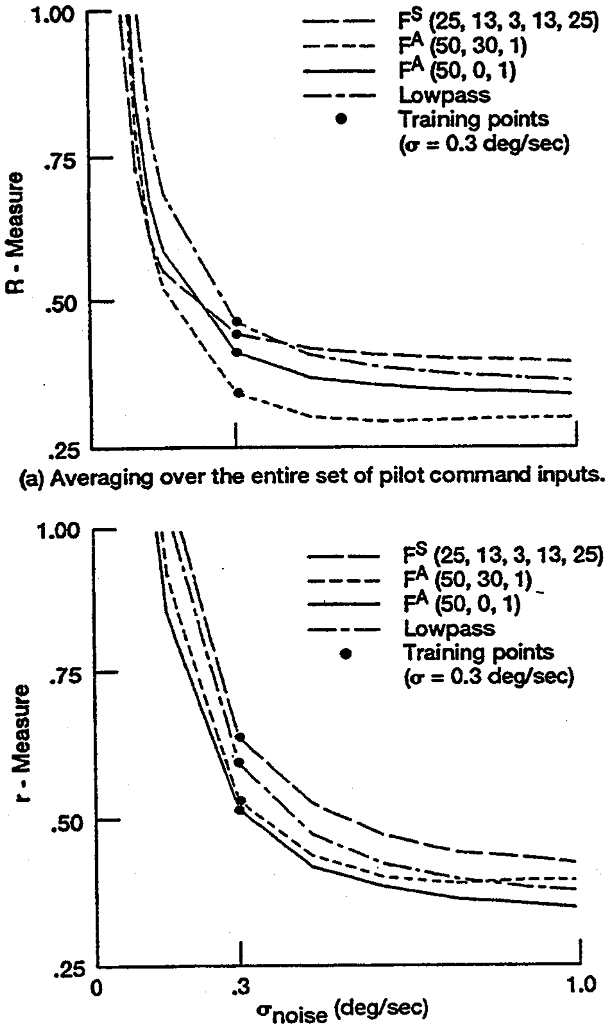


(a) Symmetric neurofilter $F^S(p, h_1, h_2, h_3, p)$ with p inputs, p outputs, and three hidden layers of h_1, h_2, h_3 neurons respectively.



(b) Asymmetric neurofilter $F^A(p, h, 1)$ with p inputs, one output, and one hidden layer of h neurons.

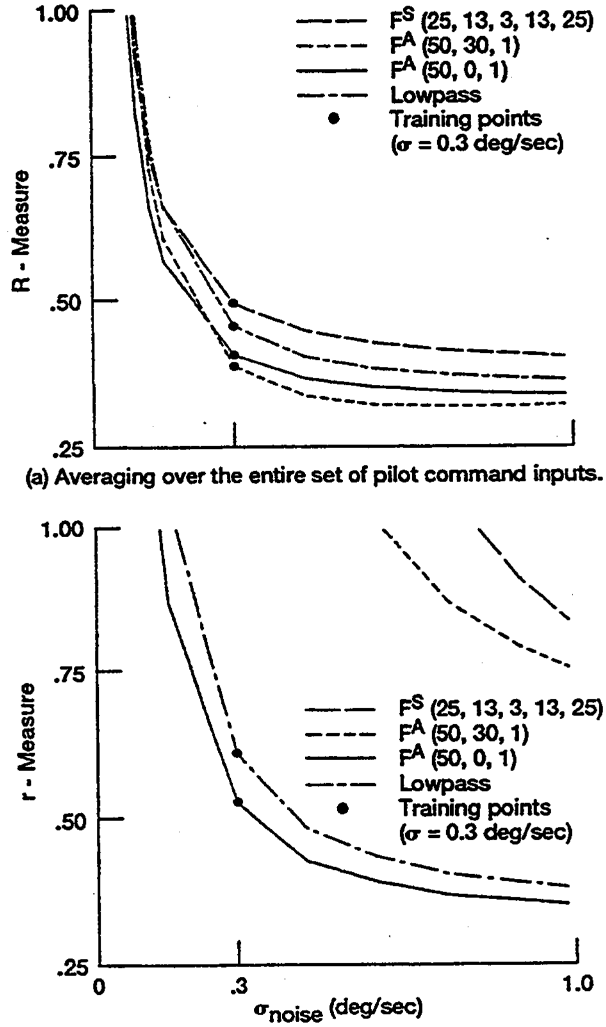
Figure 3.—Training architecture of the neurofilters.



(a) Averaging over the entire set of pilot command inputs.

(b) Averaging over the most demanding pilot command input.

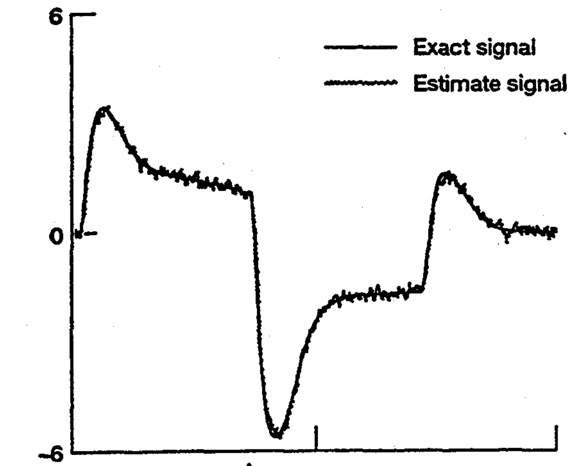
Figure 4.—Noise-filtering efficiency of the various neuro-filters trained and evaluated with pitch rate closed-loop responses of the vehicle model with nominal parameter values.



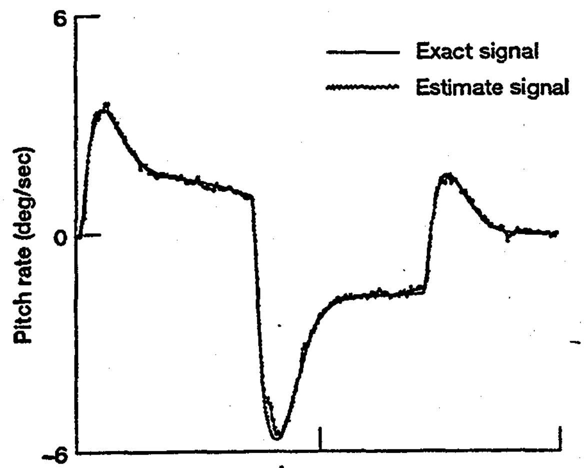
(a) Averaging over the entire set of pilot command inputs.

(b) Averaging over the most demanding pilot command input.

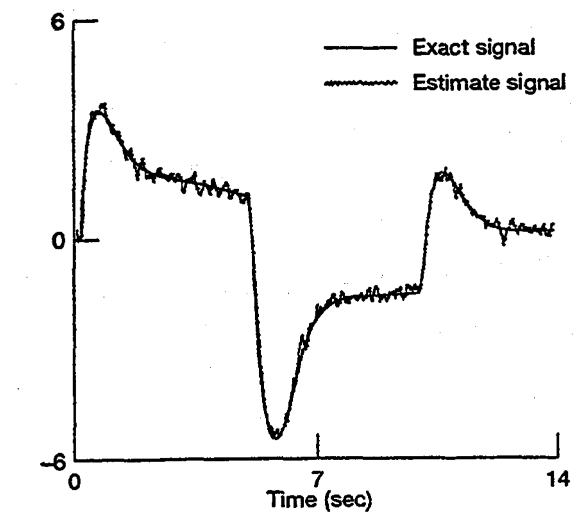
Figure 5.—Noise-filtering efficiency of the various neuro-filters evaluated with pitch rate closed-loop responses of the vehicle model with off-nominal parameter values, after being trained with pitch rate closed-loop responses of the vehicle model with nominal parameter values.



(a) Linear F^A (50, 0, 1) r = 0.52.

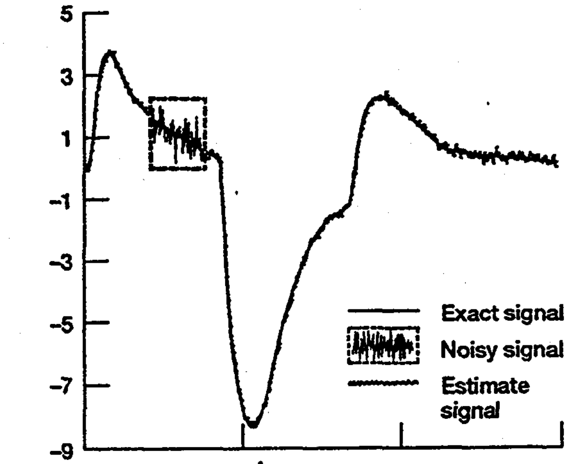


(b) Asymmetric F^A (50, 30, 1) r = 0.45.

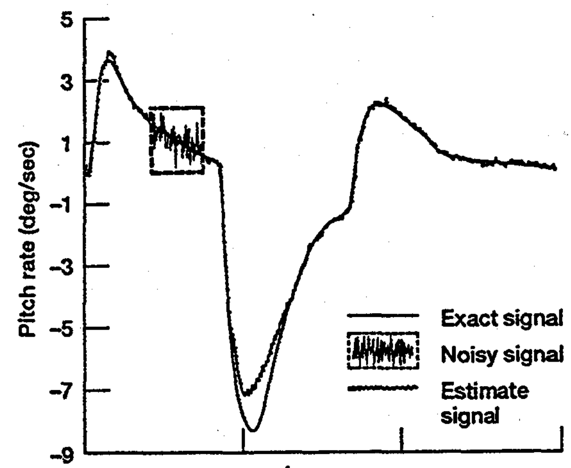


(c) Symmetric F^S (25, 13, 3, 13, 25) r = 0.54.

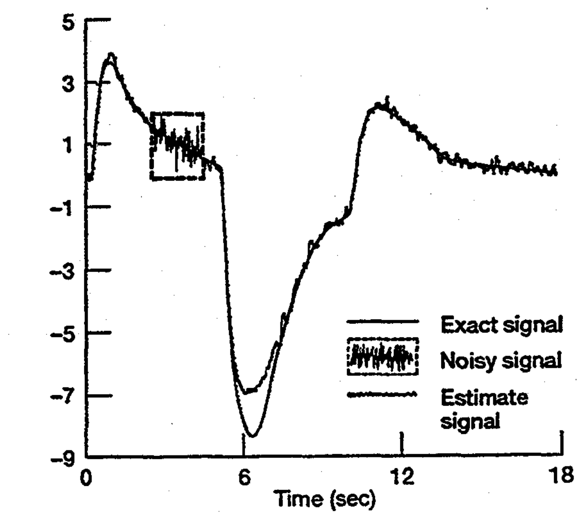
Figure 6.—Exact and estimate pitch rate responses to the most demanding pilot command input of the vehicle model with nominal parameter values, after training the non-linear neurofilters with pitch rate responses of the vehicle model with off-nominal parameter values.



(a) Linear F^A (50, 0, 1) r = 0.53.



(b) Asymmetric F^A (50, 30, 1) r = 1.34.



(c) Symmetric F^S (25, 13, 3, 13, 25) r = 1.37.

Figure 7.—Exact and estimate pitch rate responses to the most demanding pilot command input of the vehicle model with off-nominal parameter values, after training the non-linear neurofilters with pitch rate responses of the vehicle model with off-nominal parameter values.

REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. AGENCY USE ONLY (*Leave blank*)

2. REPORT DATE
December 1993

3. REPORT TYPE AND DATES COVERED
Technical Memorandum

4. TITLE AND SUBTITLE
A Comparative Robustness Evaluation of Feedforward Neurofilters

5. FUNDING NUMBERS
WU–584–03–11

6. AUTHOR(S)
Terry Troudet and Walter 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–8282

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–106440
AIAA–94–0397

11. SUPPLEMENTARY NOTES
Prepared for the 32nd Aerospace Sciences Meeting and Exhibit sponsored by the American Institute of Aeronautics and Astronautics, Reno, Nevada, January 10–13, 1994. Terry Troudet, Sverdrup Technology Inc., Lewis Research Center Group, 2001 Aerospace Parkway, Brook Park, Ohio 44142 (work funded by Contract NAS3–25266), and Walter Merrill, NASA Lewis Research Center. Responsible person, Walter Merrill, (216) 433–6328.

12a. DISTRIBUTION/AVAILABILITY STATEMENT
Unclassified - Unlimited
Subject Category 08

12b. DISTRIBUTION CODE

13. ABSTRACT *(Maximum 200 words)*
A comparative performance and robustness analysis is provided for feedforward neurofilters trained with backpropagation to filter additive white noise. The signals used in this analysis are simulated pitch rate responses to typical pilot command inputs for a modern fighter aircraft model. Various configurations of non-linear and linear neurofilters are trained to estimate exact signal values from input sequences of noisy sampled signal values. In this application, non-linear neurofiltering is found to be more efficient than linear neurofiltering in removing the noise from responses of the nominal vehicle model, whereas linear neurofiltering is found to be more robust in the presence of changes in the vehicle dynamics. The possibility of enhancing neurofiltering through hybrid architectures based on linear and non-linear neuroprocessing is therefore suggested as a way of taking advantage of the robustness of linear neurofiltering, while maintaining the nominal performance advantage of non-linear neurofiltering.

14. SUBJECT TERMS
Noise filtering; Robustness; Neural networks; Linear filtering; Non-linear filtering

15. NUMBER OF PAGES
11

16. PRICE CODE
A03

17. SECURITY CLASSIFICATION OF REPORT	18. SECURITY CLASSIFICATION OF THIS PAGE	19. SECURITY CLASSIFICATION OF ABSTRACT	20. LIMITATION OF ABSTRACT
Unclassified	Unclassified	Unclassified	