# Time and
# Neural Networks

# Thus far

- Networks have been “combinational”; input pattern presented at once

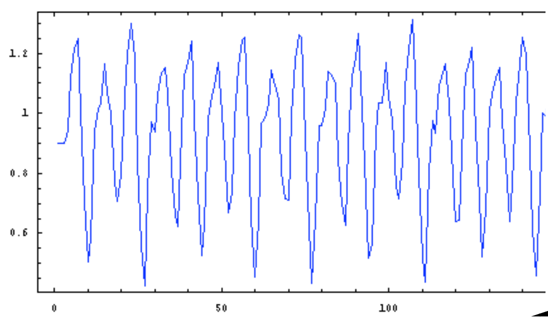
- Now we wish to consider cases where network inputs and learned behavior can include **functions of time**

# Models to be Considered Here

- Time-series prediction
- Adaptive (or Active) noise cancellation
- Time-Delay Neural Networks (TDNN, TLFF)
- Backpropagation through time (BPTT)
- FIR-Multi-layer networks (FIRNET)

# Example: Time-Series Problems: “Predict the Future”

sampled data points

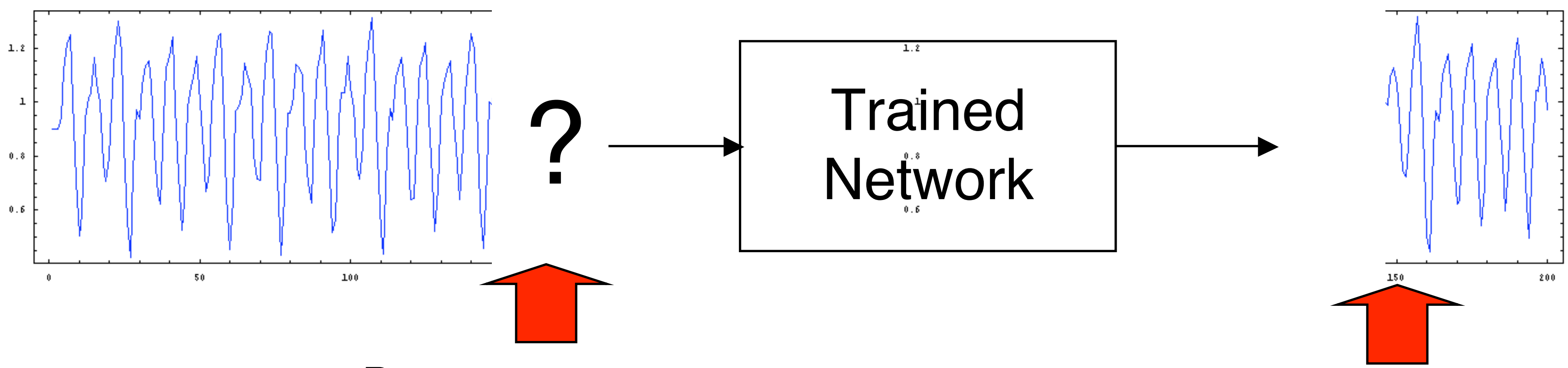



? → Trained Network → Answer (approx.)

What will the next sample input in the series be?

# Time-Series Problems: "Predict the Future"

sampled data points

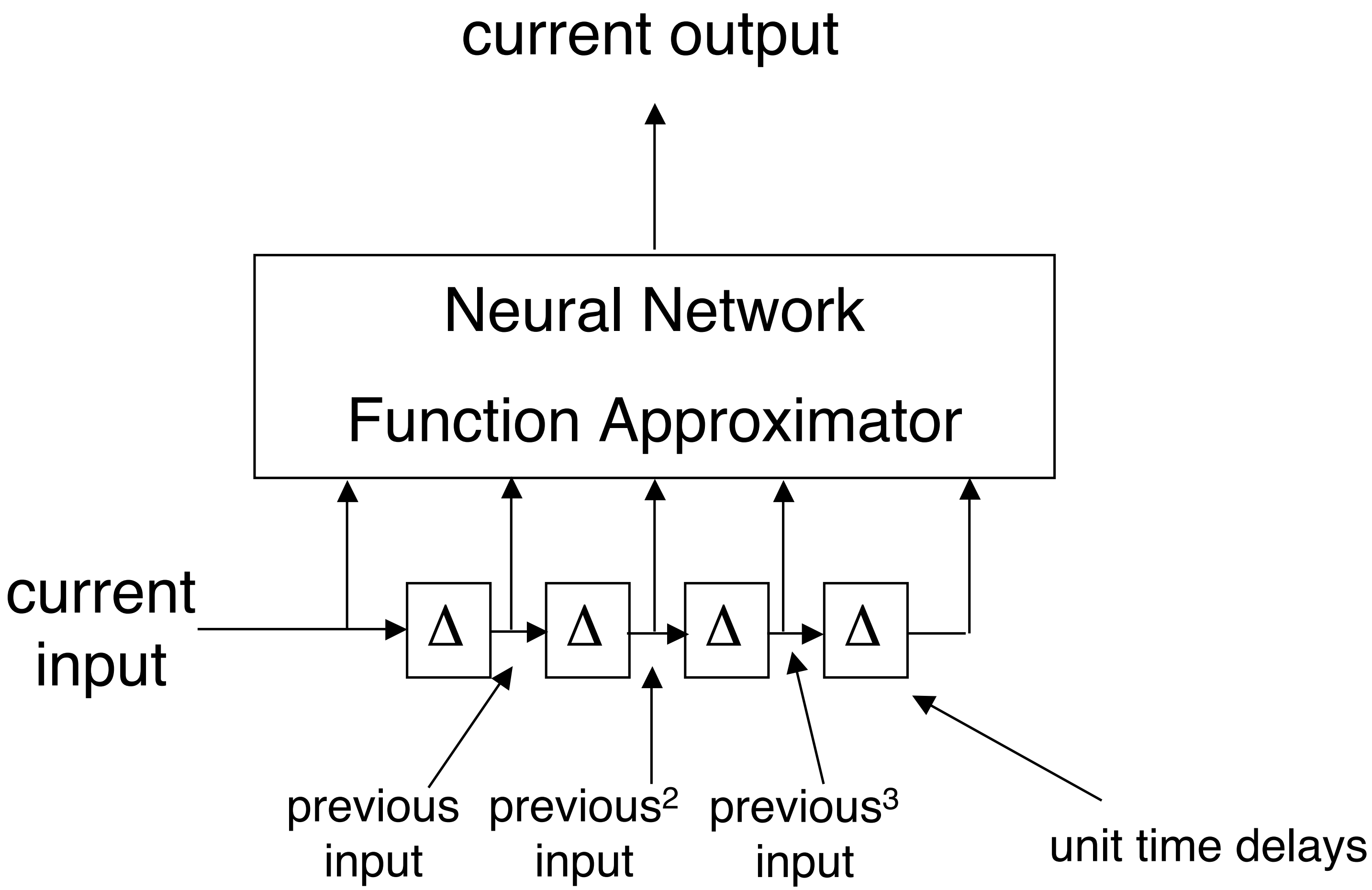



Better yet:
What will the next *n*
sample inputs be, for
nominal n?

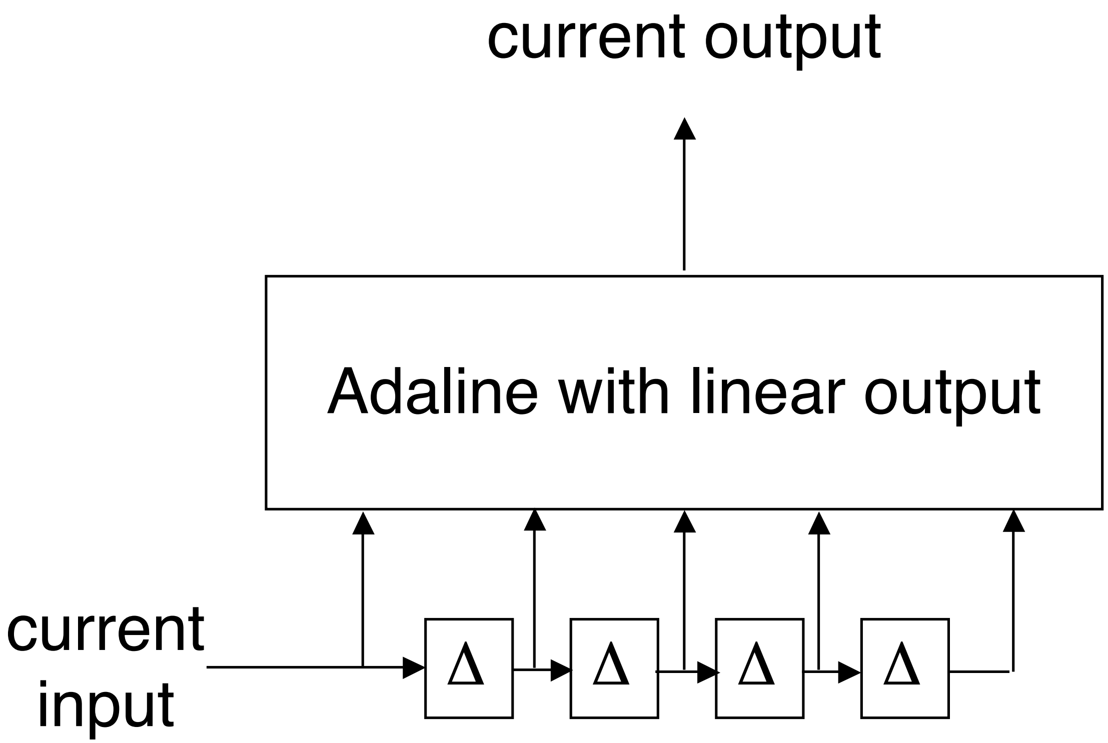
# Applications

- Signal processing
- Sun-spot prediction
- Predict the degradation of the ozone layer
- Market analysis

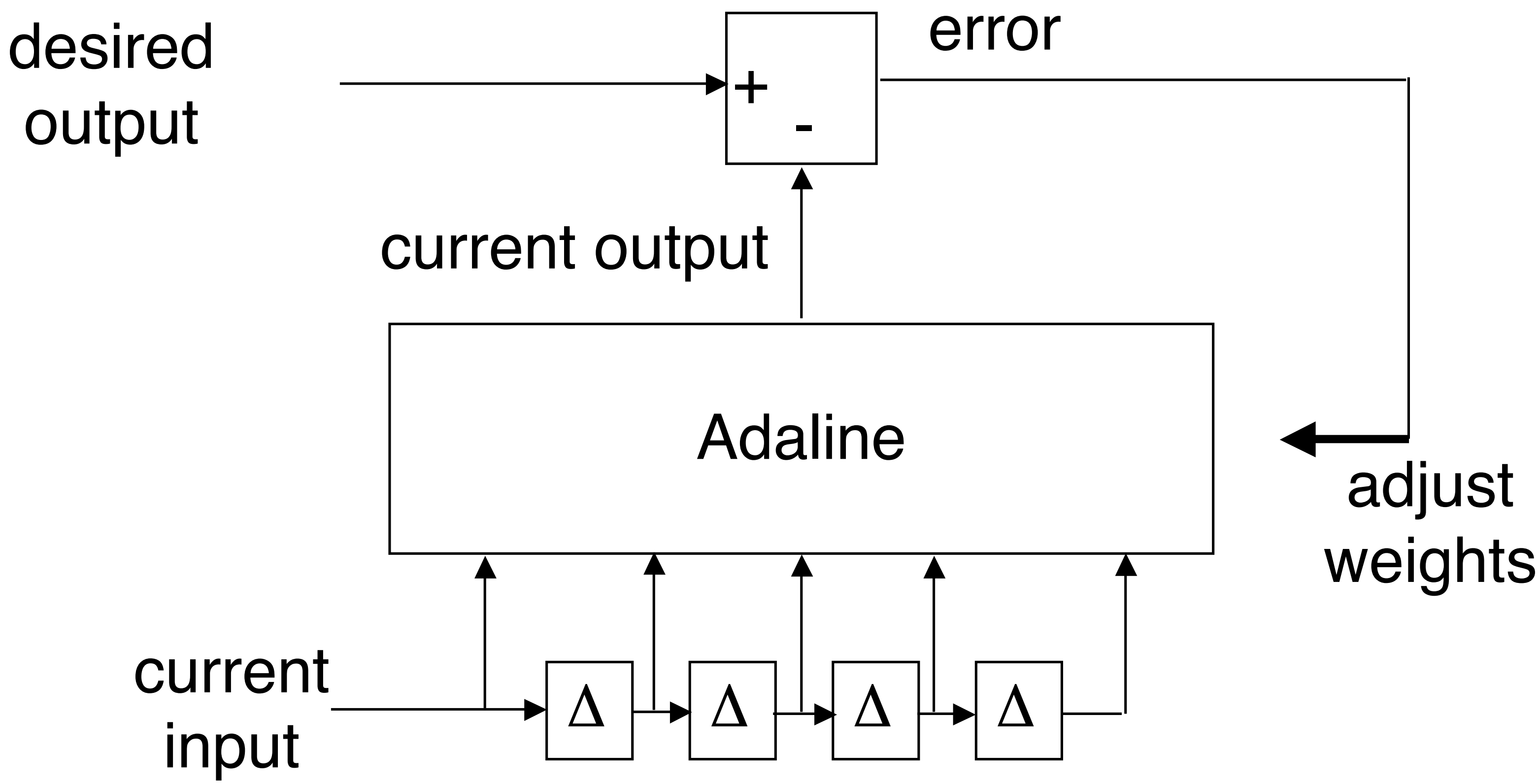
# Learning to Mimic



# Example: Adaline Mimic



# Training the Adaline Mimic



# Training the Adaline Mimic

- Recall the Adaline training rule:

$$\Delta \mathbf{W} = \eta \cdot (\text{desired - actual output}) \cdot \mathbf{input}$$

- Here input vector is the current input, along with all the delayed inputs (one per weight)

# Demo applin4

- An Adaline is trained to mimic a specific input-output behavior.
- The output is an attenuated version of the input.
- When subsequently presented with the input, the output is observed and the error computed.

# Example: applin4

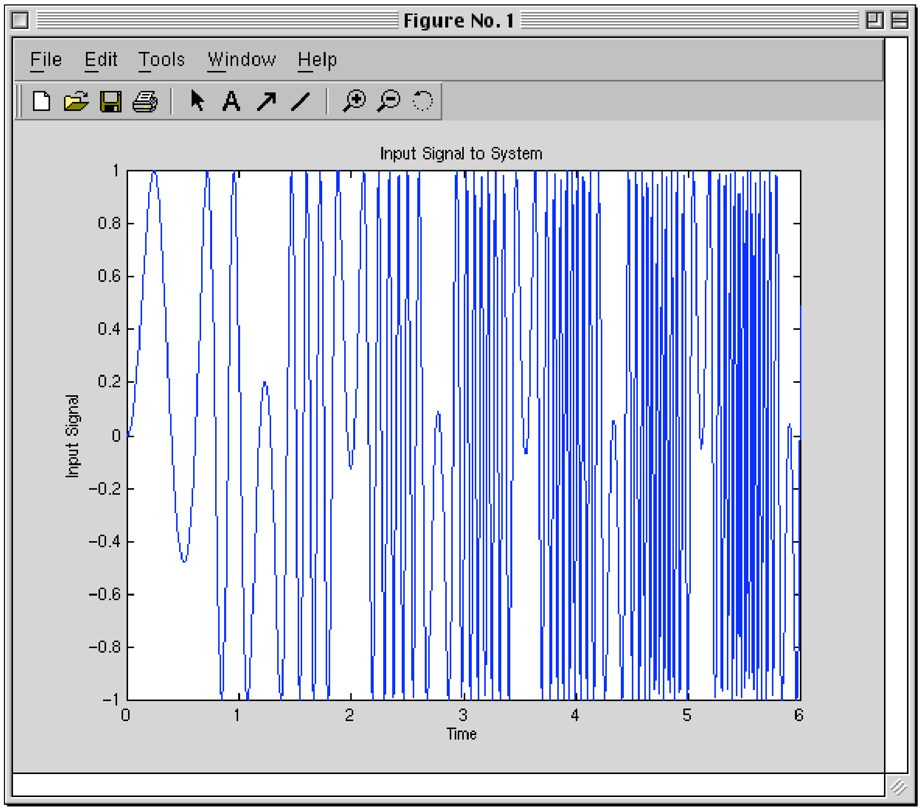
% NEWLIN - Initializes a linear layer.
% ADAPT - Trains a linear layer with Widrow-Hoff rule.

% ADAPTIVE LINEAR SYSTEM IDENTIFICATION:

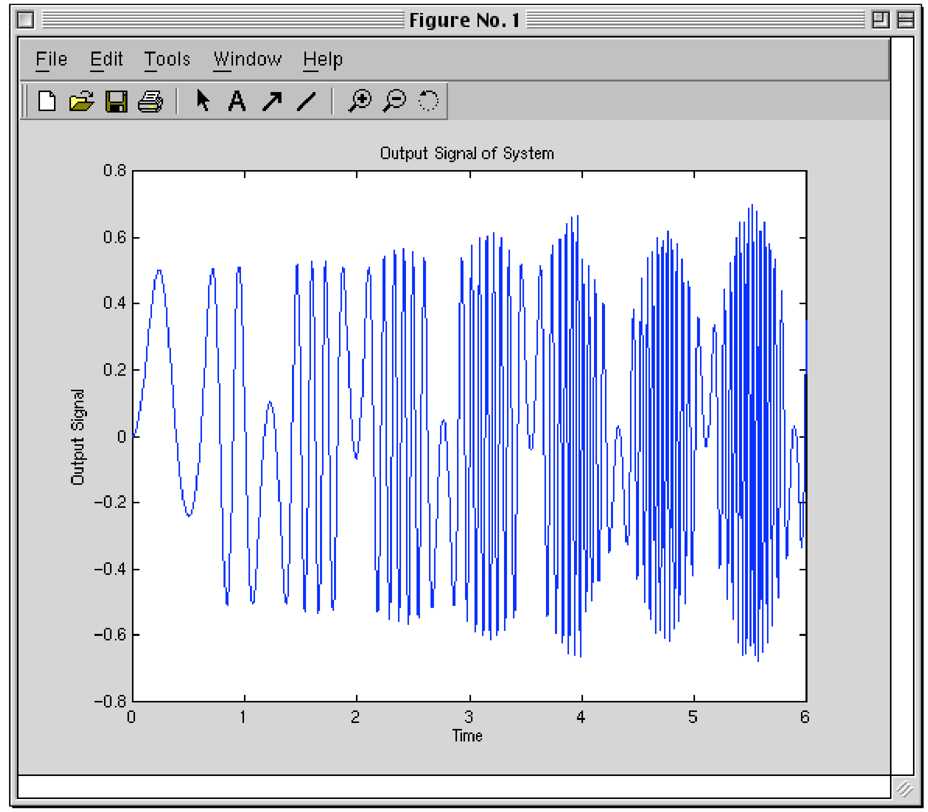
% Using the above functions a linear neuron is adaptively
% trained to model a linear system.

% **The linear neuron is able to adapt to changes in the**
% **model it is trying to mimic.**

# applin4: Input-Output Relation




Input




Desired Output

# applin: frame 2

```
%   DEFINE THE NETWORK
%   ====================

%   NEWLIN generates a linear network.

%   We will use a learning rate of 0.5, and two
%   delays in the input.  The resulting network
%   will predict the next value of the target signal
%   using the last two values of the input.

lr = 0.5;
delays = [0 1];

net = newlin(minmax(cat(2,P{:})),1,delays,lr);
```

# applin: frame 3

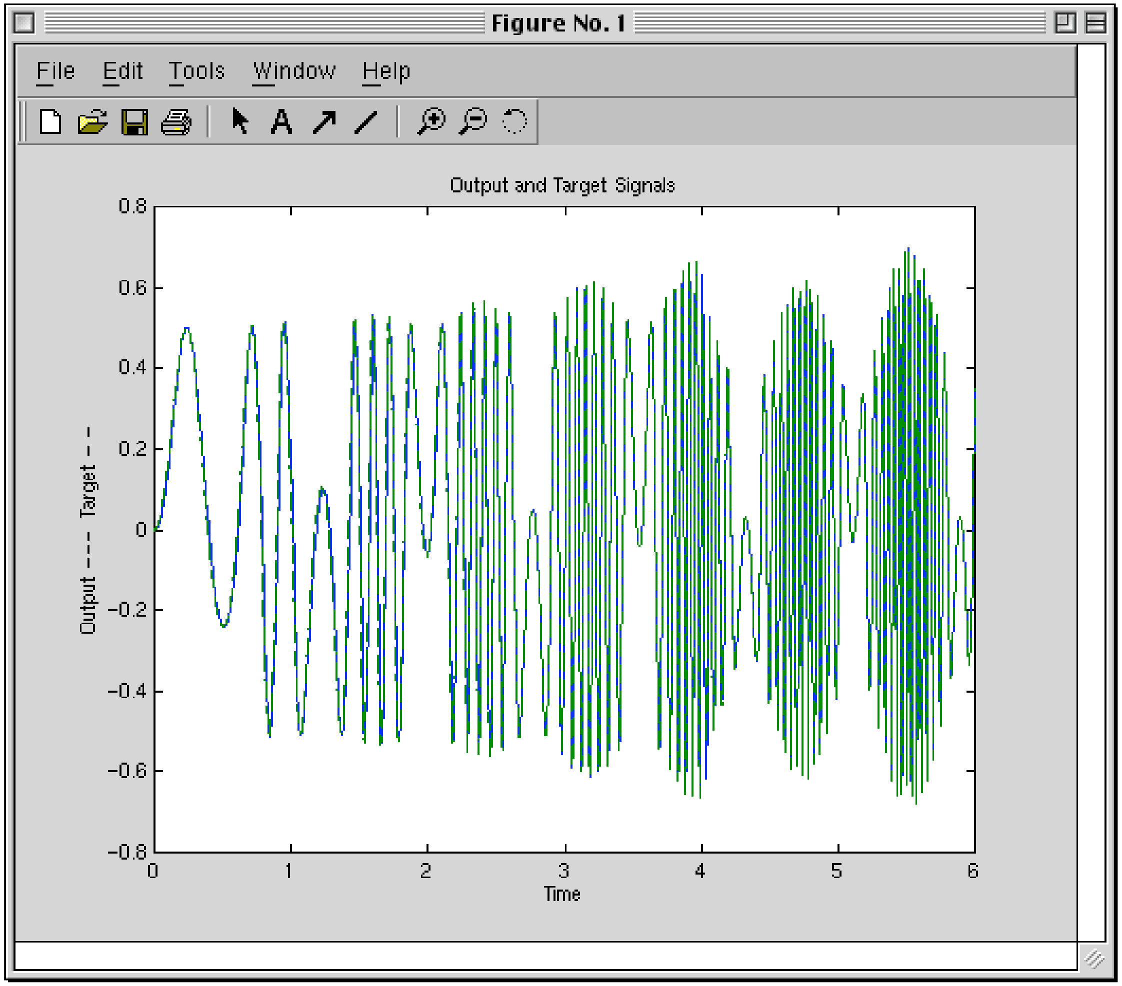
%    ADAPTING THE LINEAR NEURON

%    ADAPT simulates adaptive linear neurons.  It takes the
%    initial network, an input signal, and a target signal,
%    and filters the signal adaptively.  The output signal and
%    the error signal are returned, along with new network.

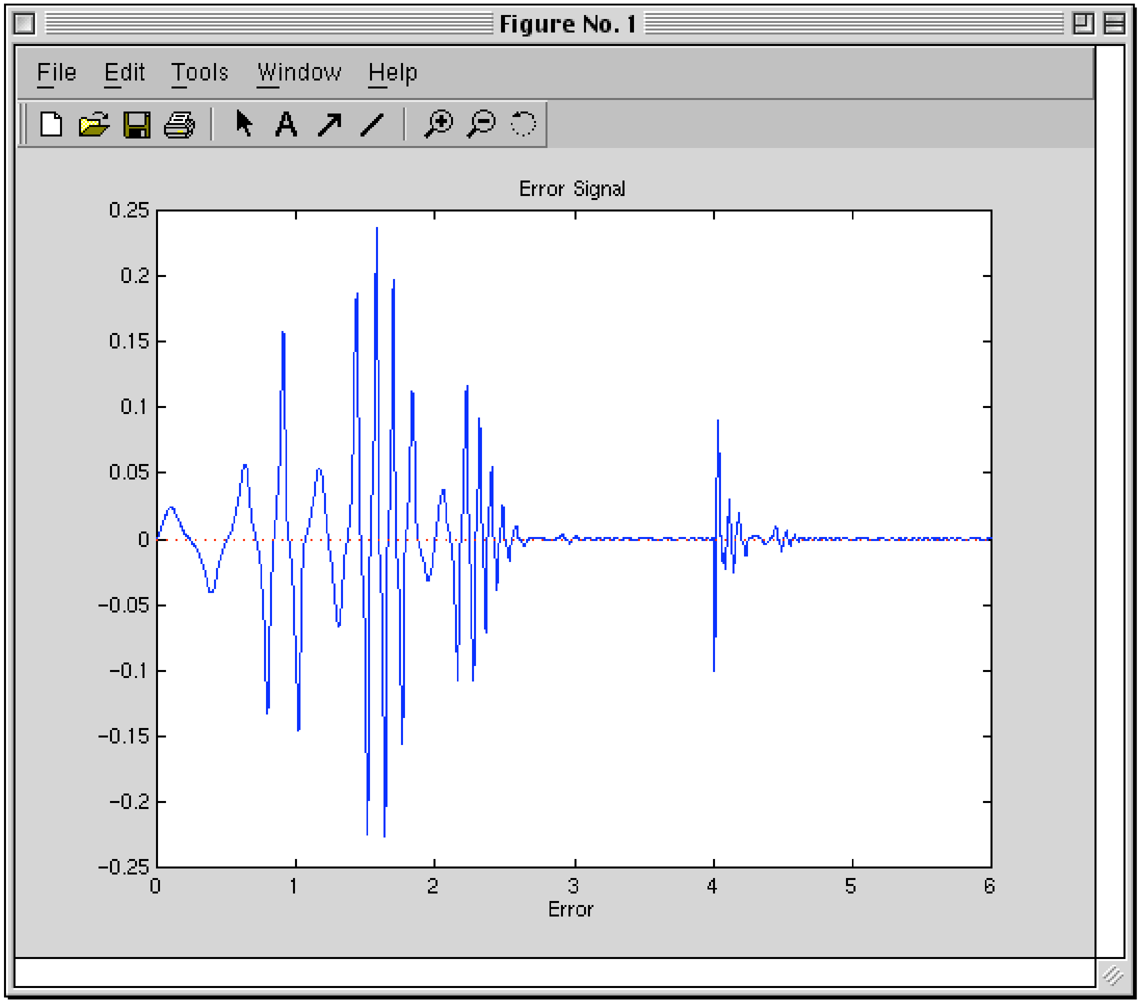
%    Adapting begins...please wait...

```
[net,y,e]=adapt(net,P,T);
```

# applin4: actual output vs. target



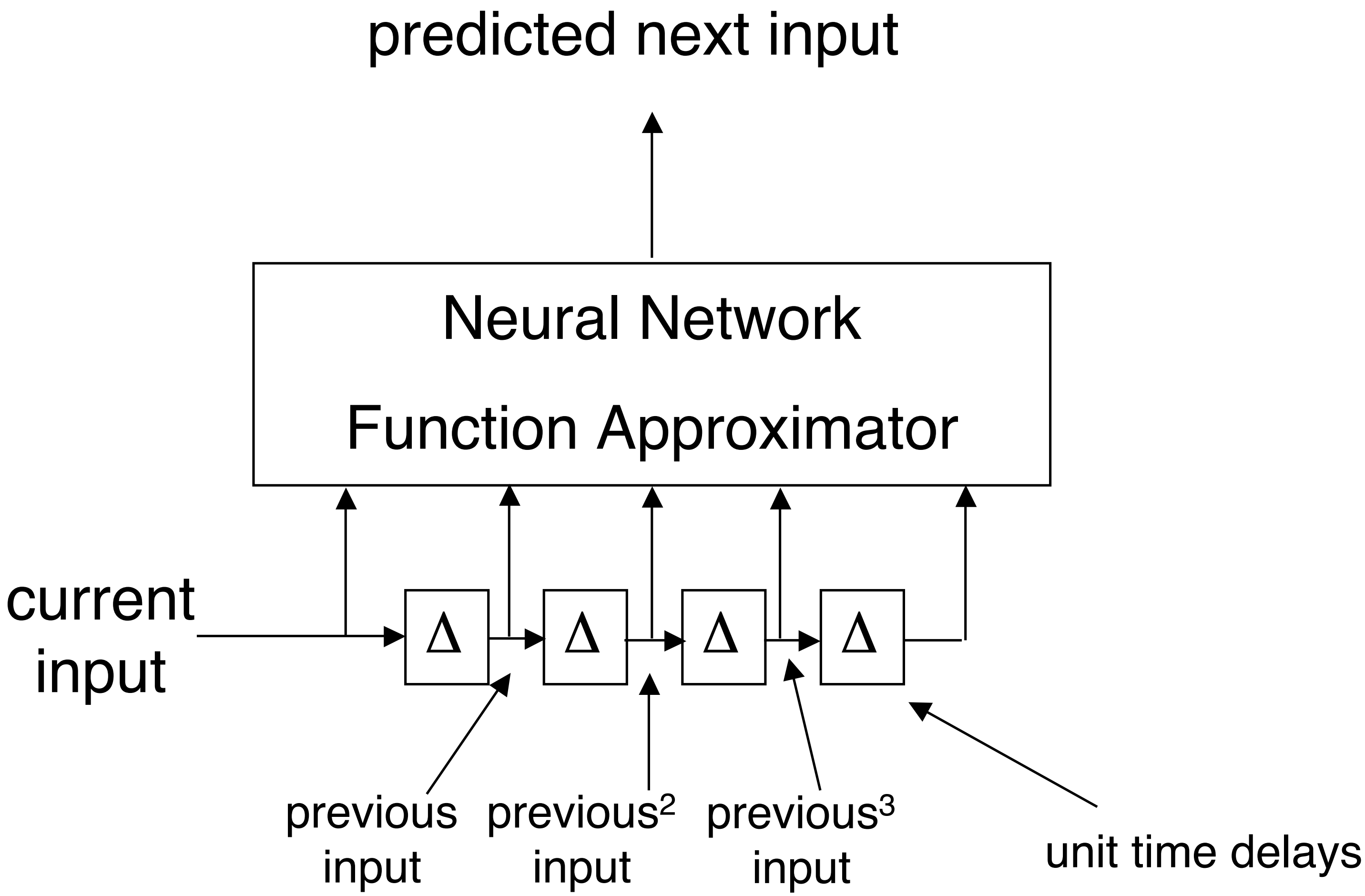
# applin4: error



# Interesting Point

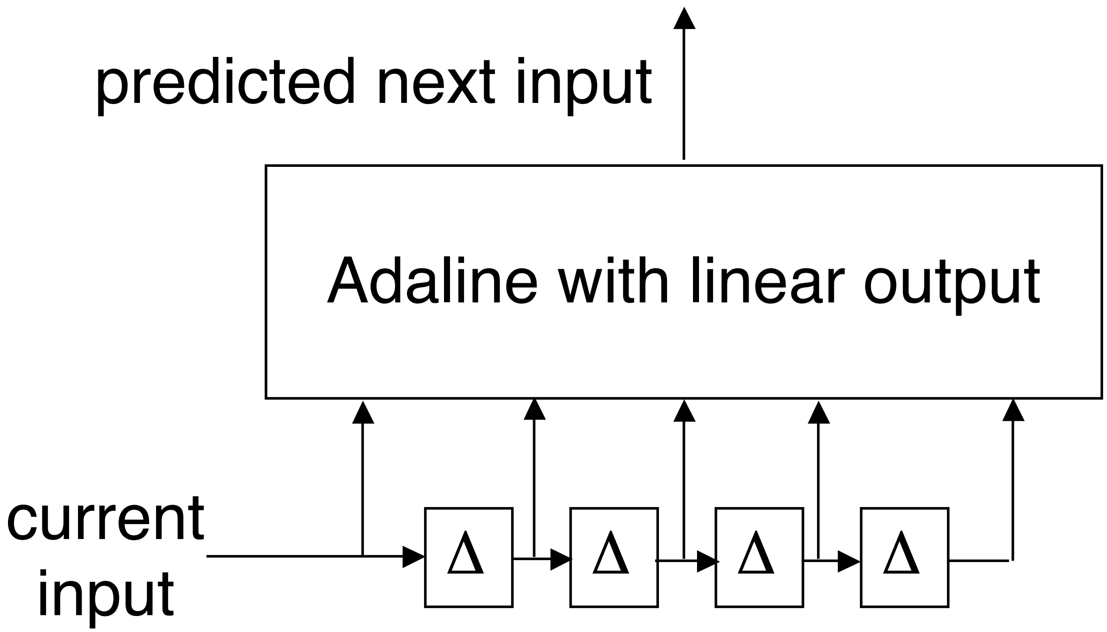
- The Adaline Predictor can be trained **during operation**.
- At each time step, one set of weight modifications can be made.
- After a transient, the network learns to mimic the desired behavior.

# How to Learn to Predict?

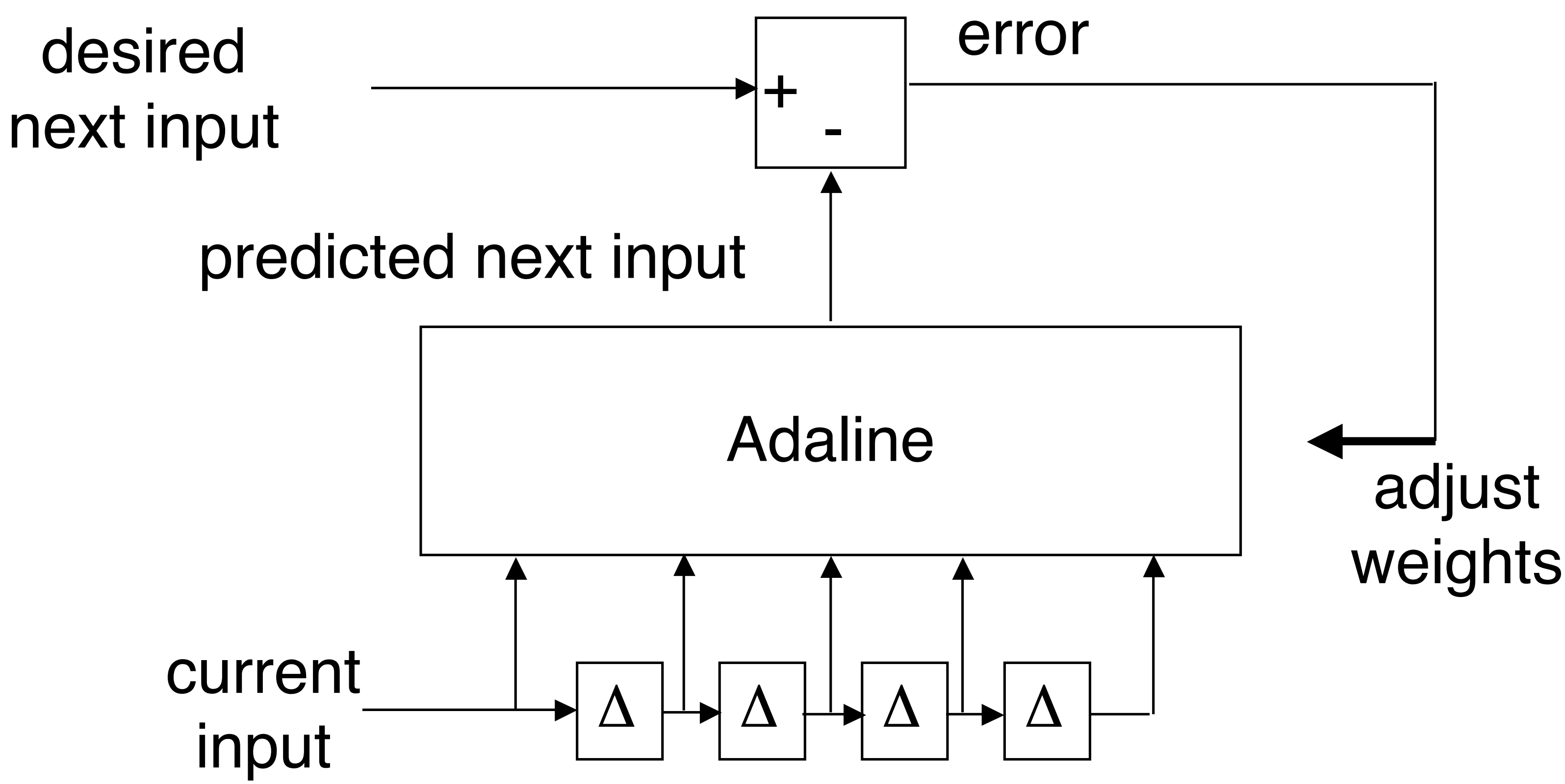


# Example: Adaline Predictor

The predictor is like a mimic, where the next input is what is to be mimicked.



# Training the Adaline Predictor



# Training the Adaline Predictor

- Recall the Adaline training rule:

$$\Delta \mathbf{W} = \eta \cdot (\text{desired - actual output}) \cdot \mathbf{input}$$

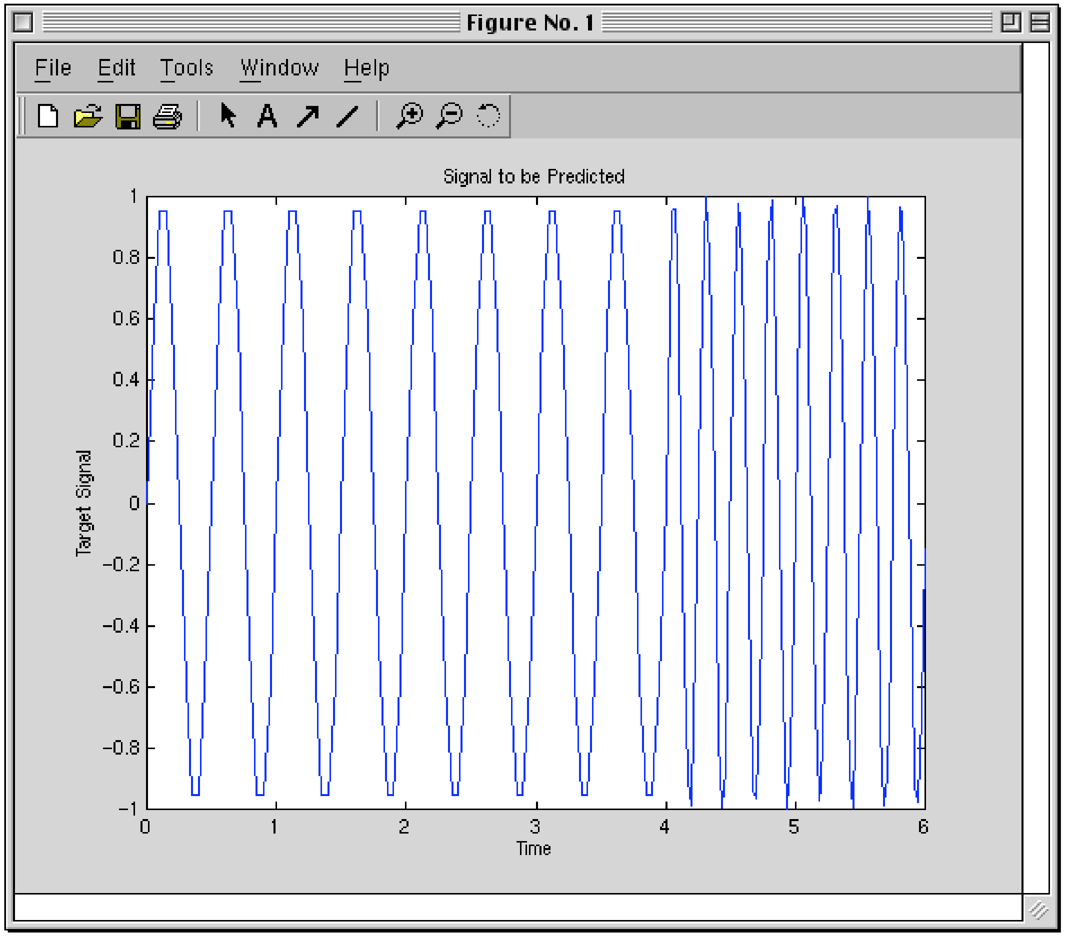
- Here "input" is the current input, along with all the delayed inputs (one per weight)

# Demonstration applin2

- Predicts the next input based on 5 previous input samples.
- The input is a sine wave, but the frequency doubles after awhile.
- It is desirable for the network to adapt its behavior to the new frequency.

# applin2

signal to be predicted (2 sine waves of different frequencies)



# applin2: frame 1

% NEWLIN - Creates and initializes a linear layer.
% ADAPT - Trains a linear layer with Widrow-Hoff rule.

% ADAPTIVE LINEAR PREDICTION:

% Using the above functions a linear neuron is adaptively
% trained to predict the next value in a signal, given the
% last five values of the signal.

% The linear neuron is able to adapt to changes in the
% signal it is trying to predict.

# applin2: frame 2

```
%    DEFINING A WAVE FORM
%    TIME1 and TIME2 define two segments of time.

time1 = 0:0.05:4;      % from 0 to 4 seconds, steps of .05
time2 = 4.05:0.024:6;  % from 4 to 6 seconds, steps of .05
%    TIME defines all the time steps of this simulation.
time = [time1 time2];  % from 0 to 6 seconds

%    T defines a signal which changes frequency once:
T = con2seq([sin(time1*4*pi) sin(time2*8*pi)]);

%    The input P to the network is the same as the target.
%    The network will use the last five
%    values of the target to predict the next value.
```

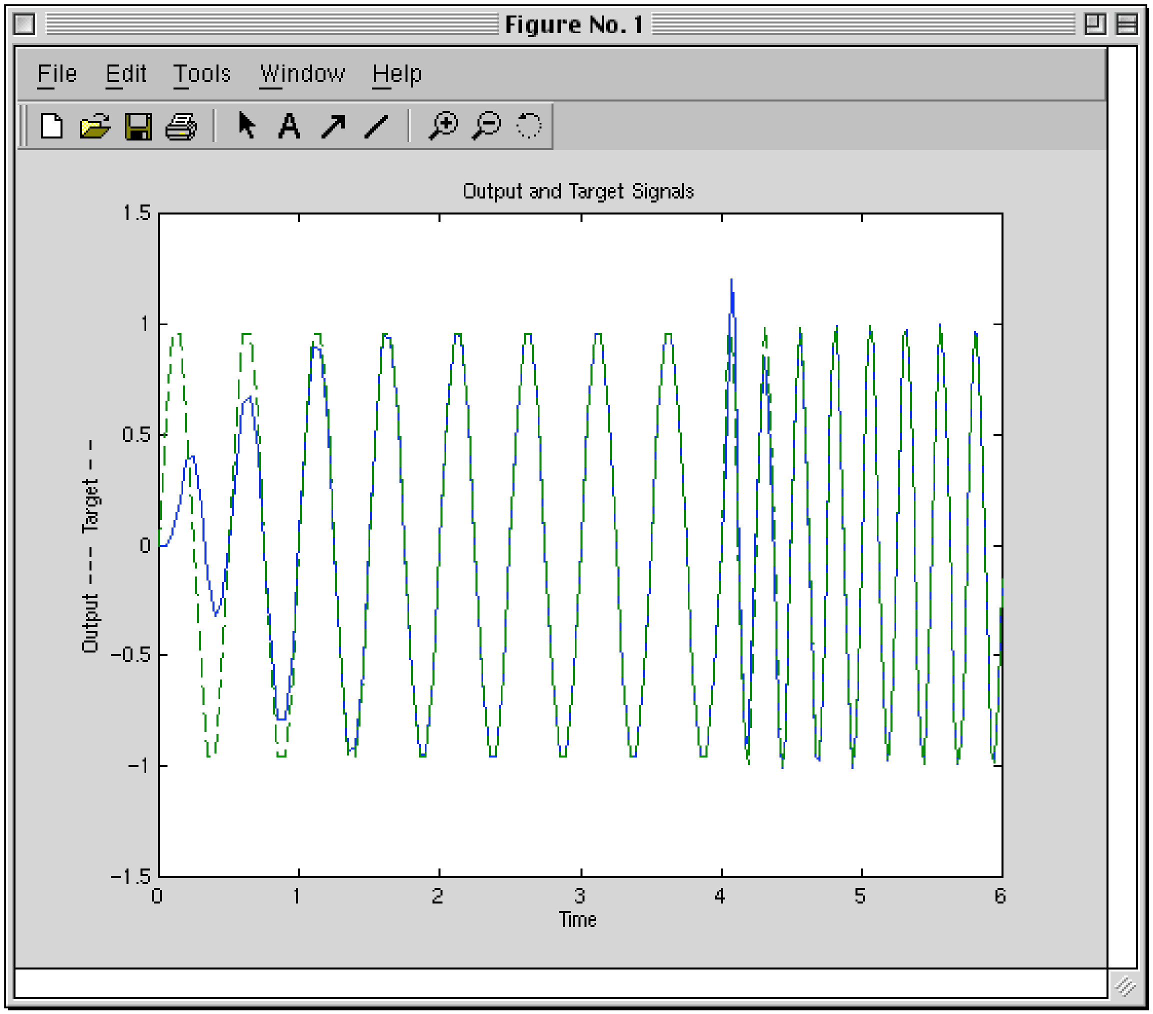
# applin2: frame 3

```
%    NEWLIN generates a linear network.

%    We will use a learning rate of 0.1, and five
%    delays in the input.  The resulting network
%    will predict the next value of the target signal
%    using the last five values of the target.

lr = 0.1;
delays = [1 2 3 4 5];

net = newlin(minmax(cat(2,P{:})),1,delays,lr);
```

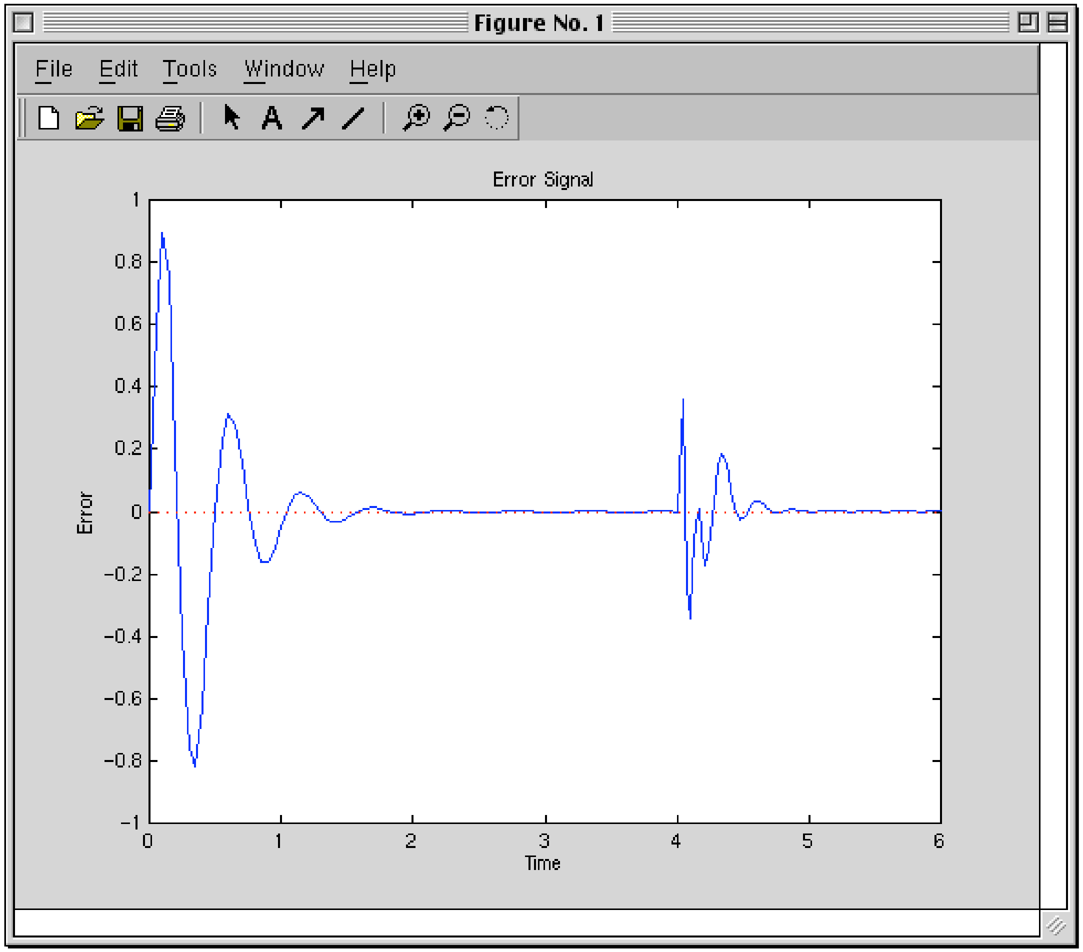
# applin2: frame 4

```
%    ADAPTING THE LINEAR NEURON
%    ==============================

%    ADAPT simulates adaptive linear neurons.  It takes the initial
%    network, an input signal, and a target signal,
%    and filters the signal adaptively.  The output signal and
%    the error signal are returned, along with new network.


%    Adapting begins...please wait...

[net,y,e]=adapt(net,P,T);
```

# applin2: actual output vs. target



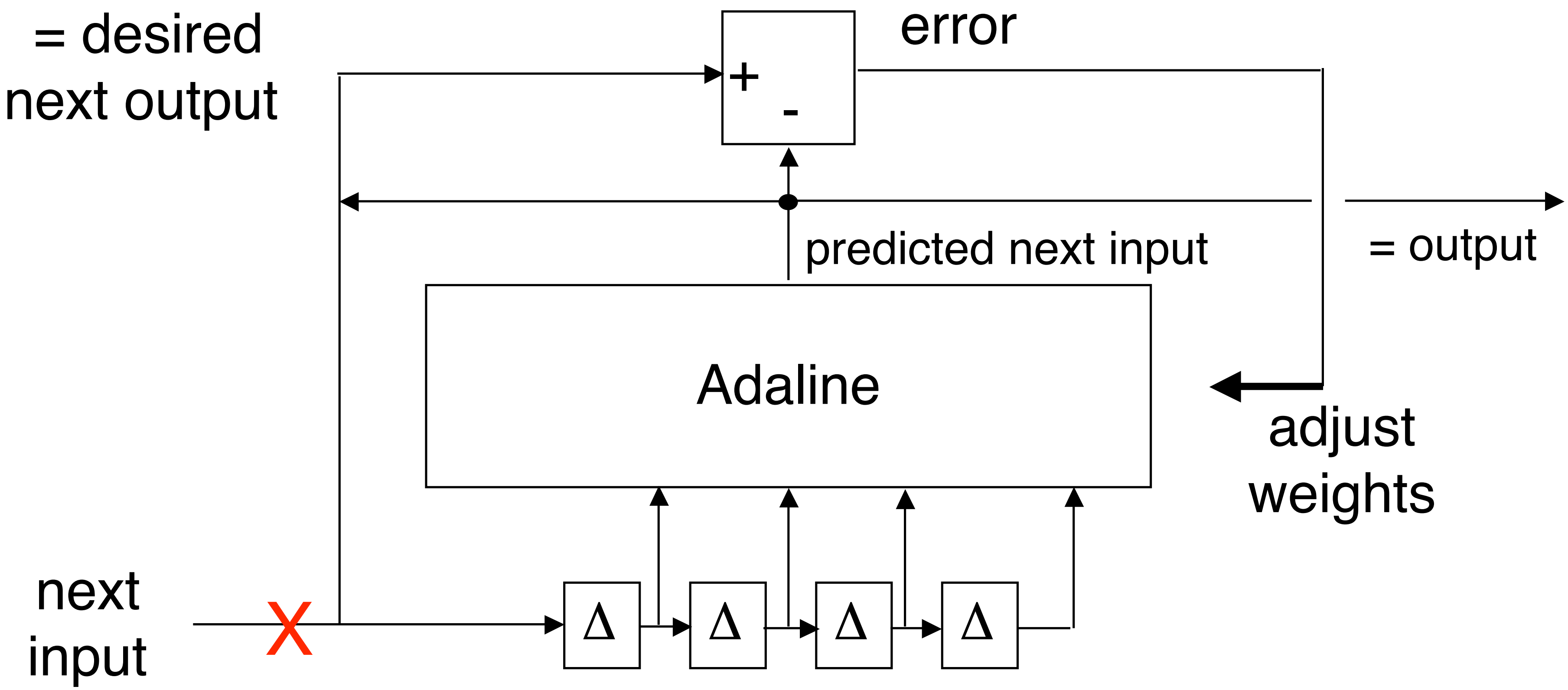
# applin2: error = target - output



# Once the Network has Been Trained

- it can use its *own* output as the next input.
- That is, it can “run free”, predicting the full output **sequence.**
- Since the output was only an approximation, the accuracy of the predicted output will *deteriorate* with time.

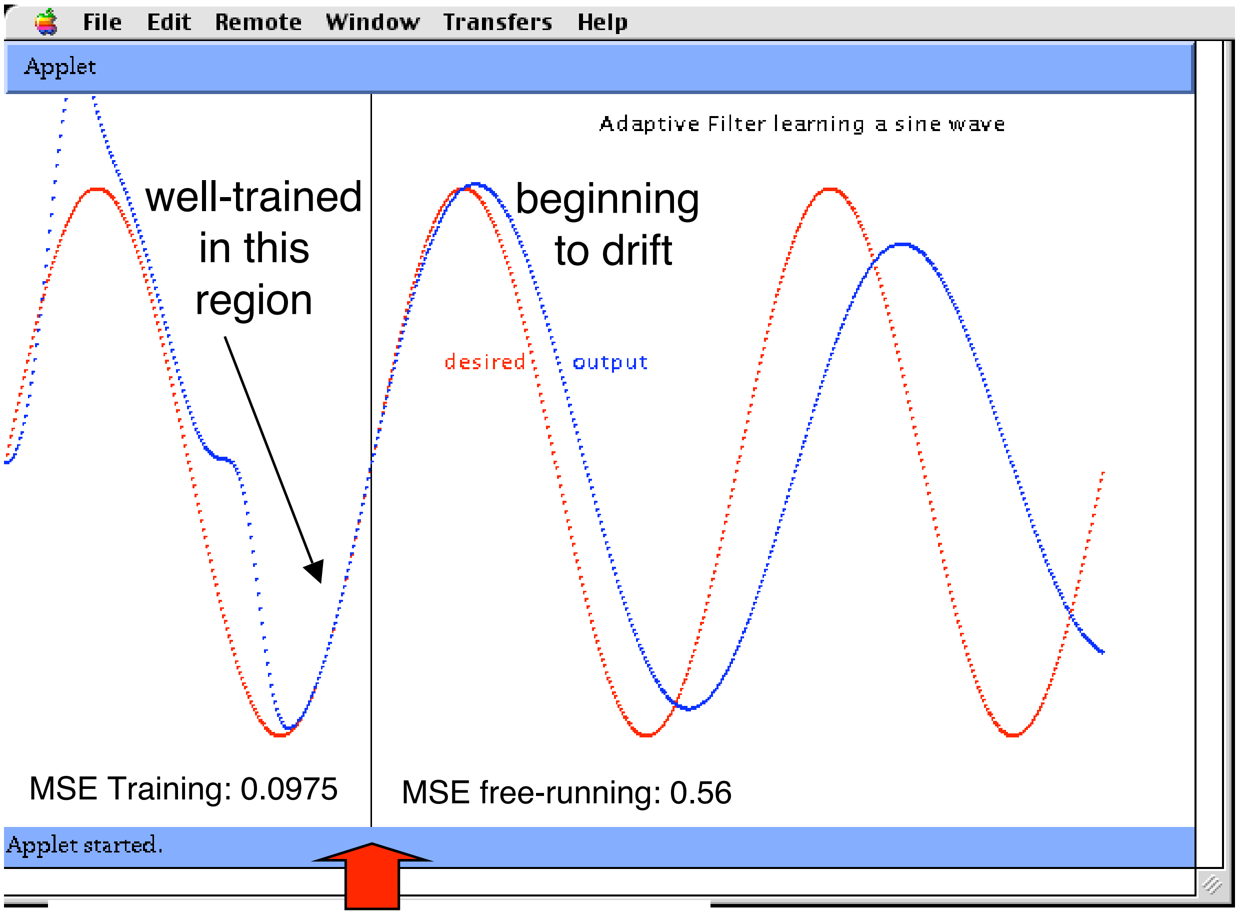
# Free-Running Mode



# Free-Running after Training (applet: cd /cs/cs152/af; go)

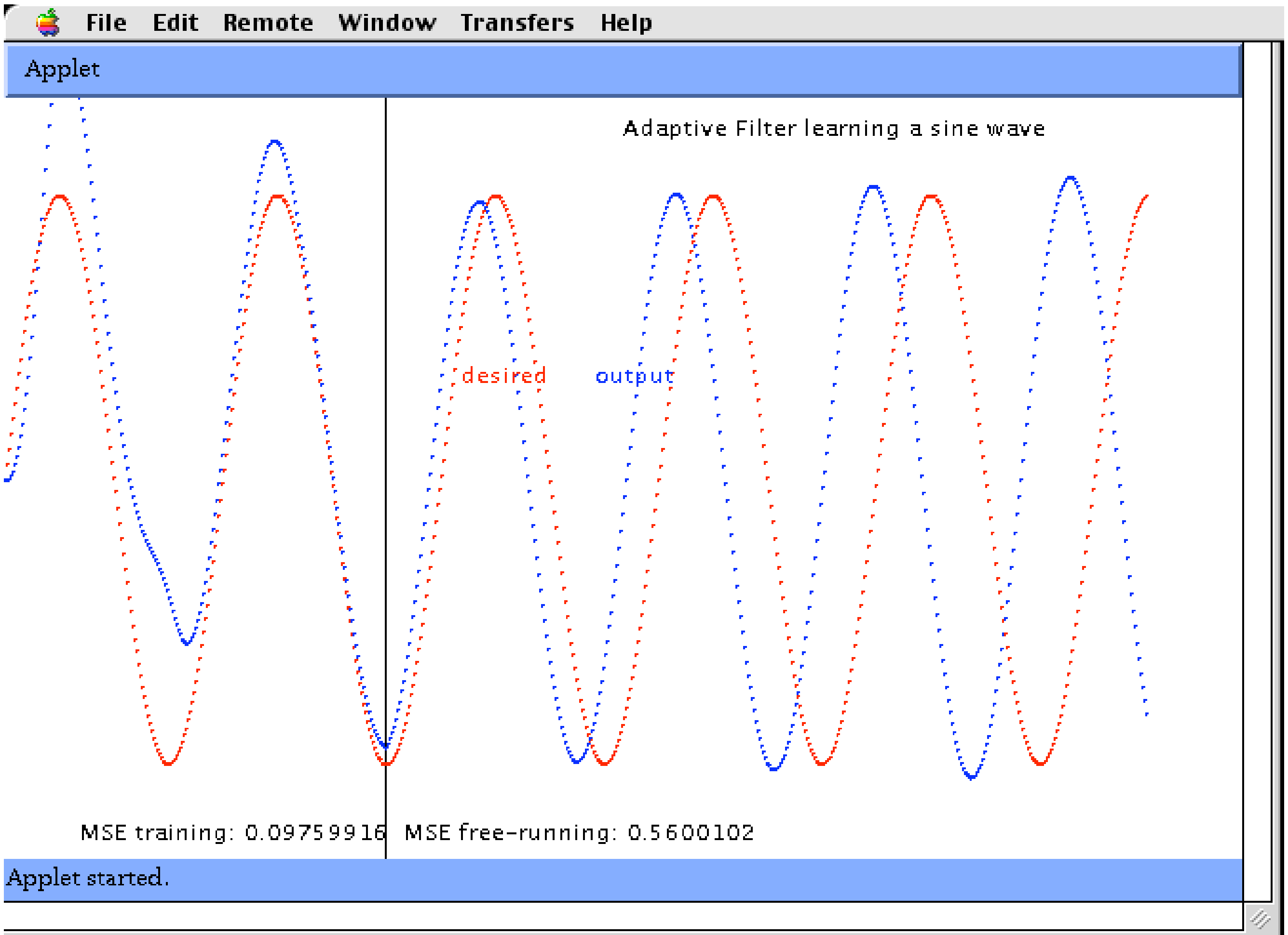
Here the filter was trained with a sine wave

red = desired
blue = actual



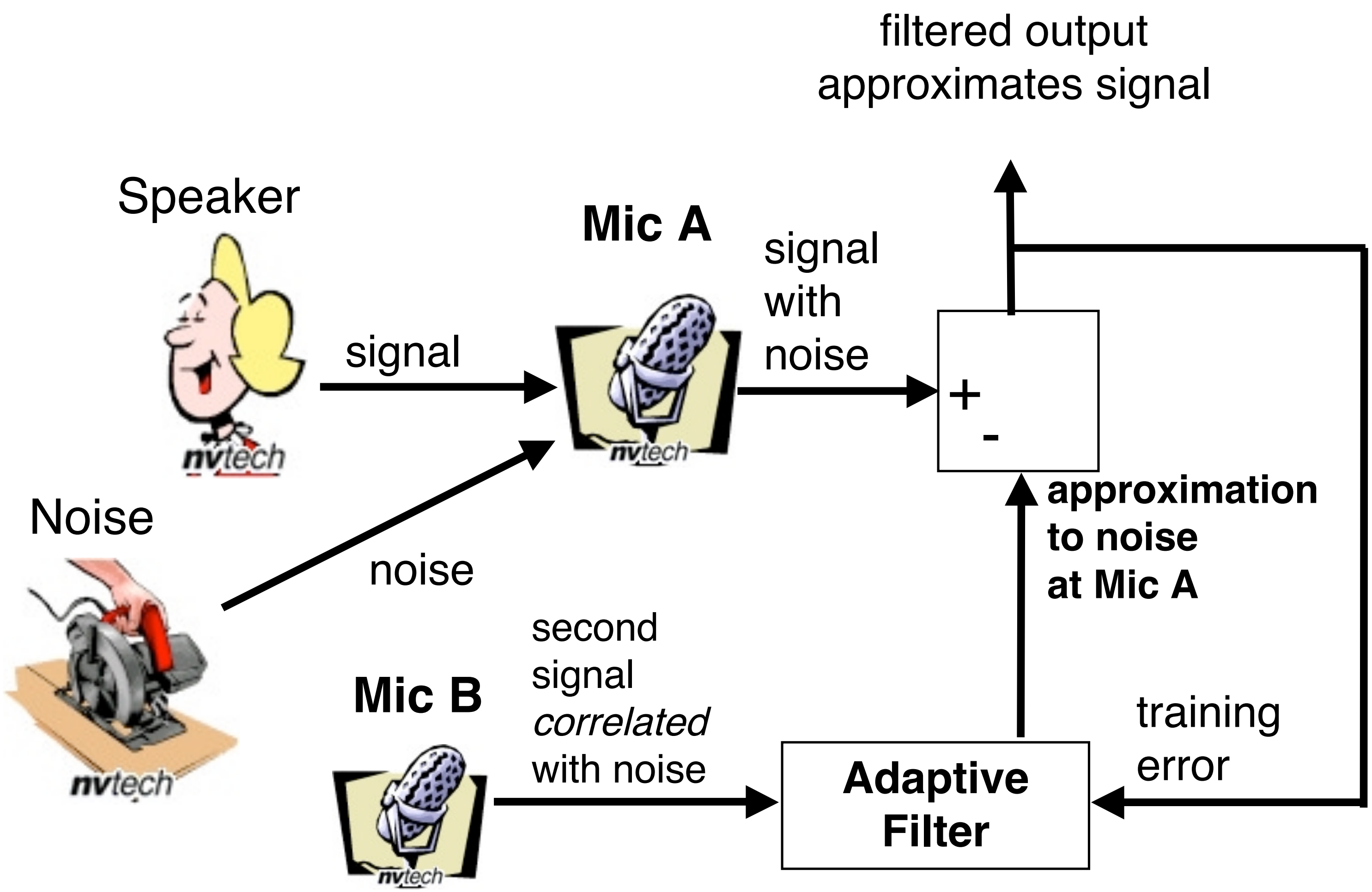

Here the sine wave was removed and the output (prediction) fed back into the input

# The same Filter at 1.75 x frequency



# Noise-Reduction Scenario

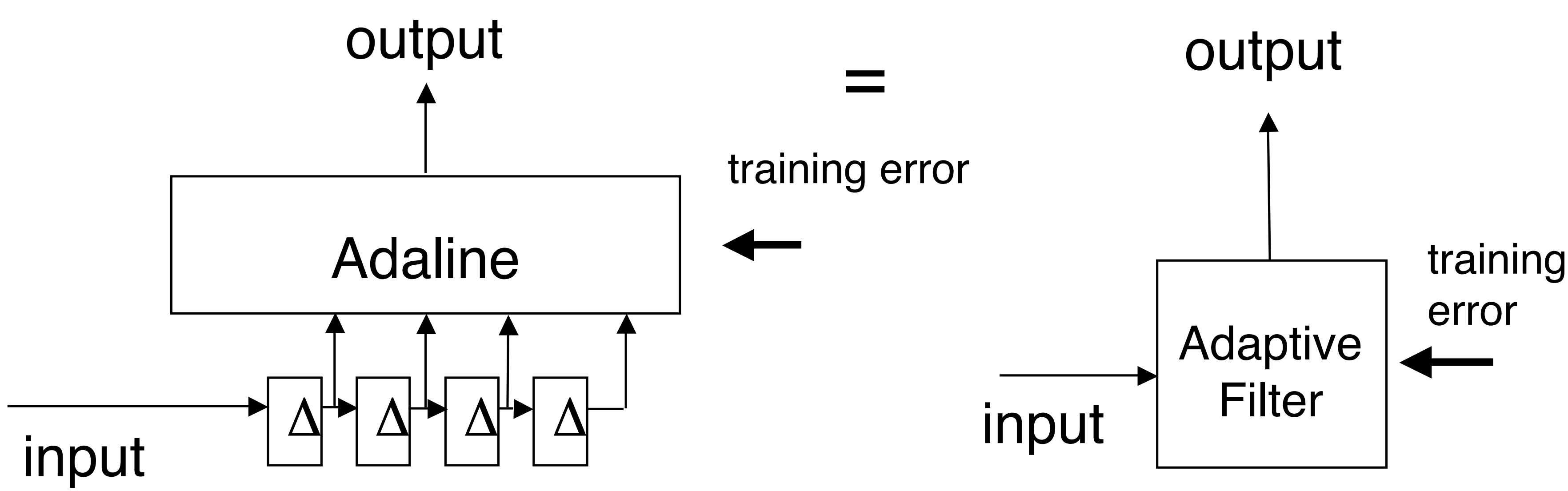
## Filter Learns to Predict the Noise




(*correlated*, but we don't know the exact amplitude or phase)

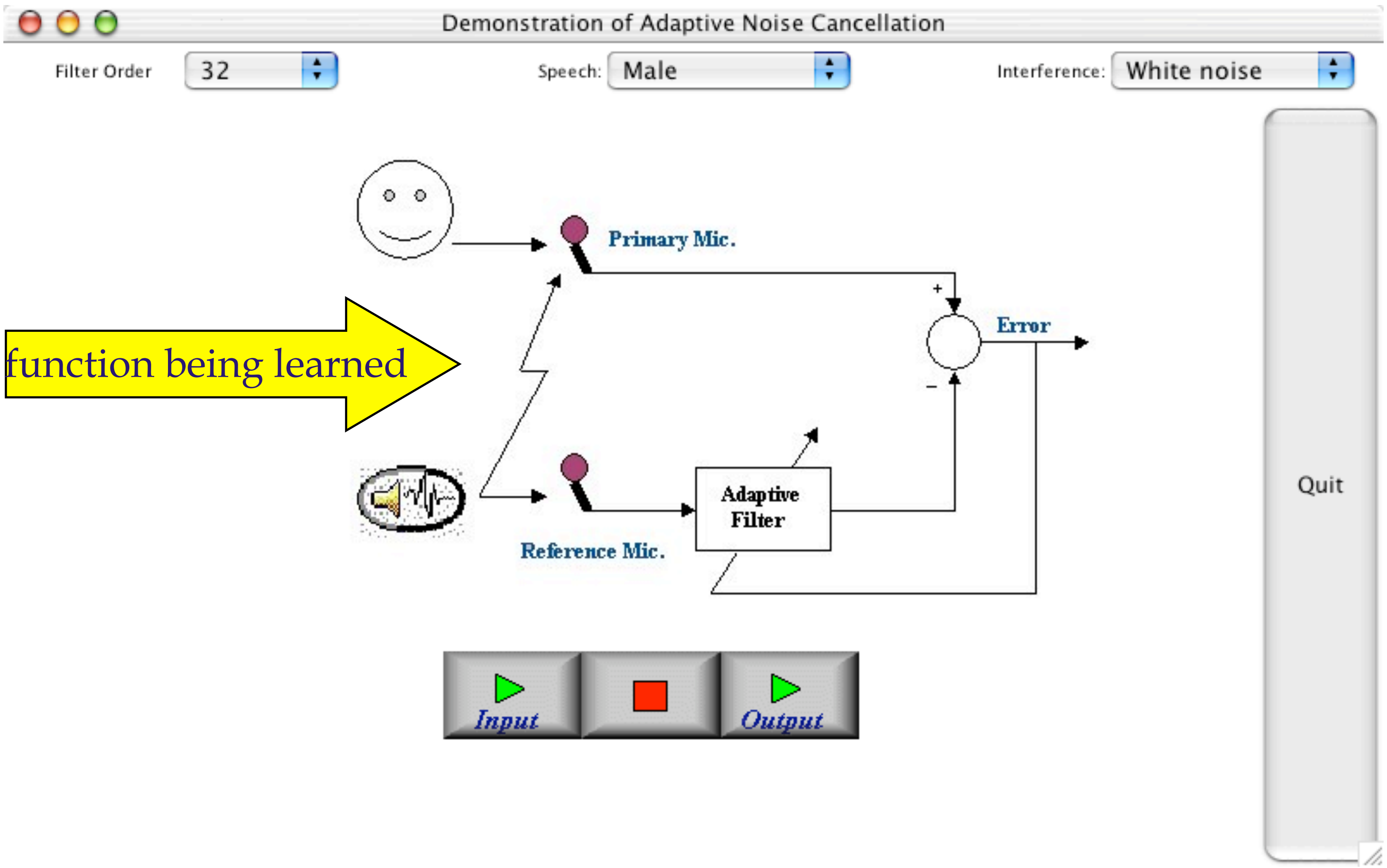
# Adaptive Filter Component

- Adaptive filter component learns produce output from input as guided by training error signal

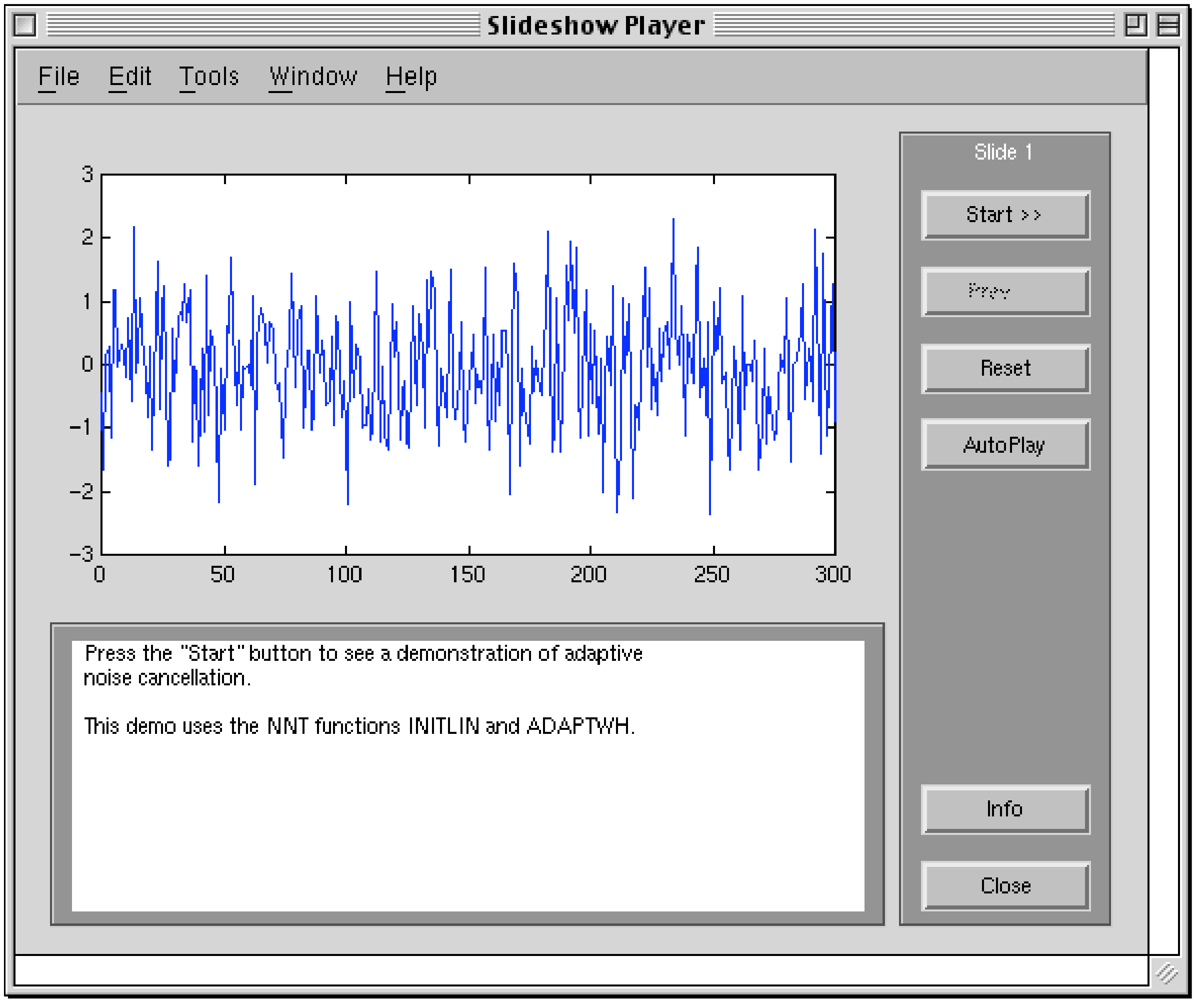


# ANC Audio Demo from Ariz. State Univ.

http://www.eas.asu.edu/~dsp/grad/anand/java/ANC/ANC.html

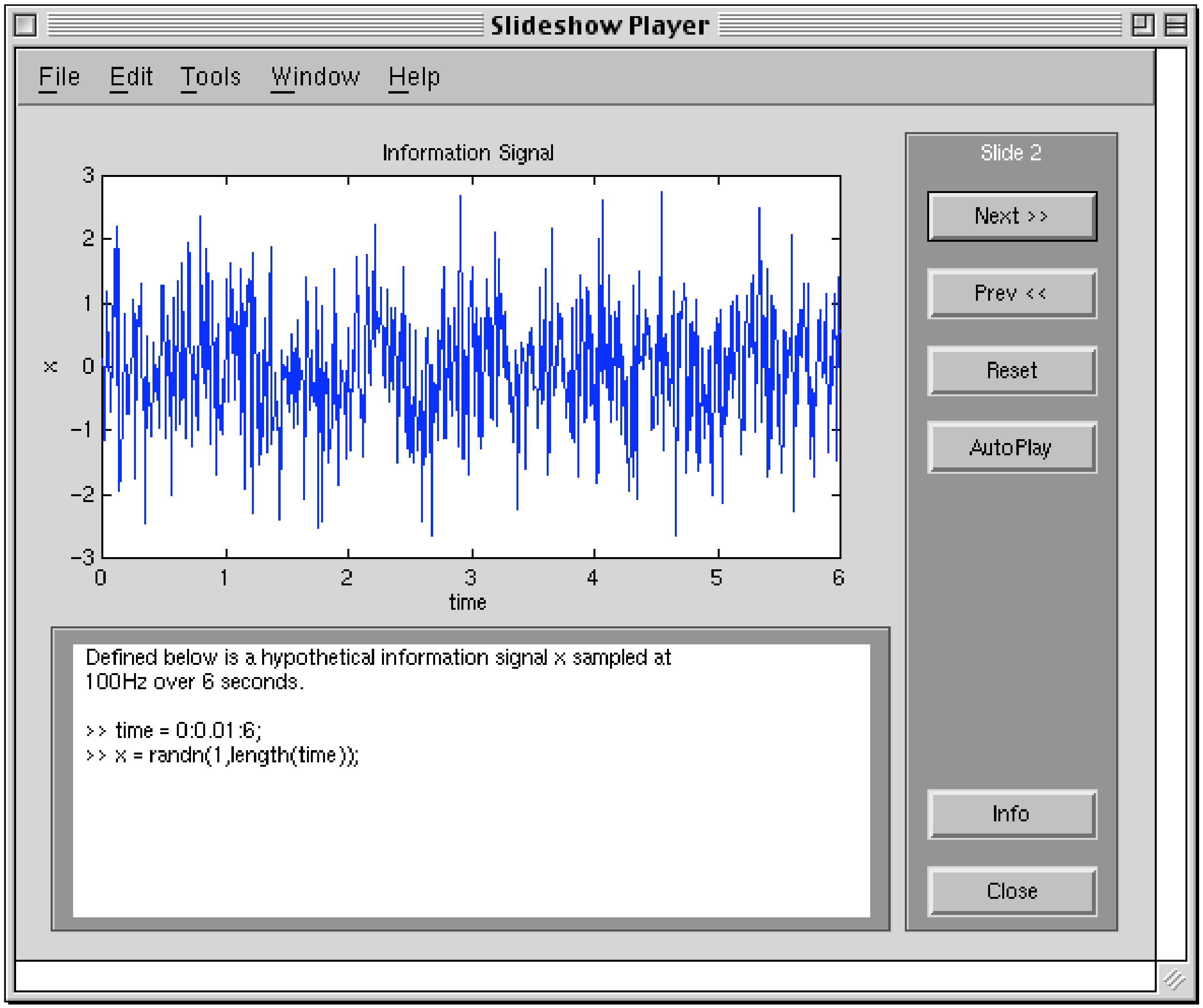


# applin5 Demo(no longer exists)



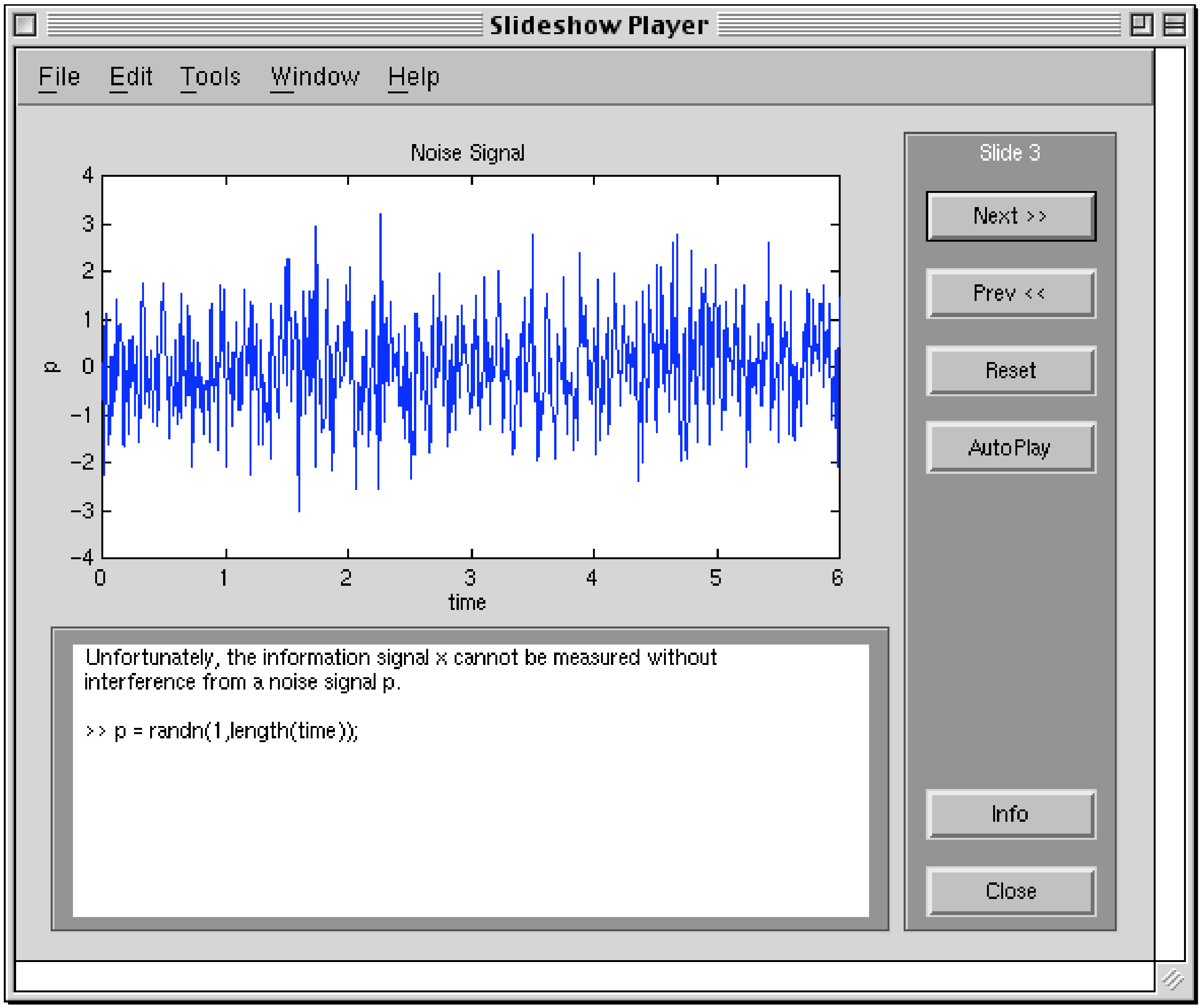
# Information Signal

(without noise, not usually known, but we're creating it)

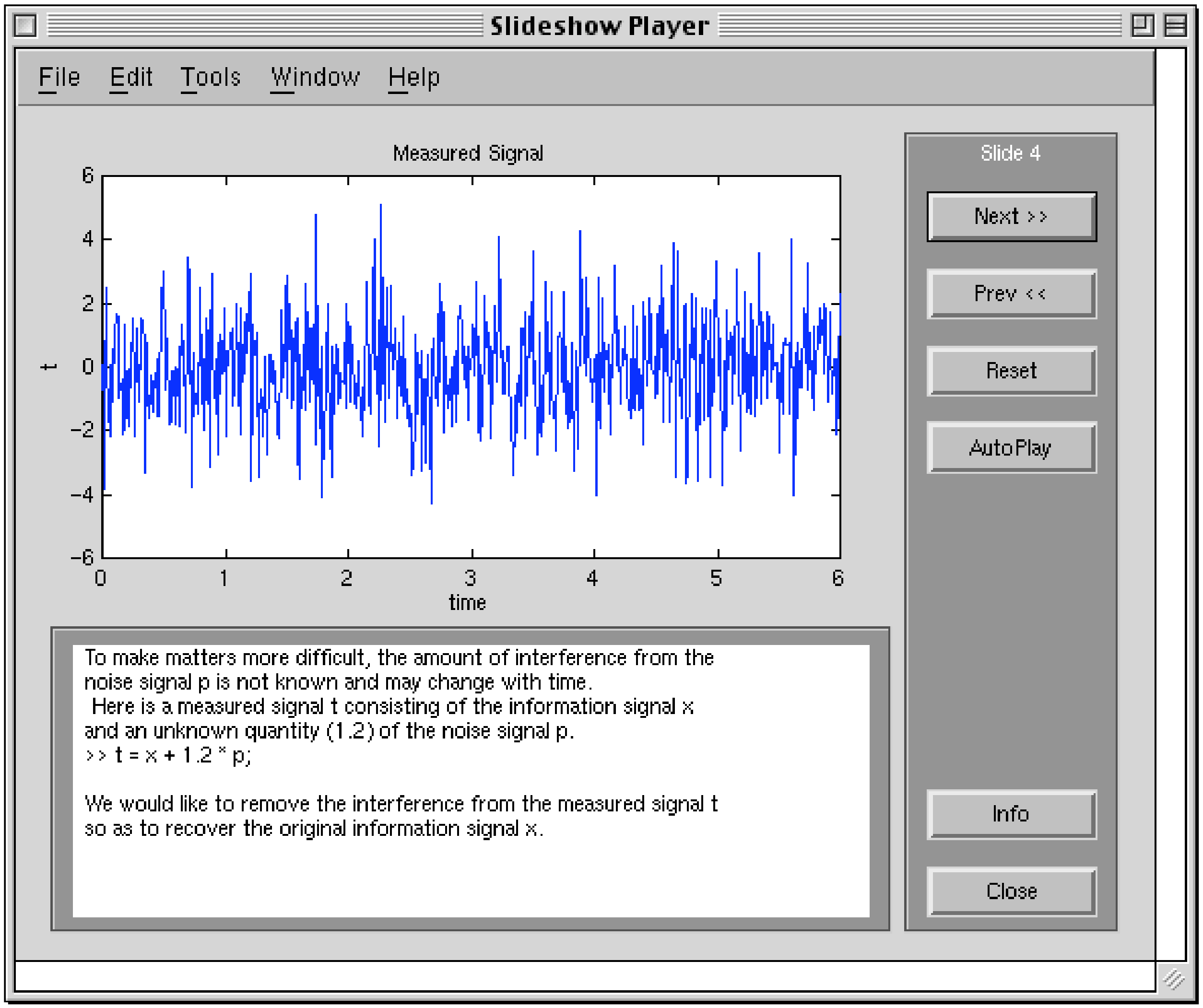


# Noise Signal

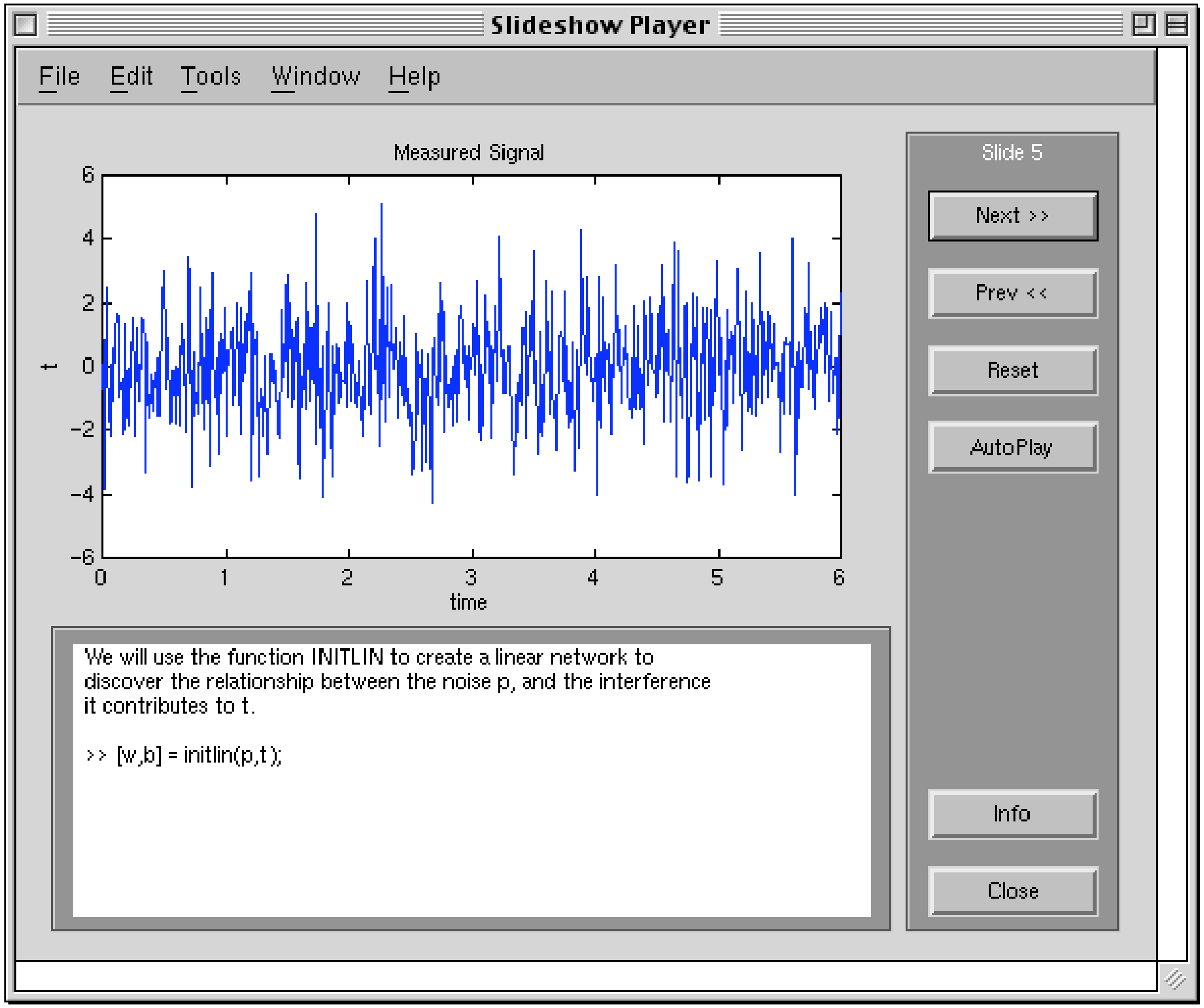
(not usually known, trying to learn it)



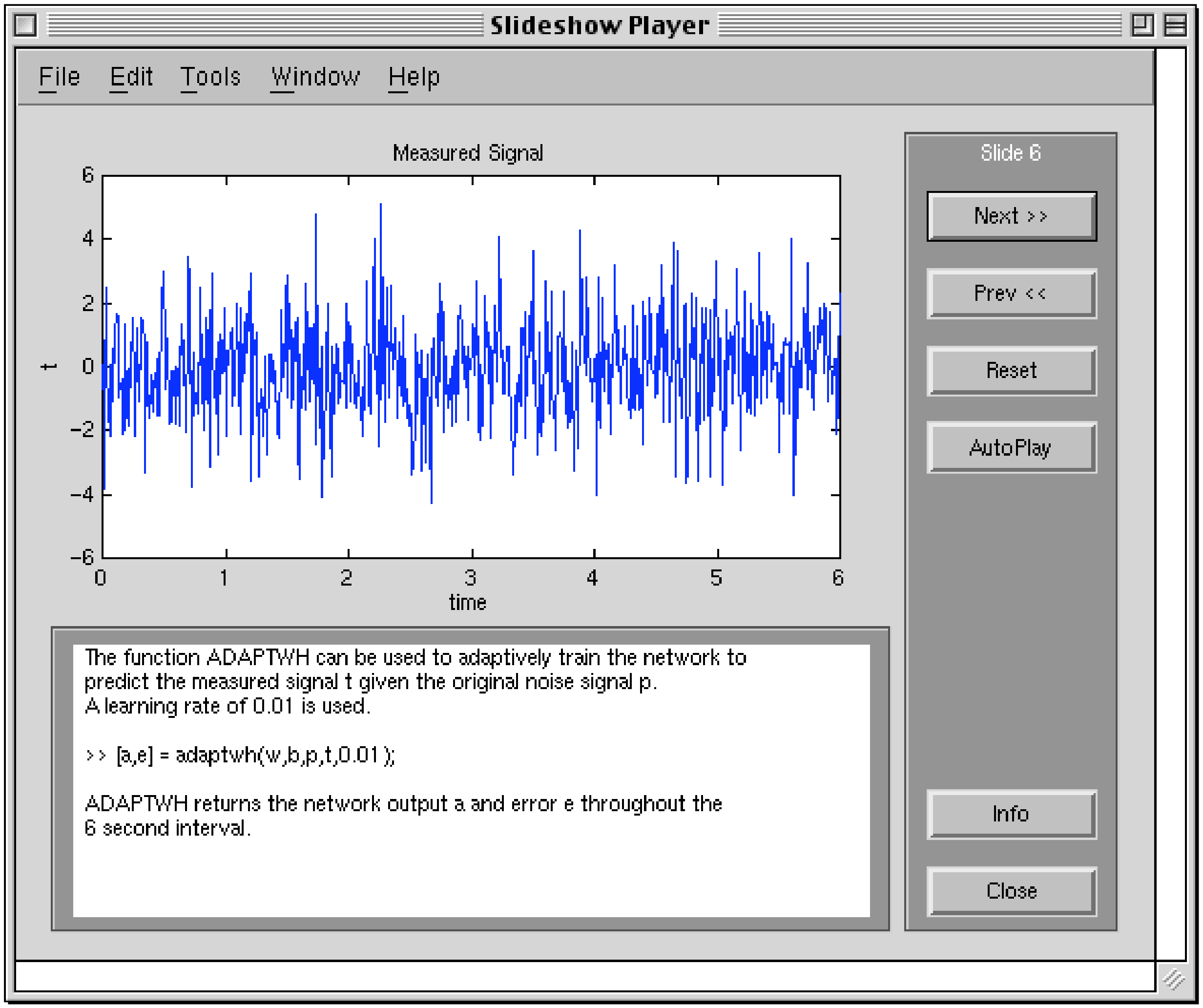
# Measured Signal (with noise)



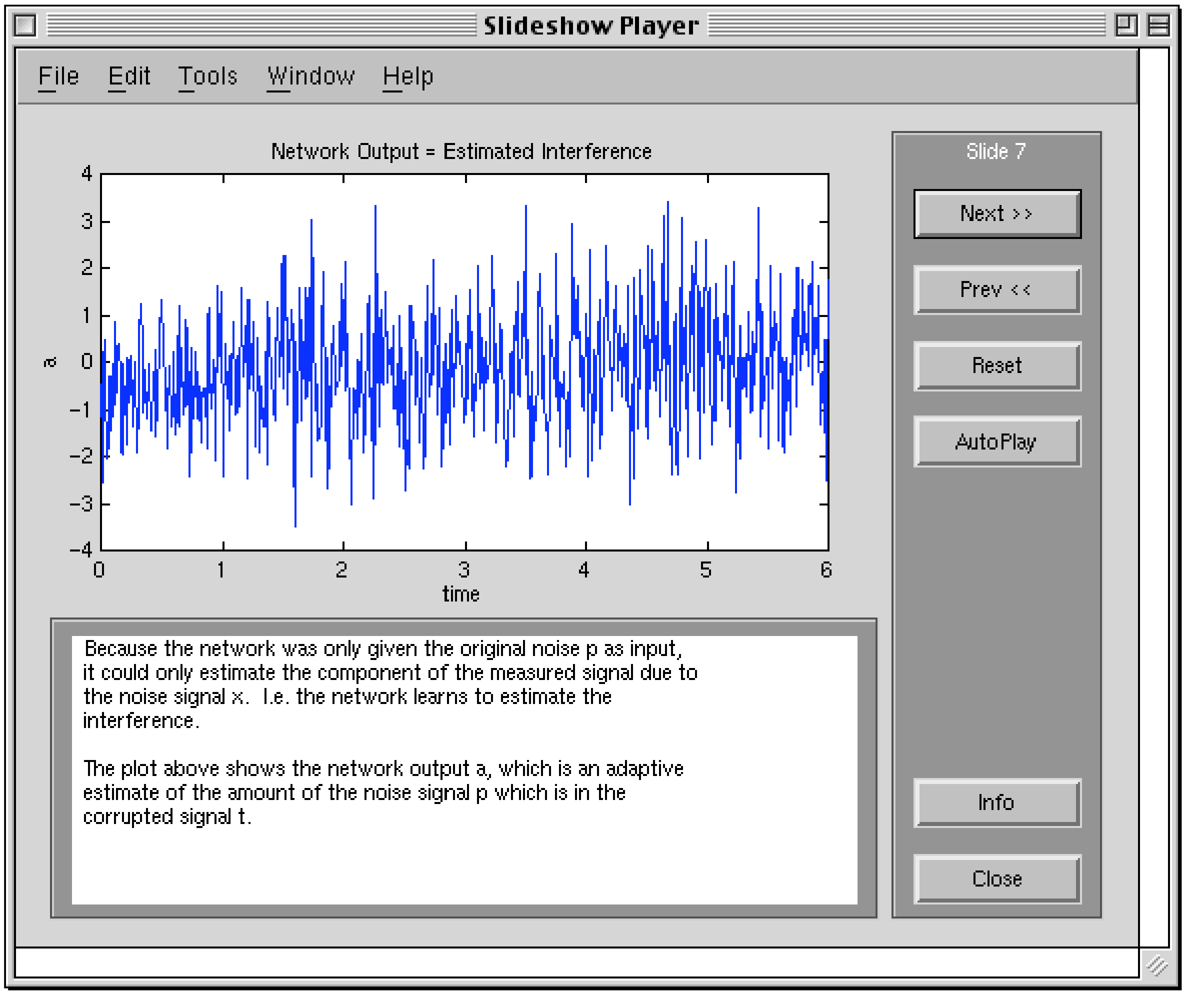
# Initializing Filter



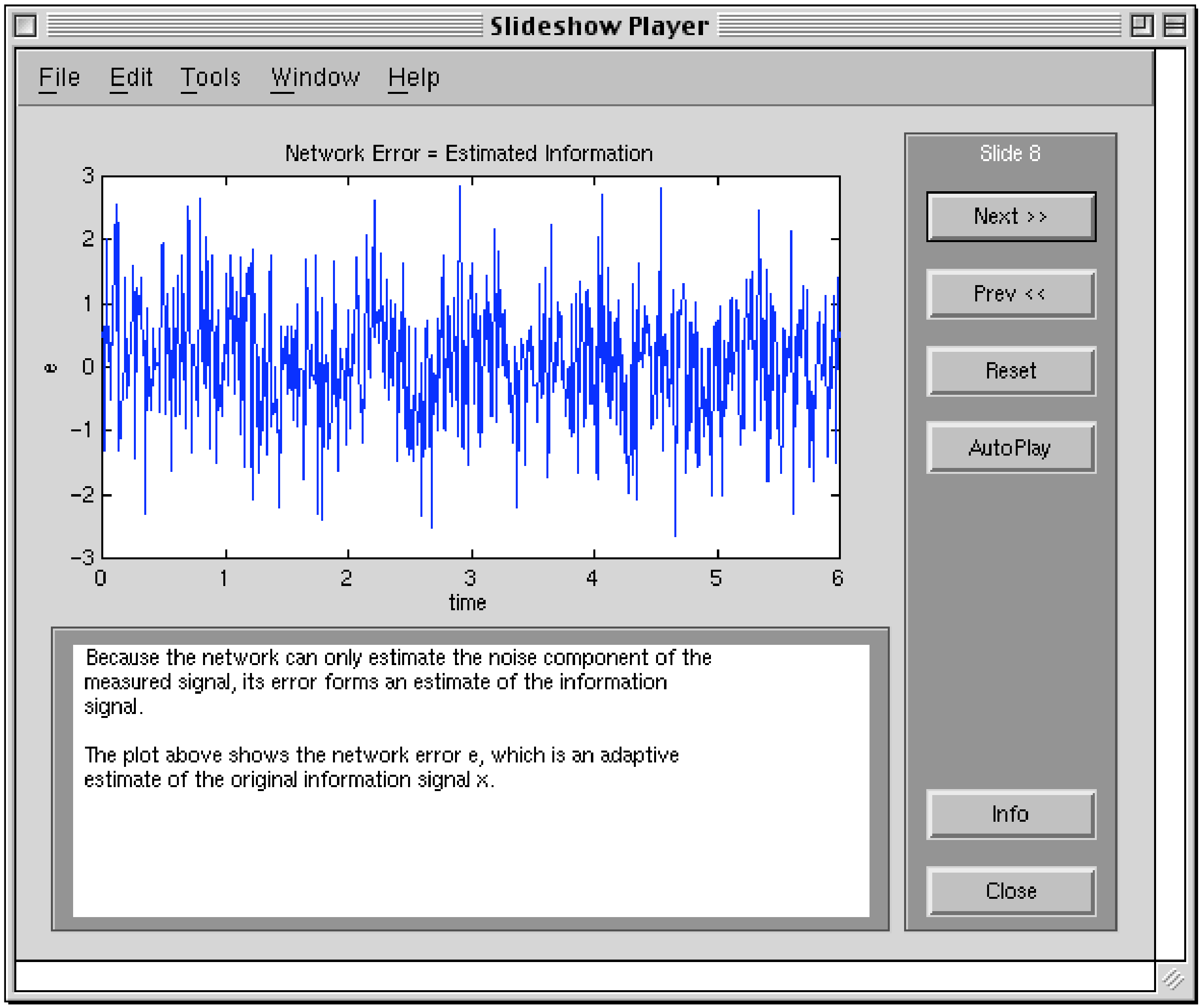
# Adapting using Widrow-Hoff



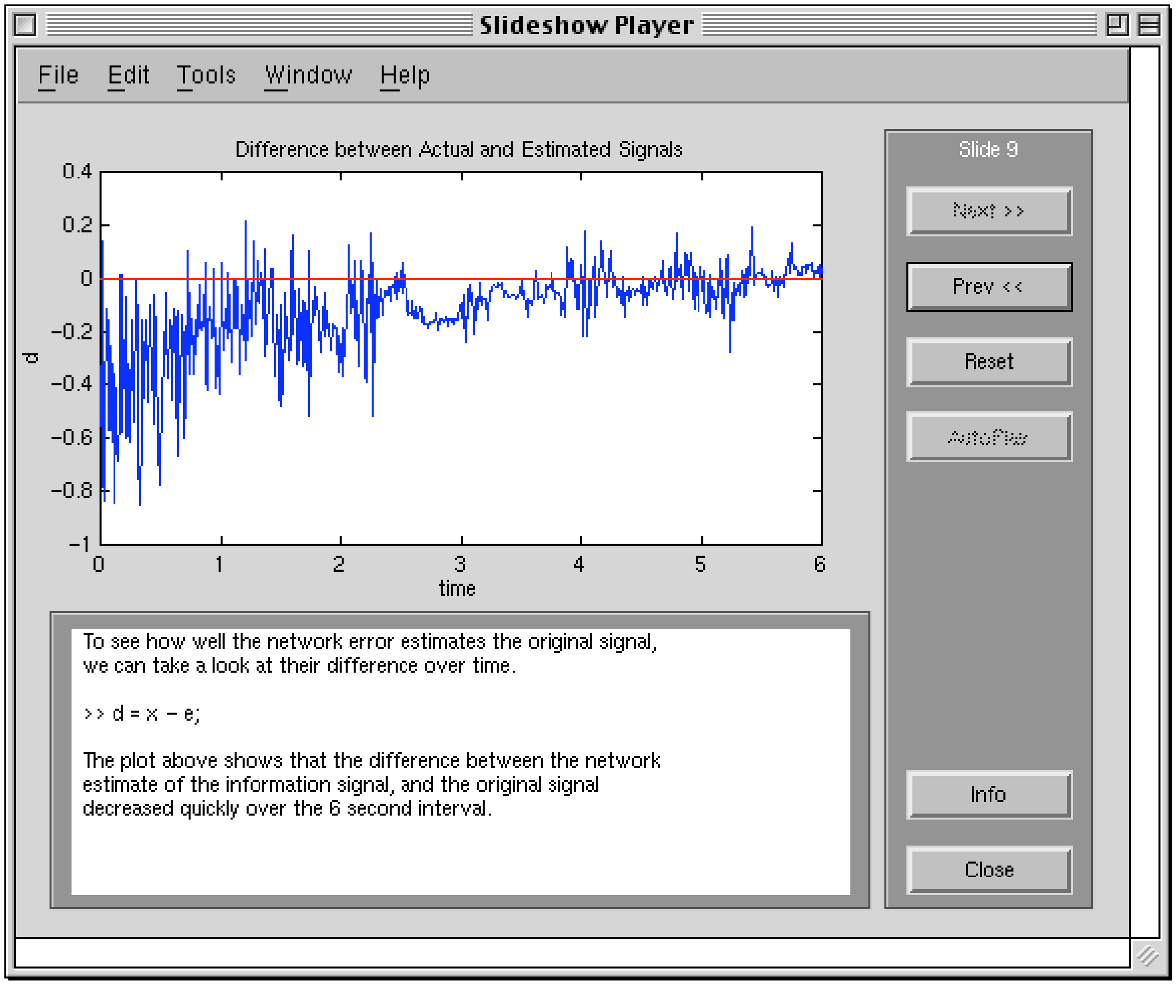
# Interference Estimated by Filter



# Estimated Information
# (= Noisy Signal - Estimated Noise)



# Error after Filtering
# (= Estimated Info - Actual Info)



# ANC (Active Noise Cancellation) Headphones

cf. http://www.nalanda.nitc.ac.in/industry/appnotes/Texas/computing/spra160.pdf

**THE FILTERED-X LMS ALGORITHM**

The filtered-X LMS algorithm developed by Widrow [8] seeks the controller coefficients (weight vector) of $C(q^{-1},k)$, which minimize the mean-squared error, $\xi = E[e^2(k)]$. The mean-squared error is the average power of the error microphone signal. To accomplish this task, a gradient method is used. In the feedforward configuration, the component of $e(k)$ that is correlated with $x(k)$ is removed, leaving only $v(k)$. It is this feature that allows the selectivity property in an ANC system.

The controller weight vector, $\theta_C(k) = [c_0(k), c_1(k), \ldots, c_{n_C}(k)]^T$ is adjusted in the direction of the gradient

$$\nabla = \frac{\partial}{\partial \theta_C} E[e^2(k)] \quad . \tag{1}$$

Because the exact gradient is unavailable, an estimate must be used. In the LMS algorithm, the instantaneous value of the error squared, $e^2(k)$, is used

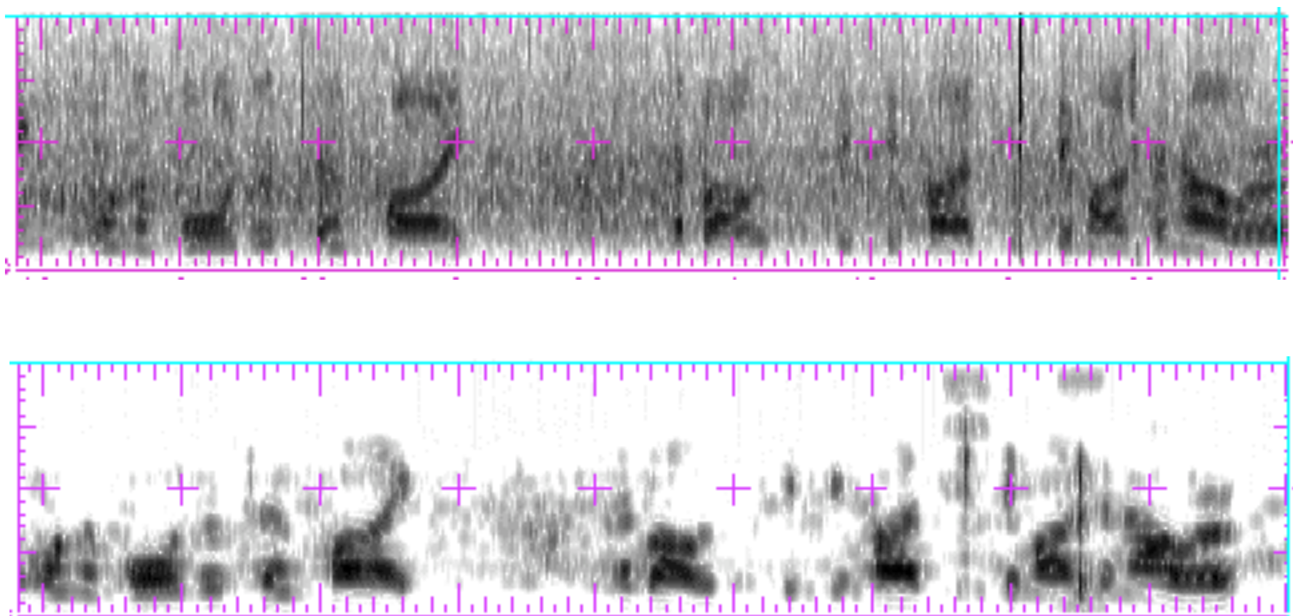
# Contextual Nomenclature

- Classical filters *don't adapt*
  - (Lowpass / Highpass / Bandpass) filters
- Adaptive filters adapt
  - LMS filter (least-mean-squared)
  - RLS filter (recursive least squares, based on pseudo-inverse, not as stable)
  - Kalman filter (based on a stochastic state-space model)

# Eric Wan (OGI) NN Audio demo

http://www.cse.ogi.edu/Neural/noise/noise.html

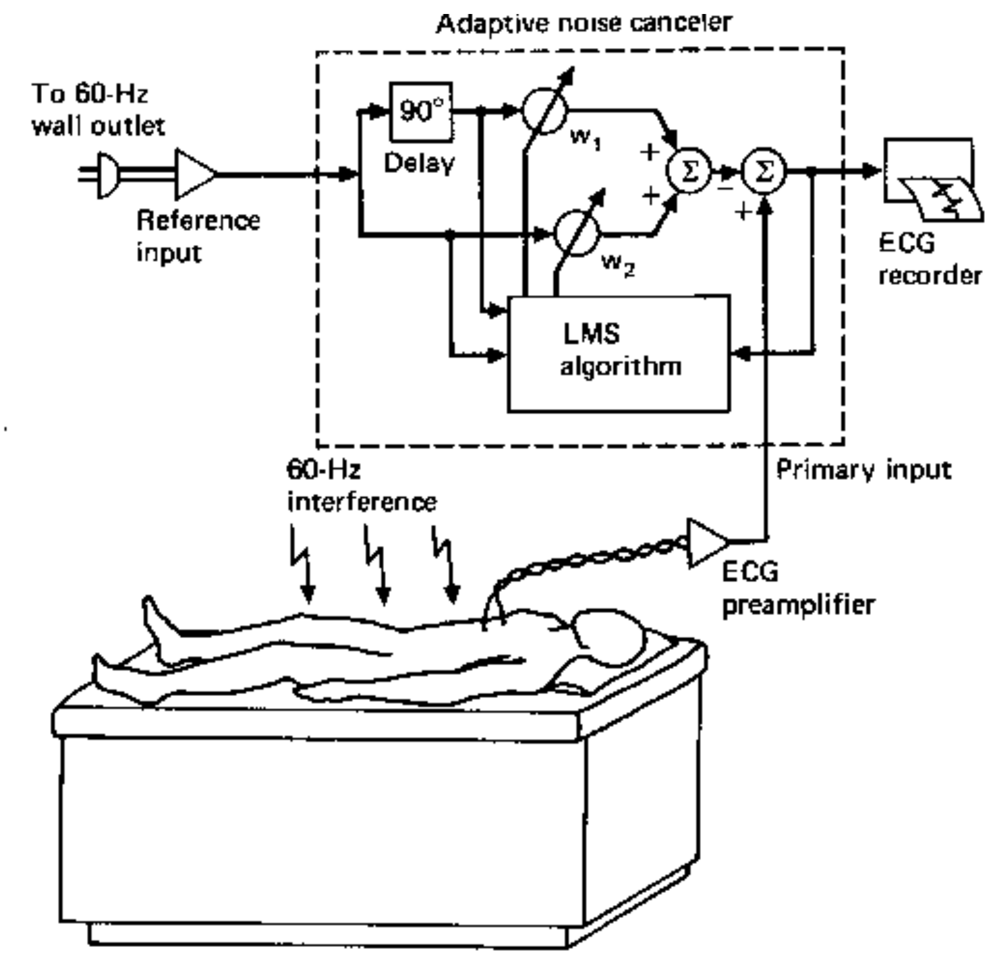
spectra before and after neural-network filtering



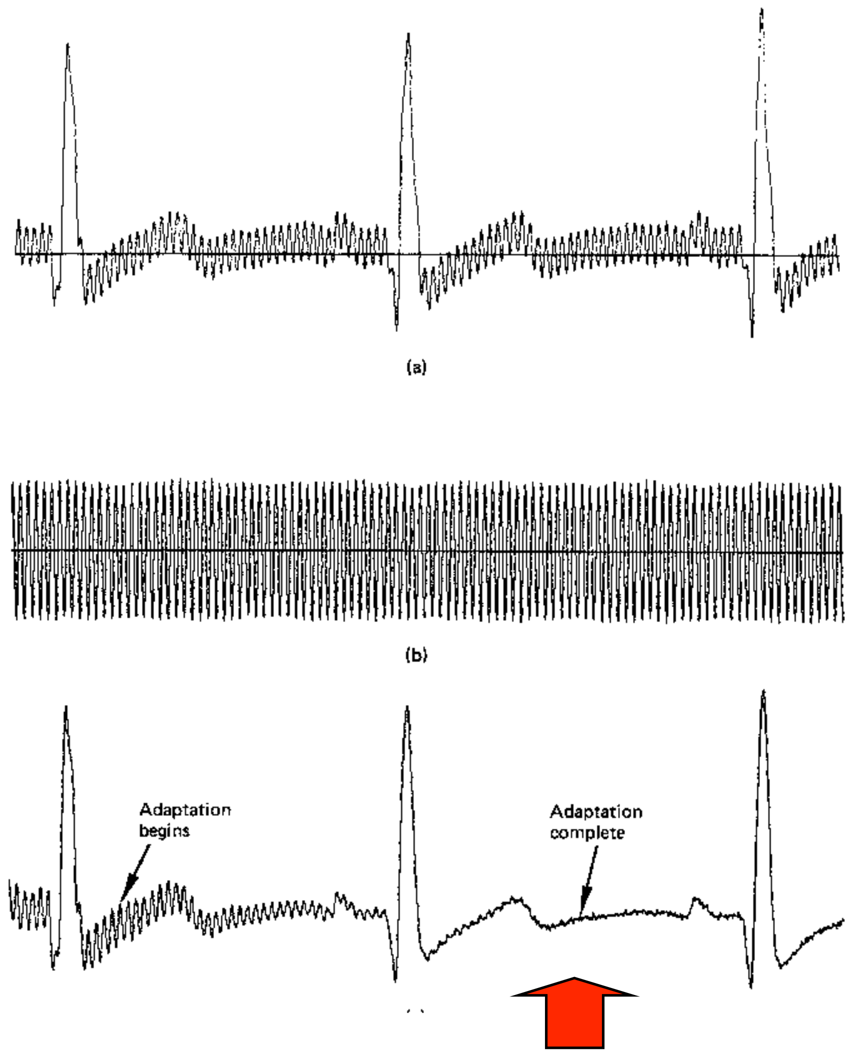
# Other Applications

- EKG filtering (60 Hz noise)
- Fetal monitoring (baby's heart - mother's heart)
- Telephone echo cancellation
- Conference telephones

# 60 Hz Noise in EKG



# 60 Hz Noise in EKG



# Fetal Heartbeat Monitoring

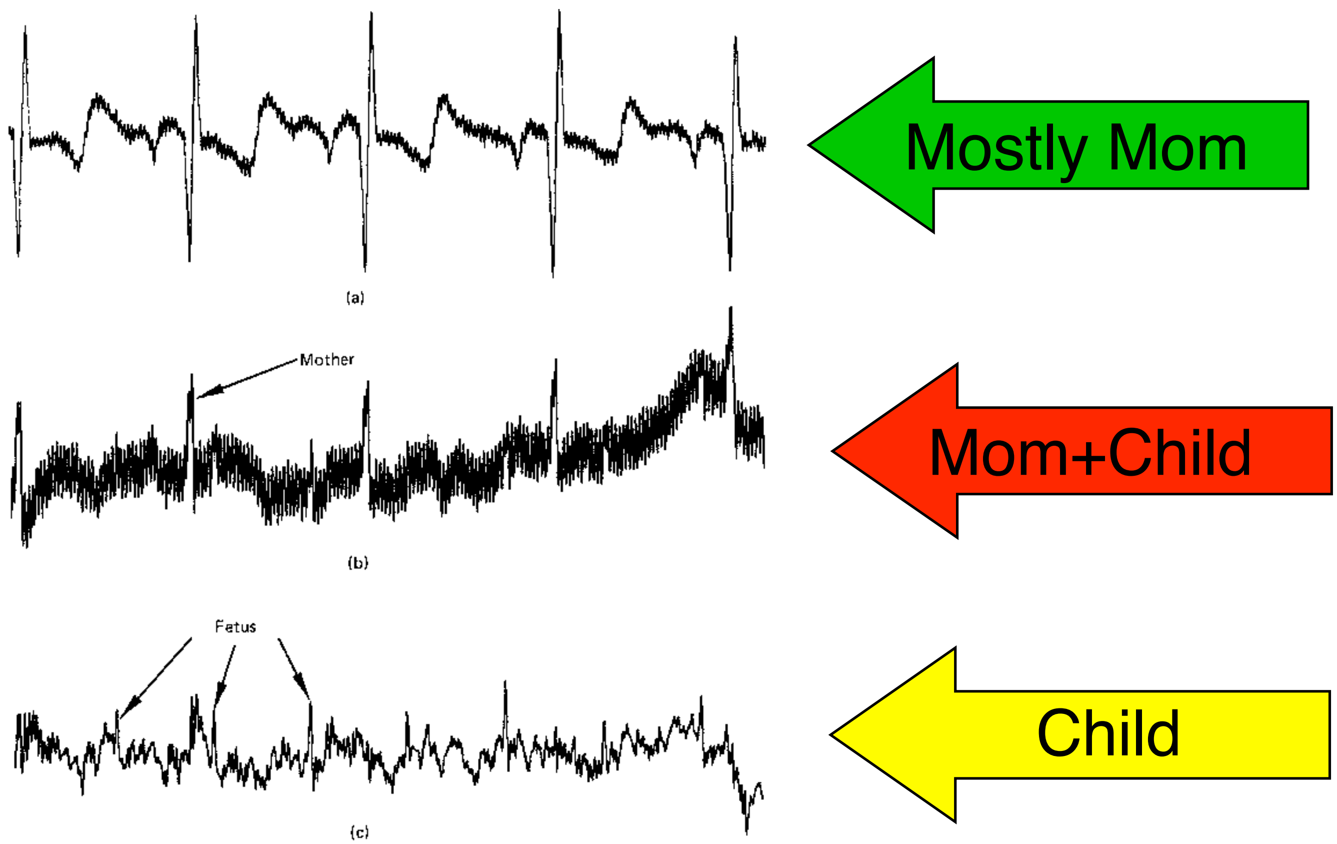
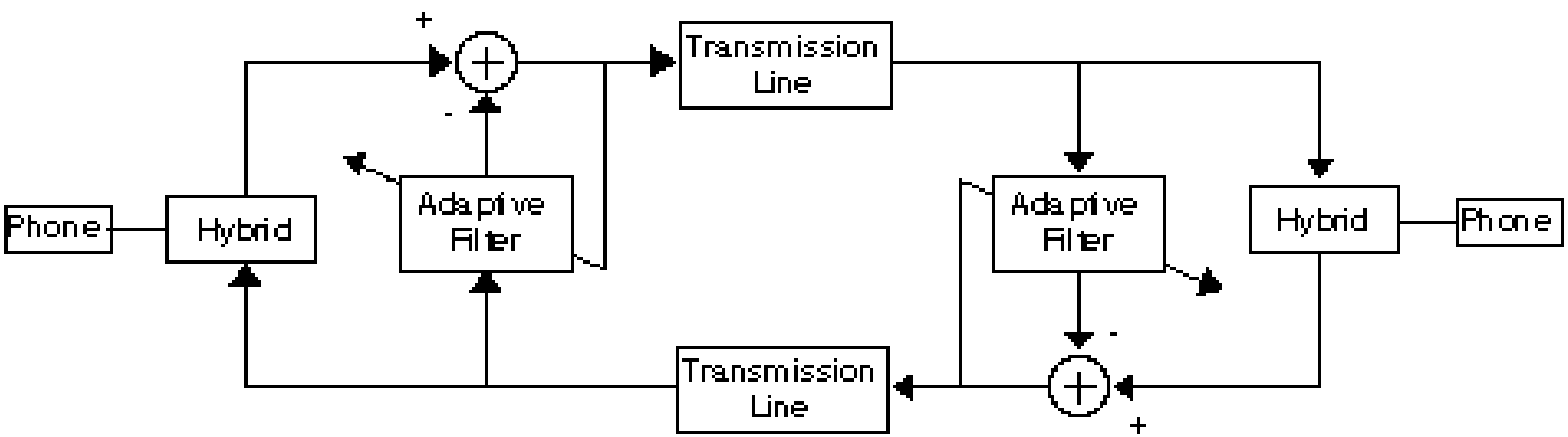
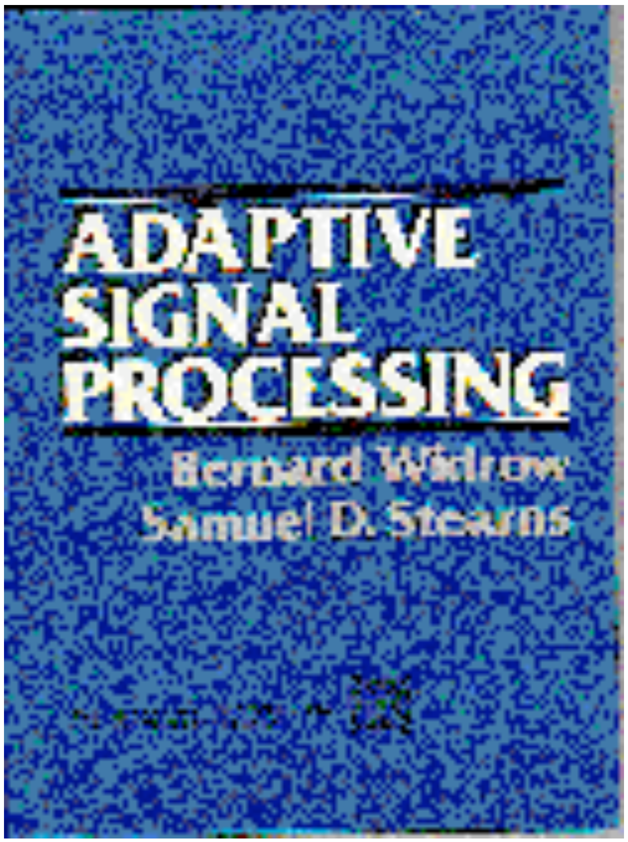



**Figure 12.21** Result of wide-band fetal ECG experiment (bandwidth, 0.3–75 Hz; sampling rate, 512 Hz): (a) reference input (chest lead); (b) primary input (abdominal lead); (c) noise canceller output. From B. Widrow et al., *Adaptive Noise Canceling: Principles and Applications*, © December 1975, IEEE.

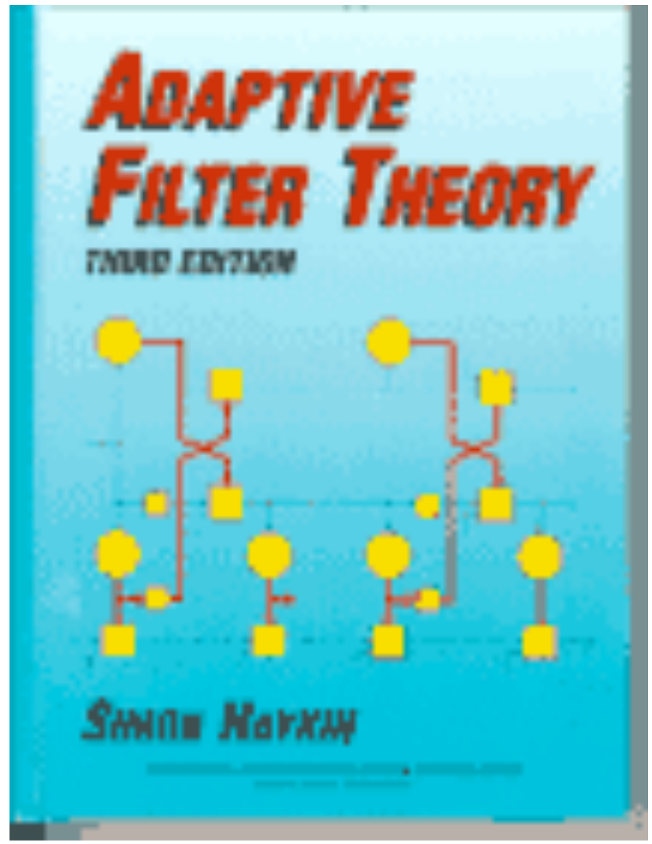
# Telephone Echo Cancellation



# References



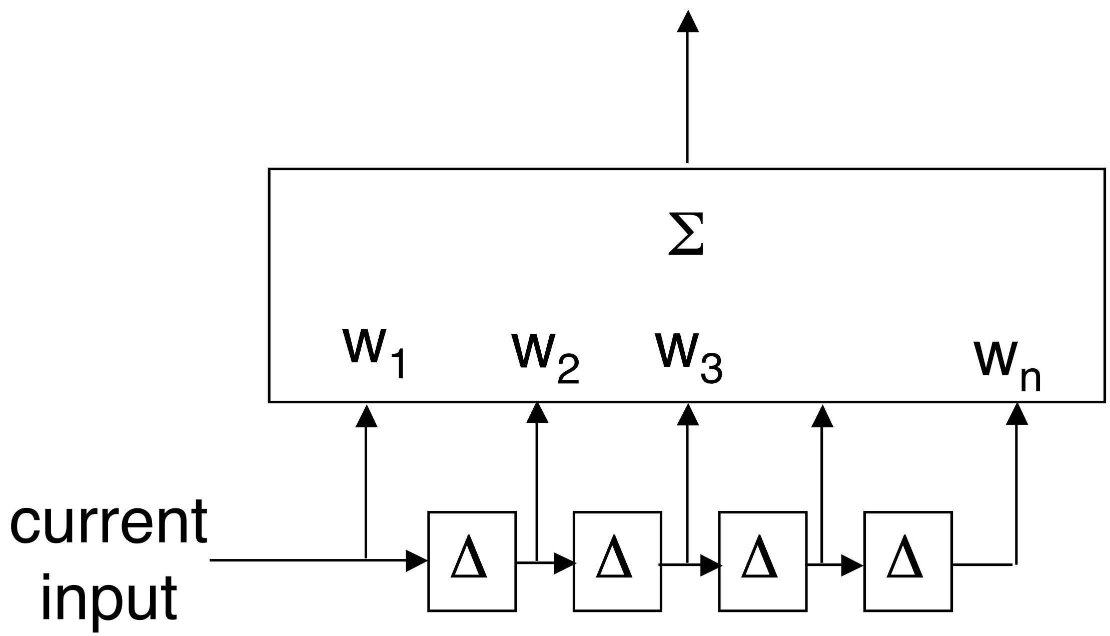

Widrow & Stearns, 1985




Haykin, 1995

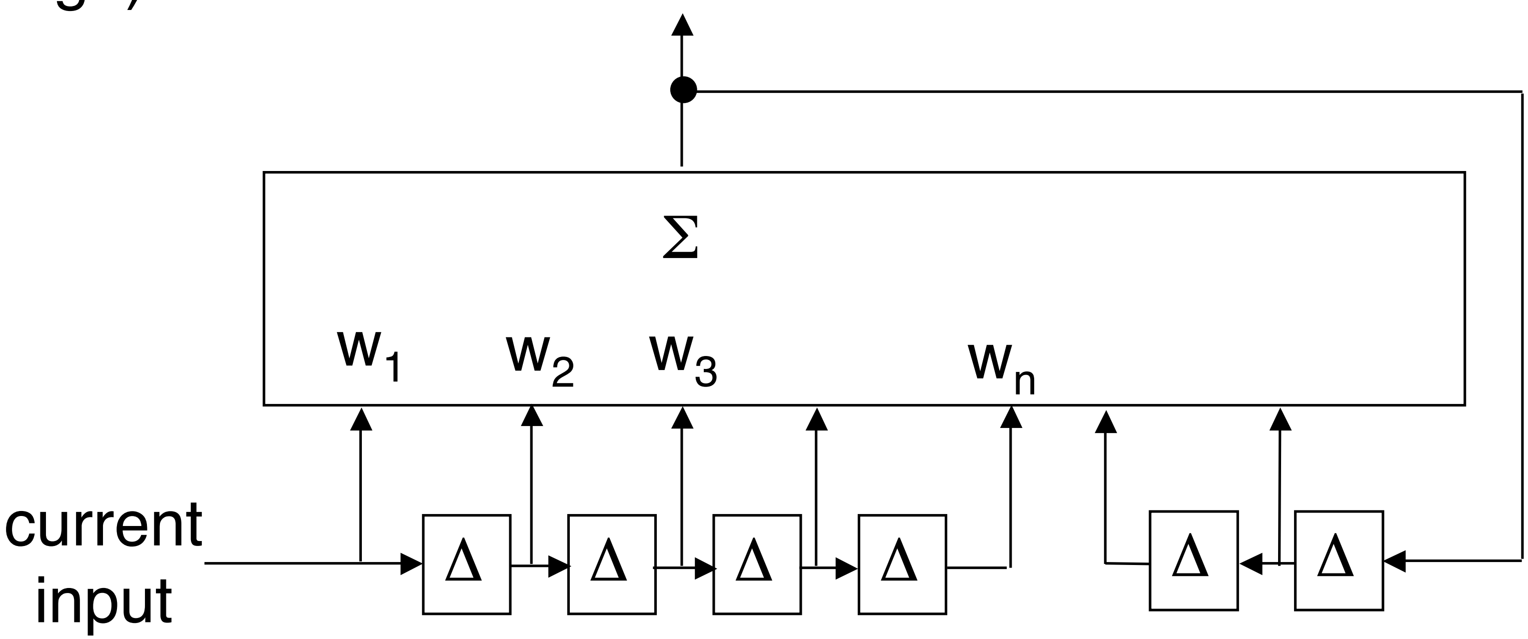
# Additional Nomenclature

Filter form is also called a **FIR** (**F**inite **I**mpluse **R**esponse) filter.
In statistics, it is called an **MA** (**M**oving **A**verage) filter.



# Additional Nomenclature

When we add **feedback**, we have an **IIR** (**I**nfinite **I**mpluse **R**esponse) filter.
In statistics, it is called an AR**MA** (**A**uto**R**egressive **M**oving **A**verage) filter.

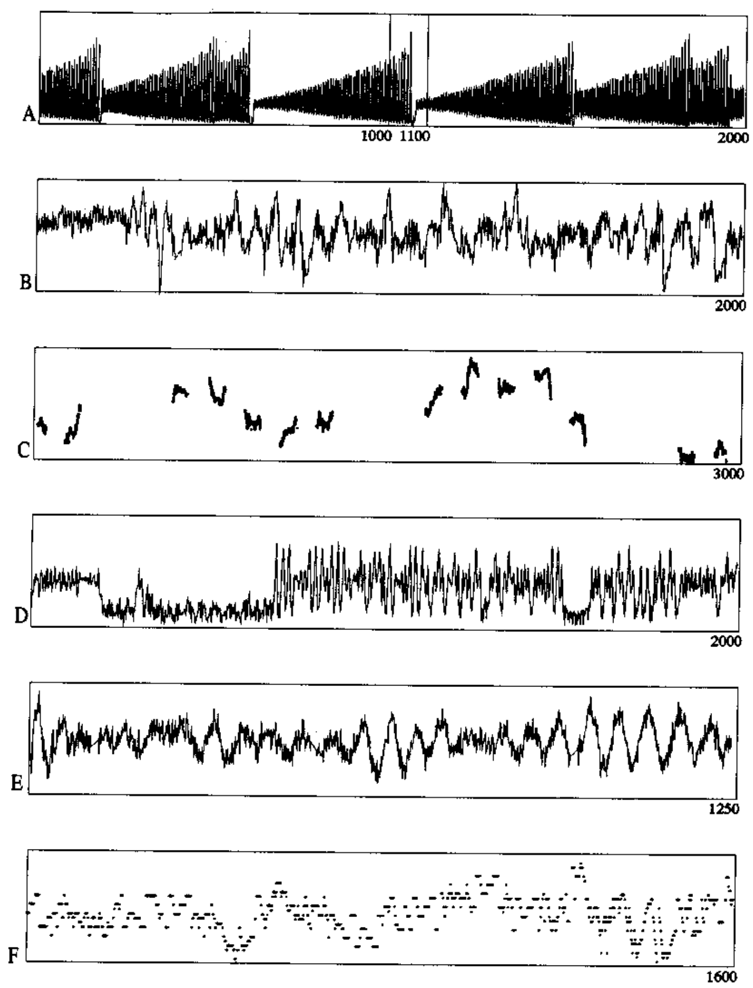


# Classical Fitting of Time-Series

- A given ARMA's coefficients can be fit to generate ***approximately*** a given time series by using least-squares estimation on a set of simultaneous linear equations known as the "Yule-Walker equations".

- Reference: Weigend and Gershenfeld (eds.), Time series prediction, Addison-Wesley, 1994.

# Sante Fe Institute Competition
# 6 unknown time series



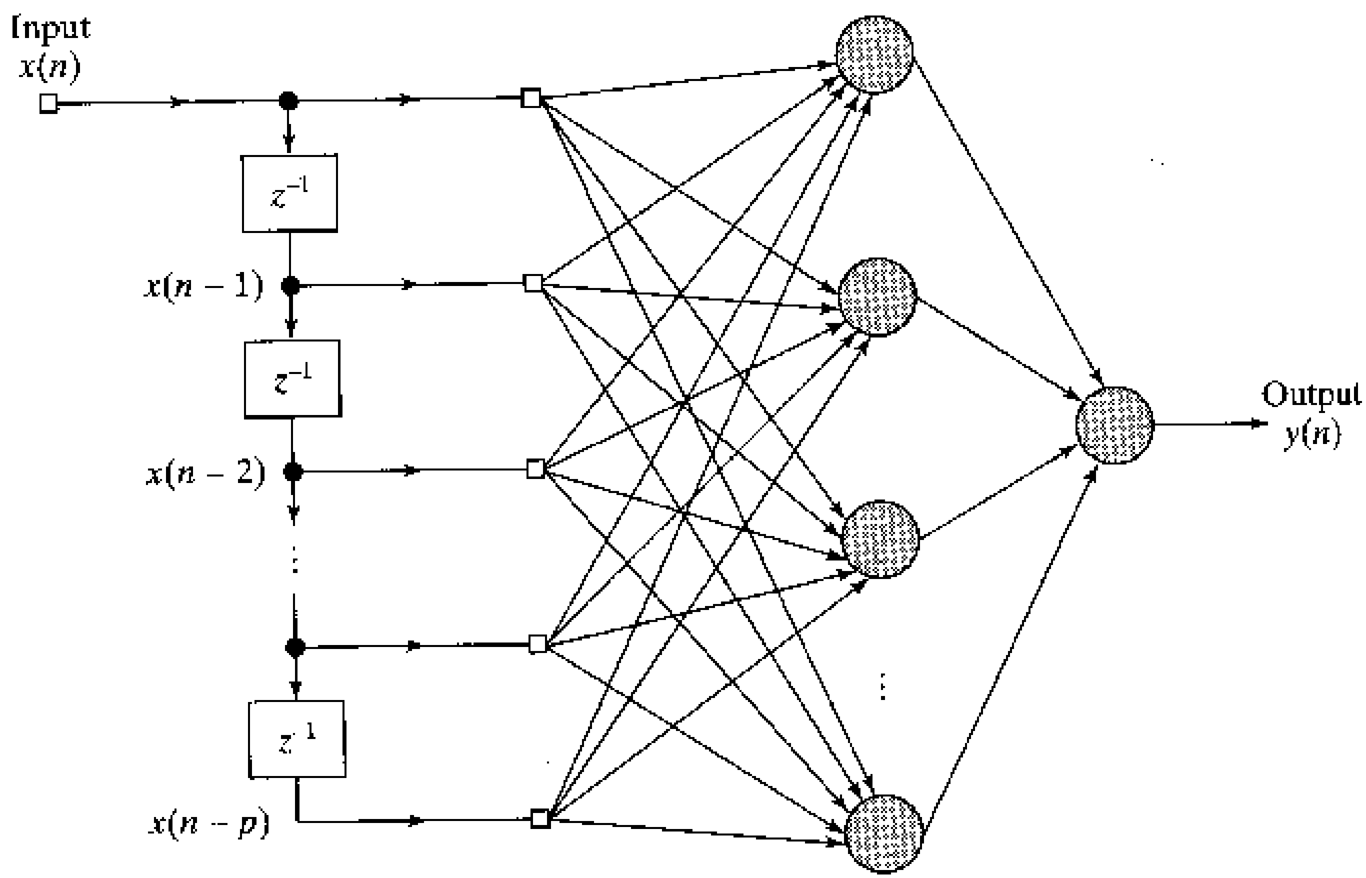
# Other Models

- Time-Lagged Feed-Forward Networks, Time-Delay Neural Networks (TLFF, TDNN)
- FIR-Multi-layer networks (FIRNET)
- Backpropagation through time (BPTT)
- Real-Time Recurrent Learning (RTRL)
- Elman nets, Jordan nets
- Temporal difference method (TD($\lambda$))

# Time-Lagged Feed-Forward Networks (TLFF)

- An extension of the “Adaline” adaptive filter model
- Use an arbitrary feed-forward net (MLP) in place of the Adaline
- Train using ordinary backpropagation, analogous to LMS

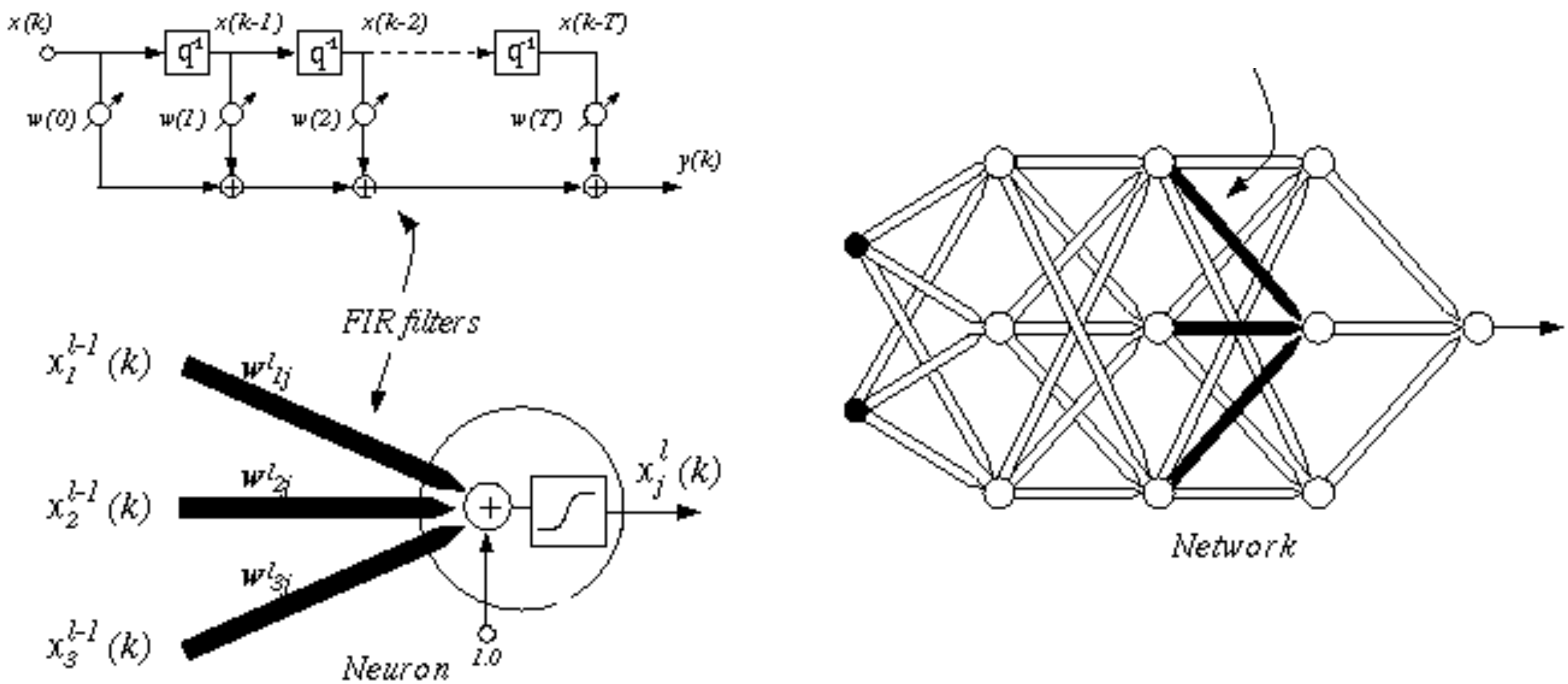
# Time-Lagged Feed-Forward Networks (TLFF)



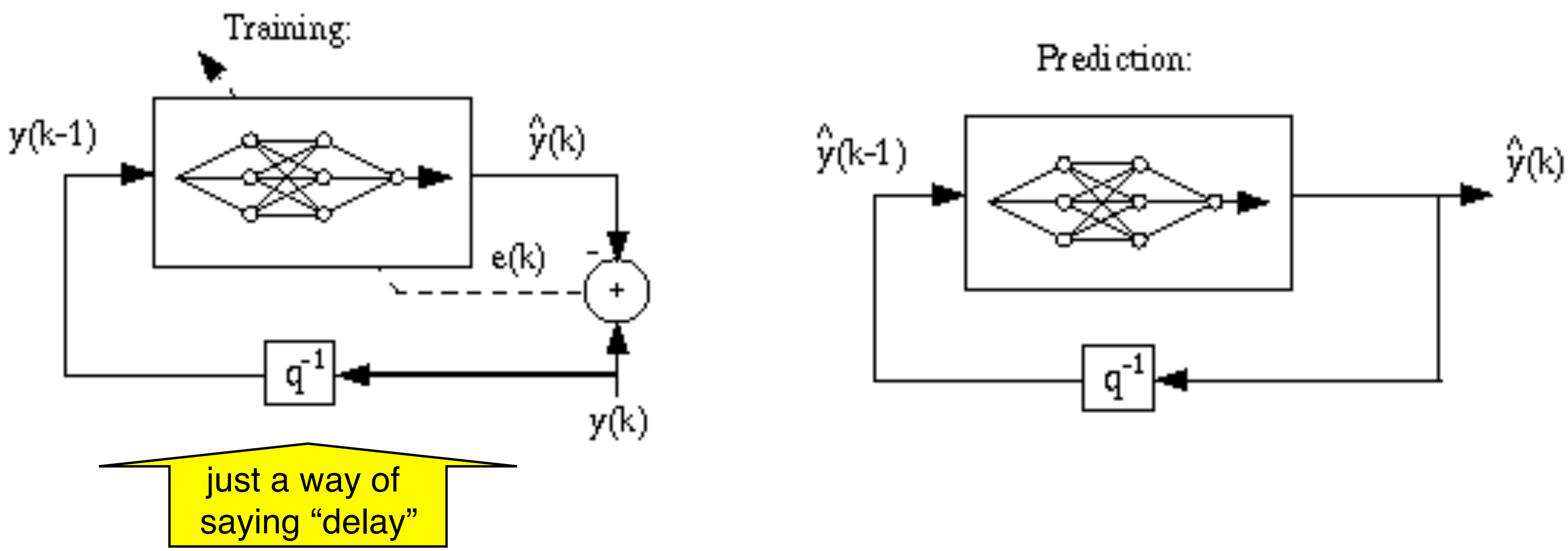
# Another Approach: FIR Backpropagation

- Eric Wan (Stanford, OGI) came up with the idea of putting FIR filters **inside** a backprop network.
- In place of each single weight there is an entire FIR filter.
- Wan developed the training algorithm for such networks.

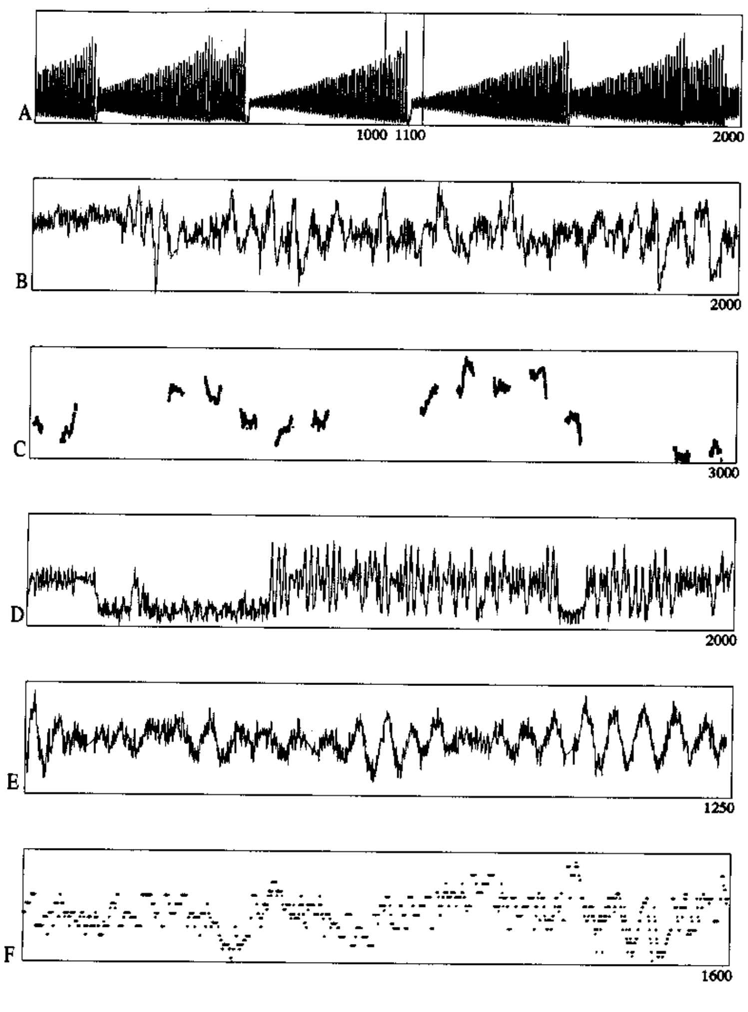
# Wan's FIR Backprop Net



# Recall: Training vs. Prediction



# Sante Fe Institute Competition
# 6 unknown series




- A A clean physics experiment. 1000 points of the **fluctuations in a far-infrared laser**, approximately described by three coupled non-linear DE's.
- B Physiological data from a patient with sleep apnea. 34,000 points of heart rate, chest volume, blood oxygen concentration, and EEG state of a sleeping patient.
- C High-frequency **currency exchange rate** data. Ten segments of 3,000 points each of the exchange rate between the Swiss franc and the U.S. dollar, 1-2 minutes apart.
- D Numerically generated series. A driven particle in a 4-dimensional nonlinear multiple-well potential (9 degrees of freedom) with a small nonstationary drift in the depths.
- E Astrophysical data from a **variable white dwarf** star. 27,704 points in 17 segments of the time variation of the intensity.
- F J.S. Bach's final **(unfinished) fugue** from *The Art of the Fugue*.

# Wan's Entry in
# Sante Fe Institute Competition

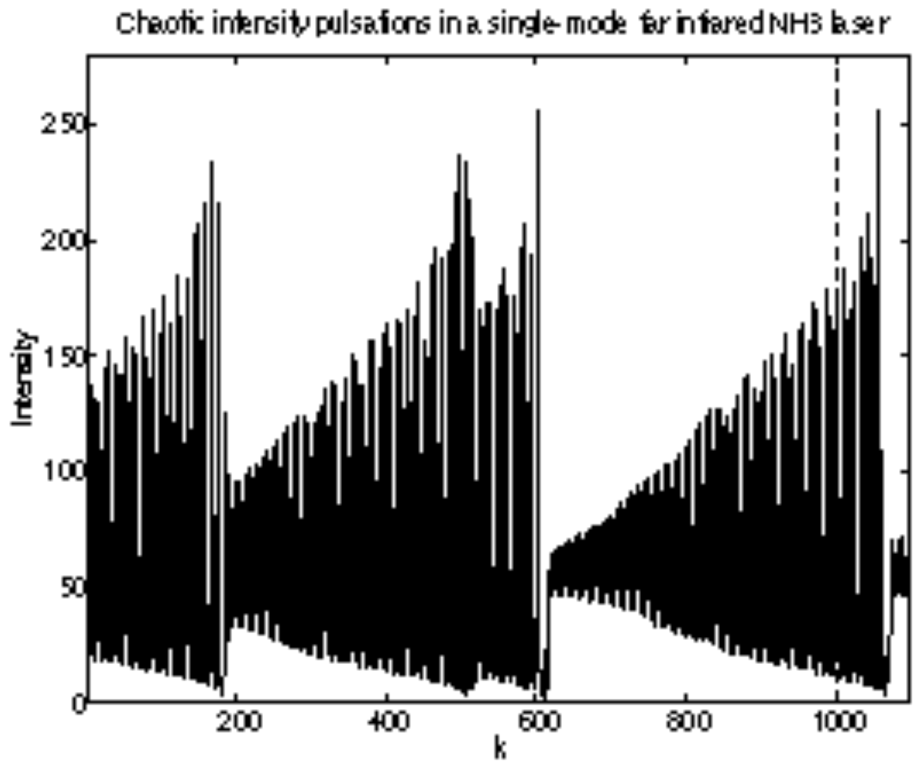
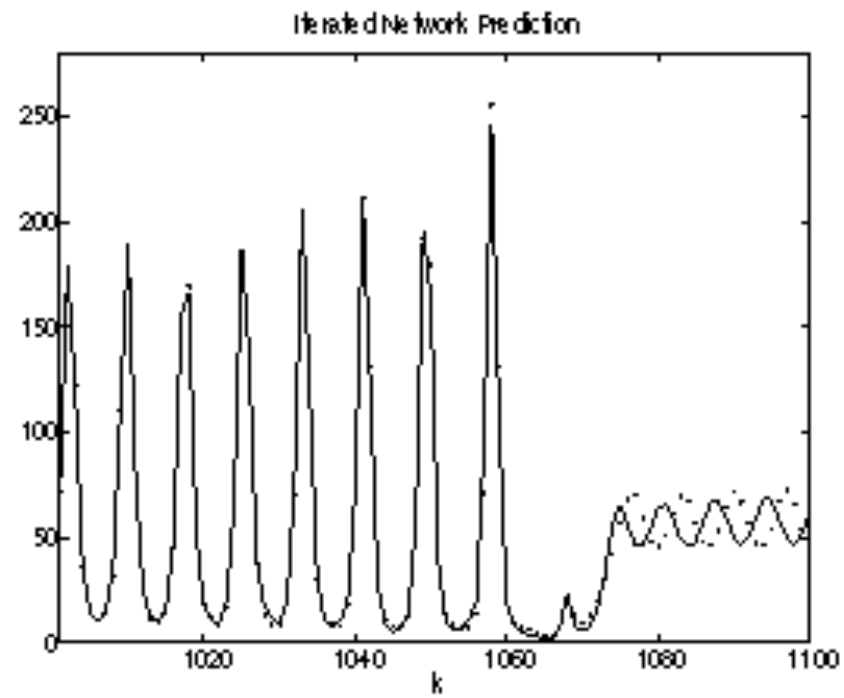
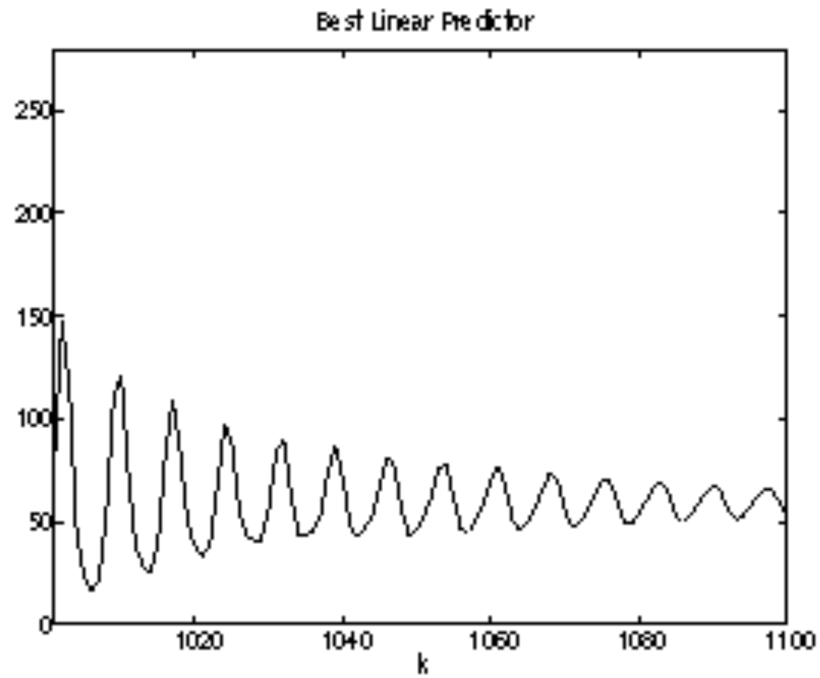



**Fig. 3: 1000 points of laser data.**

# Wan's Prediction Expanded in Sante Fe Institute Competition



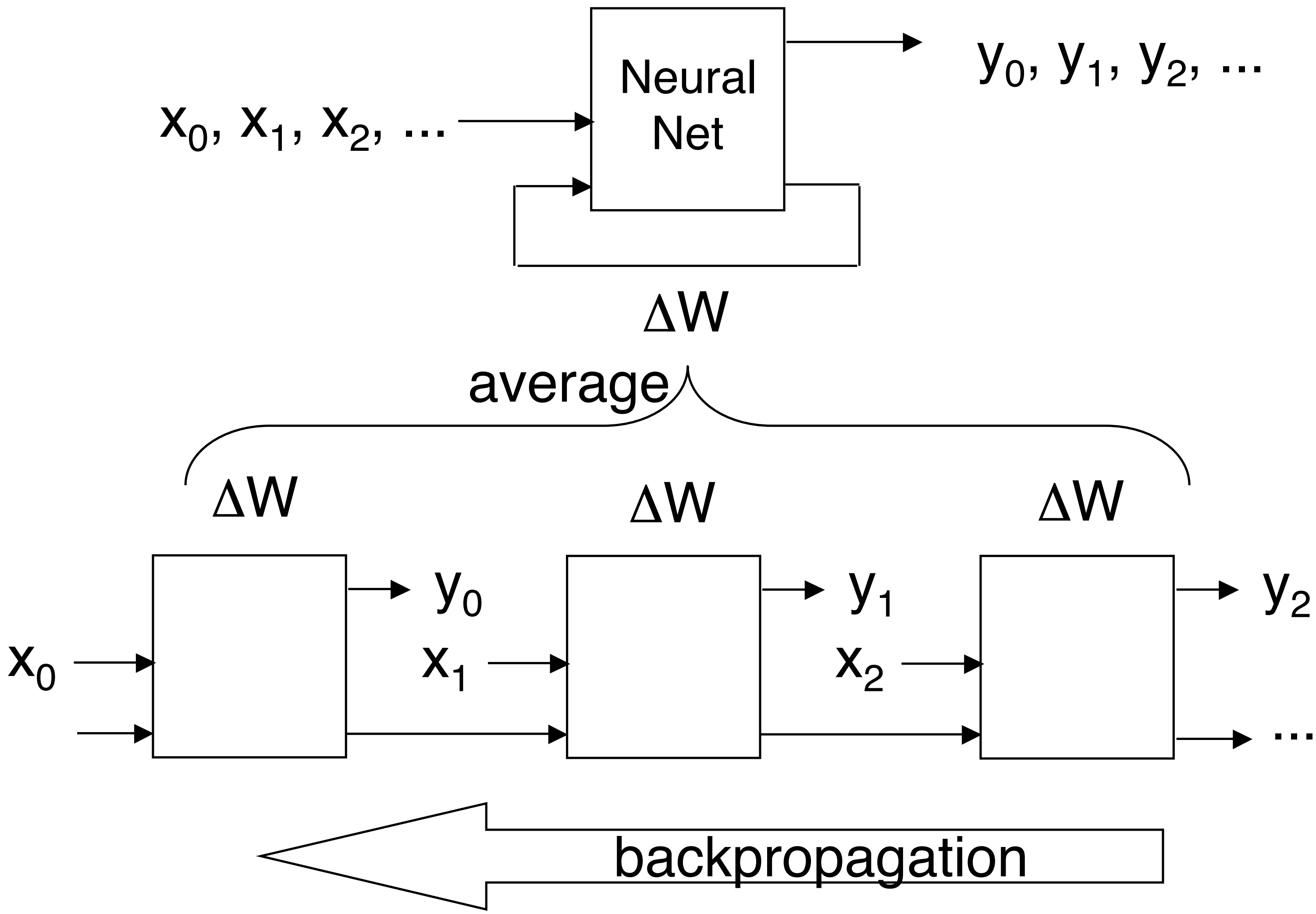

Solid line is actual

dashed line is predicted.

# Backpropagation through time (BPTT)

- Unlike TLFF (Time-Lagged Feed-Forward), input samples are not kept in explicit delay lines.
- Instead, input fed sequentially into network (also used in FIR backprop).
- Training is **as if** the network were **unrolled** to accommodate the entire sequence of input samples.
- Only one set of weights is actually used in operation; the weight changes are **averaged** across stages to get the actual weight change

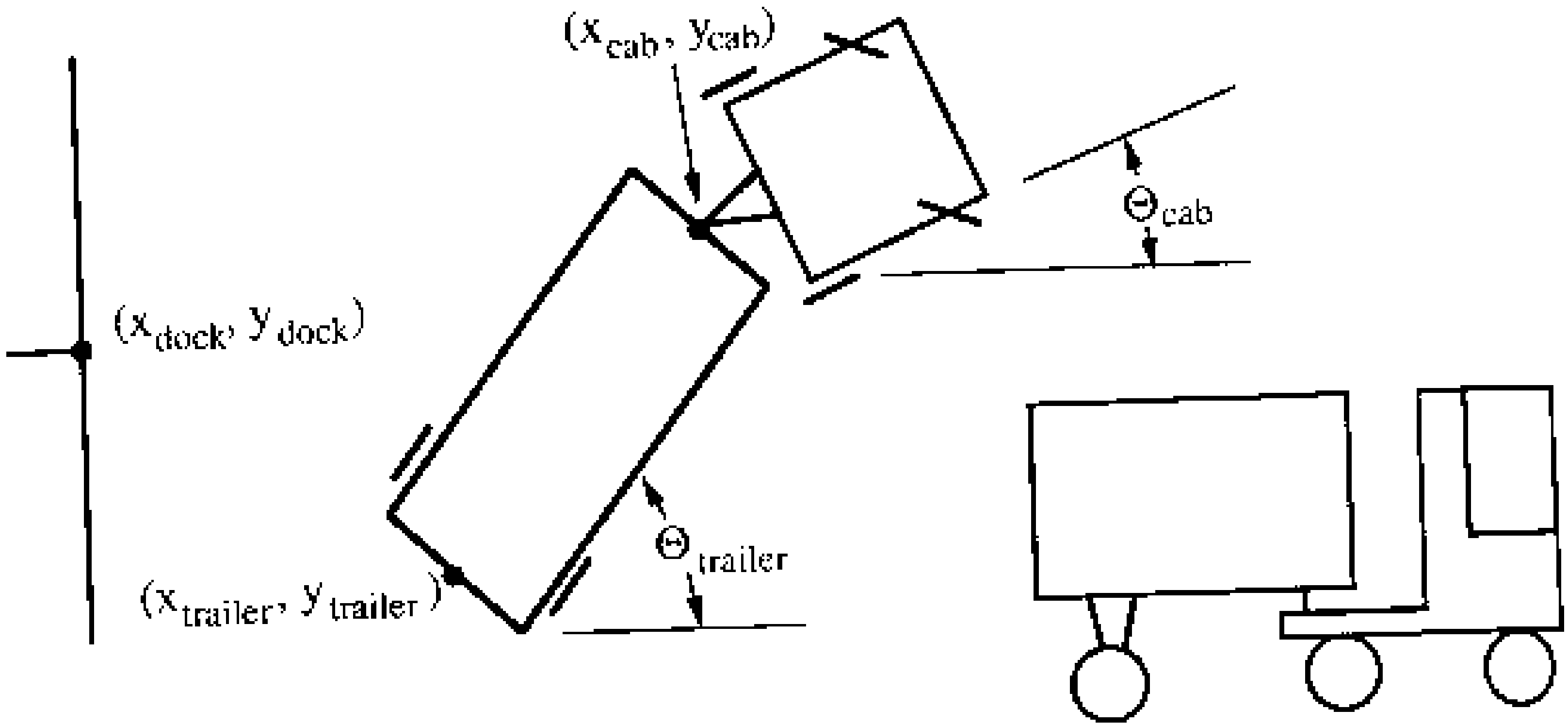
# Backpropagation through time (BPTT)



# BPTT Application

- The Truck Backer-Upper, D. Nguyen and B. Widrow
- reprinted in Miller, Sutton, and Werbos (eds.), Neural Networks for Control, MIT Press, 1990.
- Problem: Back up a truck so that $(x_{trailer}, y_{trailer}) = (x_{dock}, y_{dock})$, given initial values for $(x_{trailer}, y_{trailer}, x_{cab}, y_{cab}, \theta_{trailer}, \theta_{cab})$

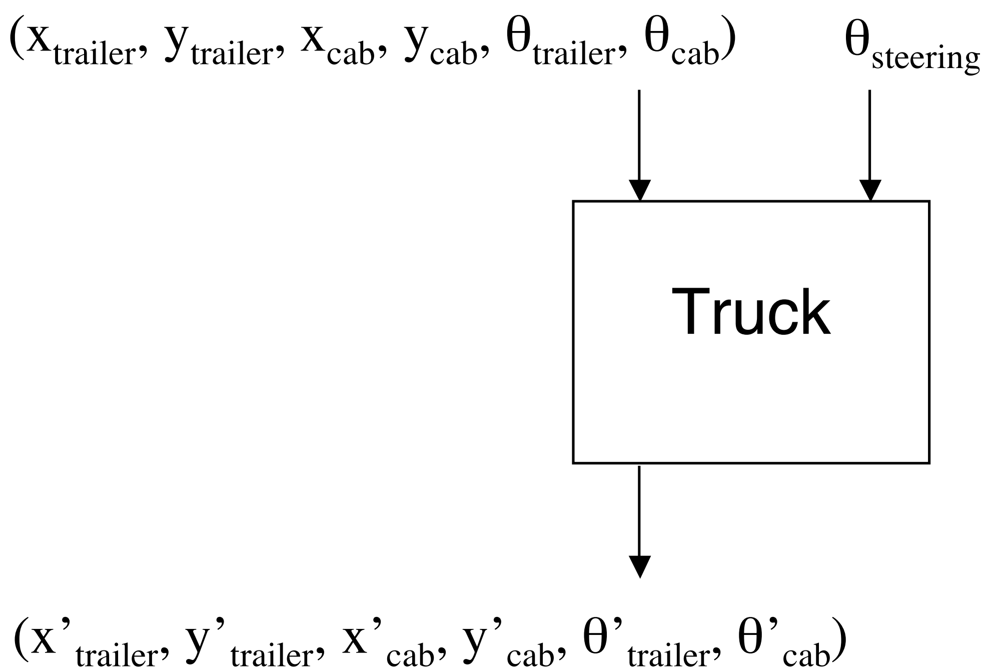
# Truck-Backer Problem



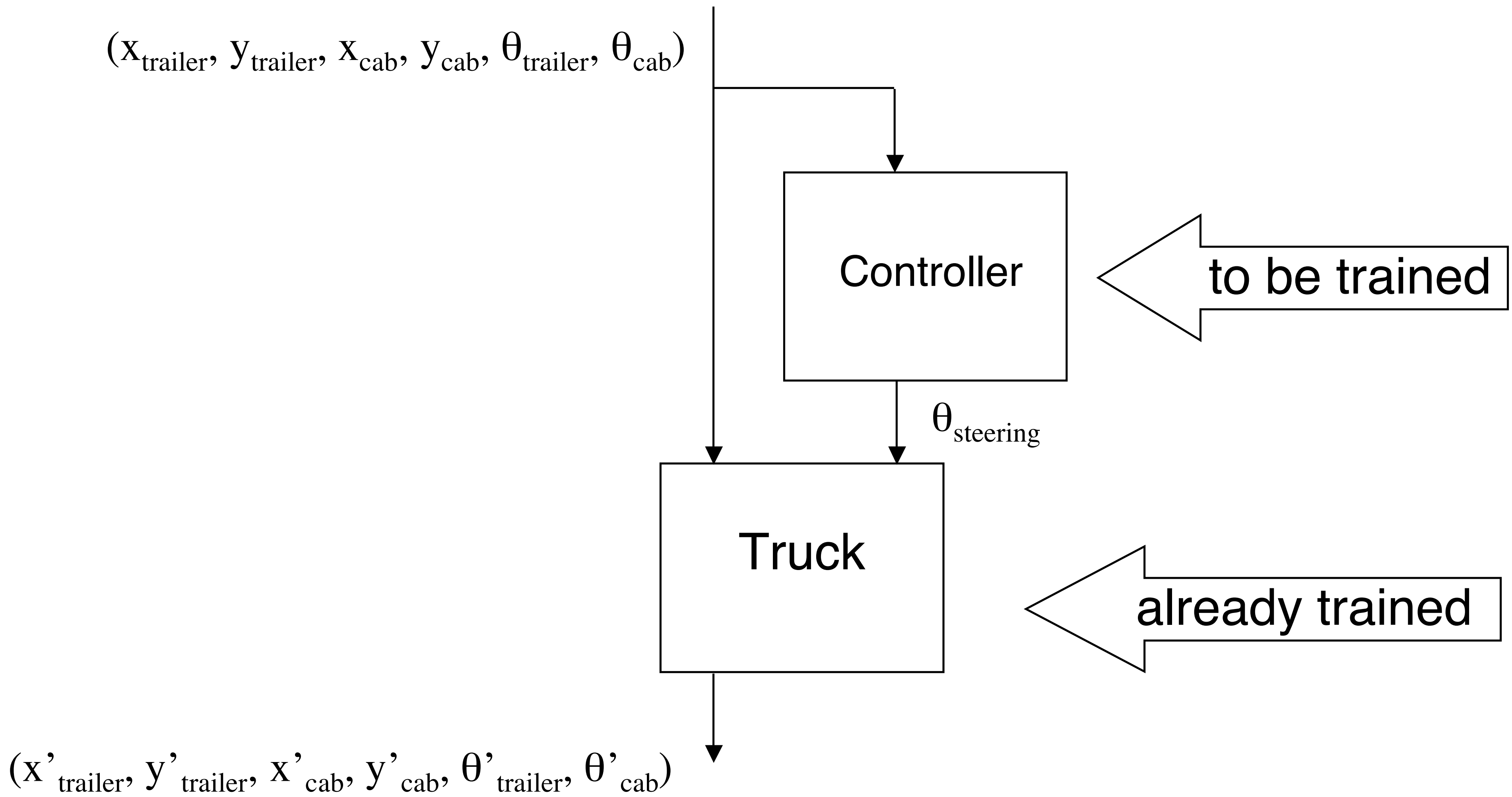
# Training the Truck-Backer

- The truck moves in small time increments $\Delta$
- A neural net is first trained to mimic the truck backing using **real truck dynamics**.
- Given the current state at a time t (which includes the steering angle), the network learns to determine the next state (at time $t + \Delta$)
- This is done by starting the truck in a random state, observing the error between what the network does and the dynamic model, and adjusting the weights.

# The function being learned



# Truck-Controller Combo

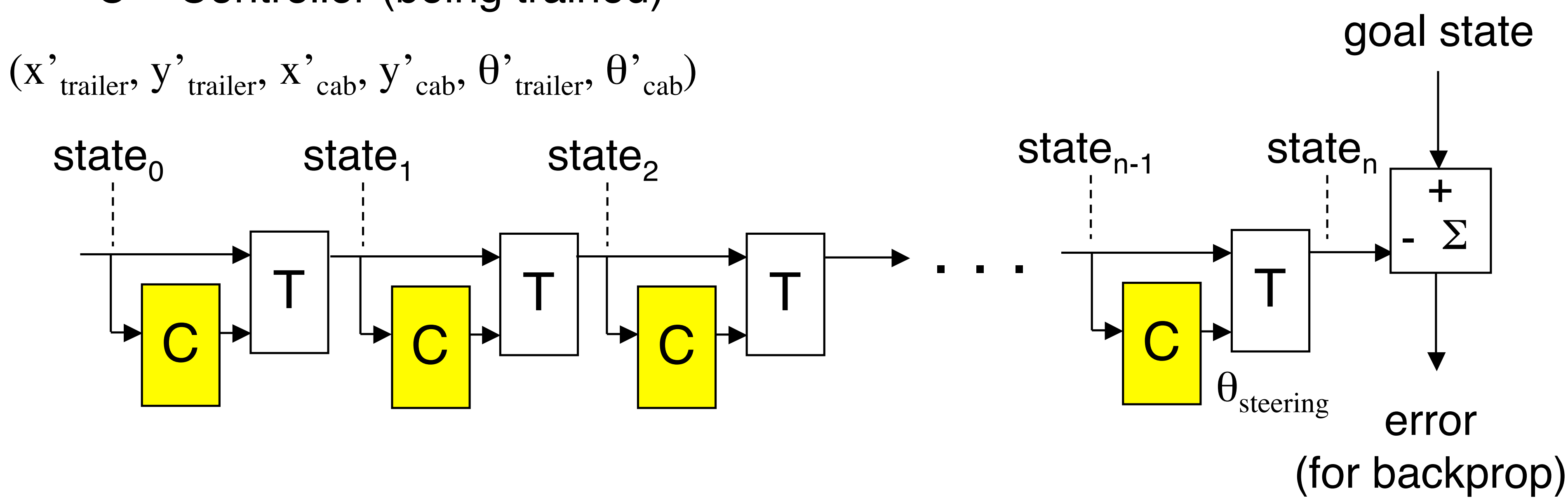


# Training the Truck-Backer

- Starting from a random position, the controller backs up the truck one step at a time, until the goal is reached, or an obstacle (such as a side wall) is hit.
- An error value is produced by comparing the desired final state with the goal.
- The error value is backpropagated through the controller-truck combination to adjust the controller's weights, using BPTT.

# BPTT for truck training

T = Truck (already trained, weights fixed),
C = Controller (being trained)



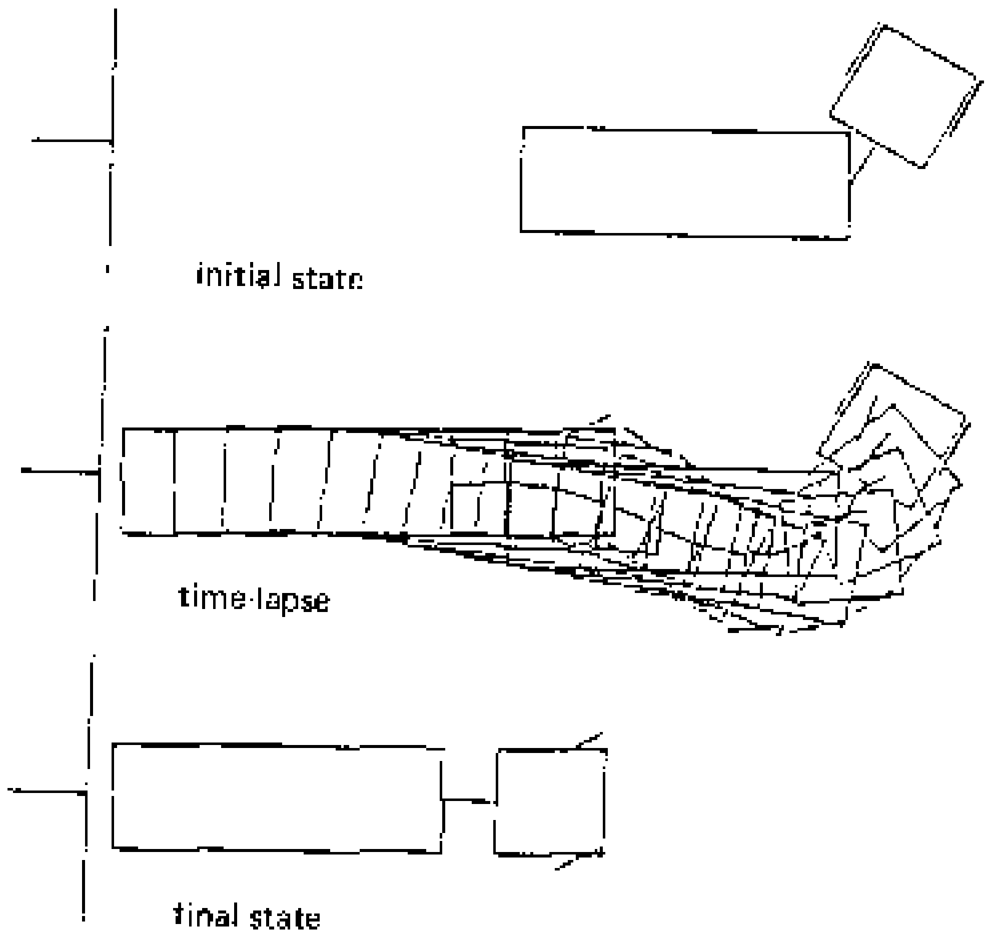
# Network Statistics

- Truck Emulator:
  - 6-45-6 tansig-tansig network
- Controller
  - 6-25-1 tansig-tansig network

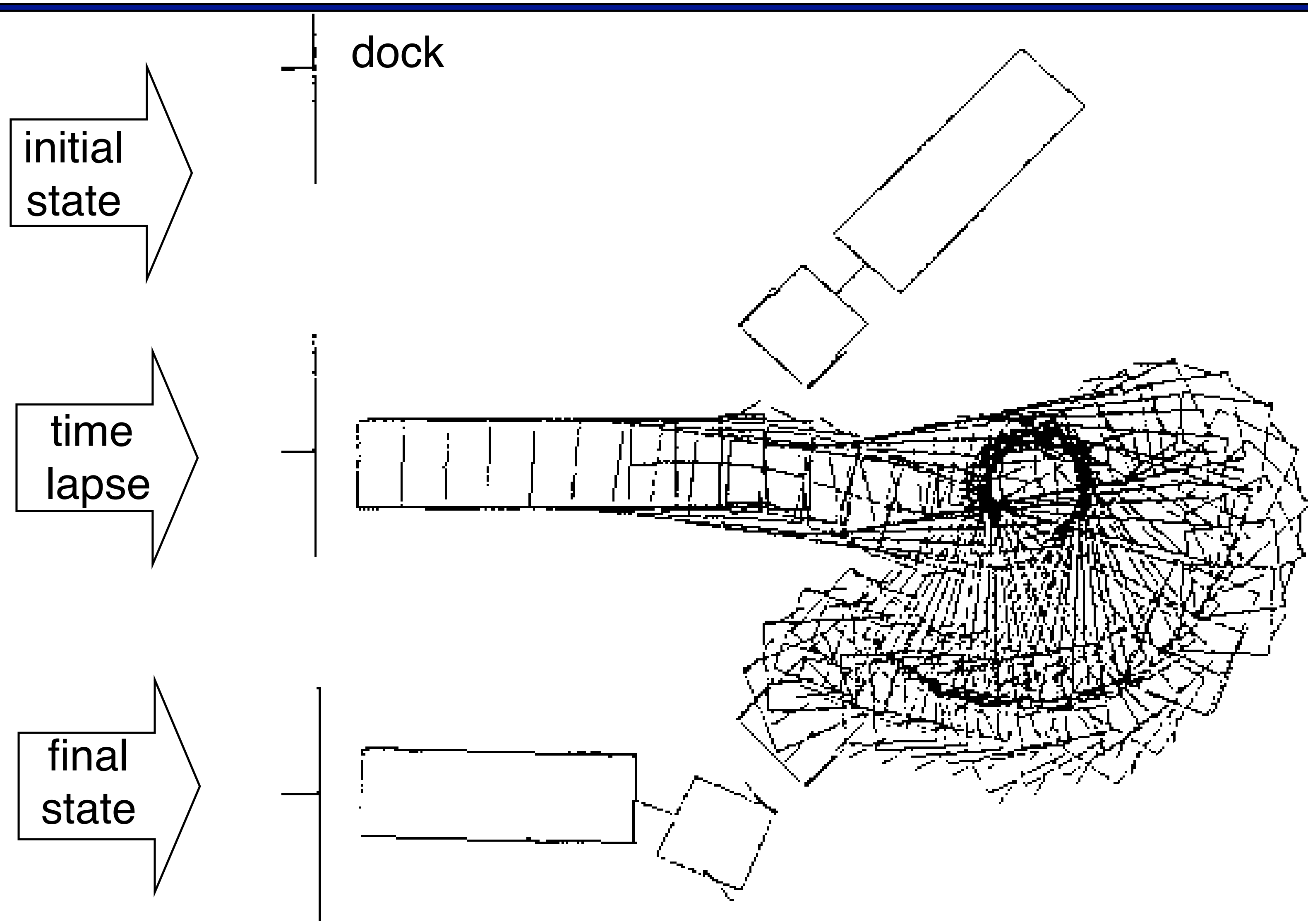
# Training

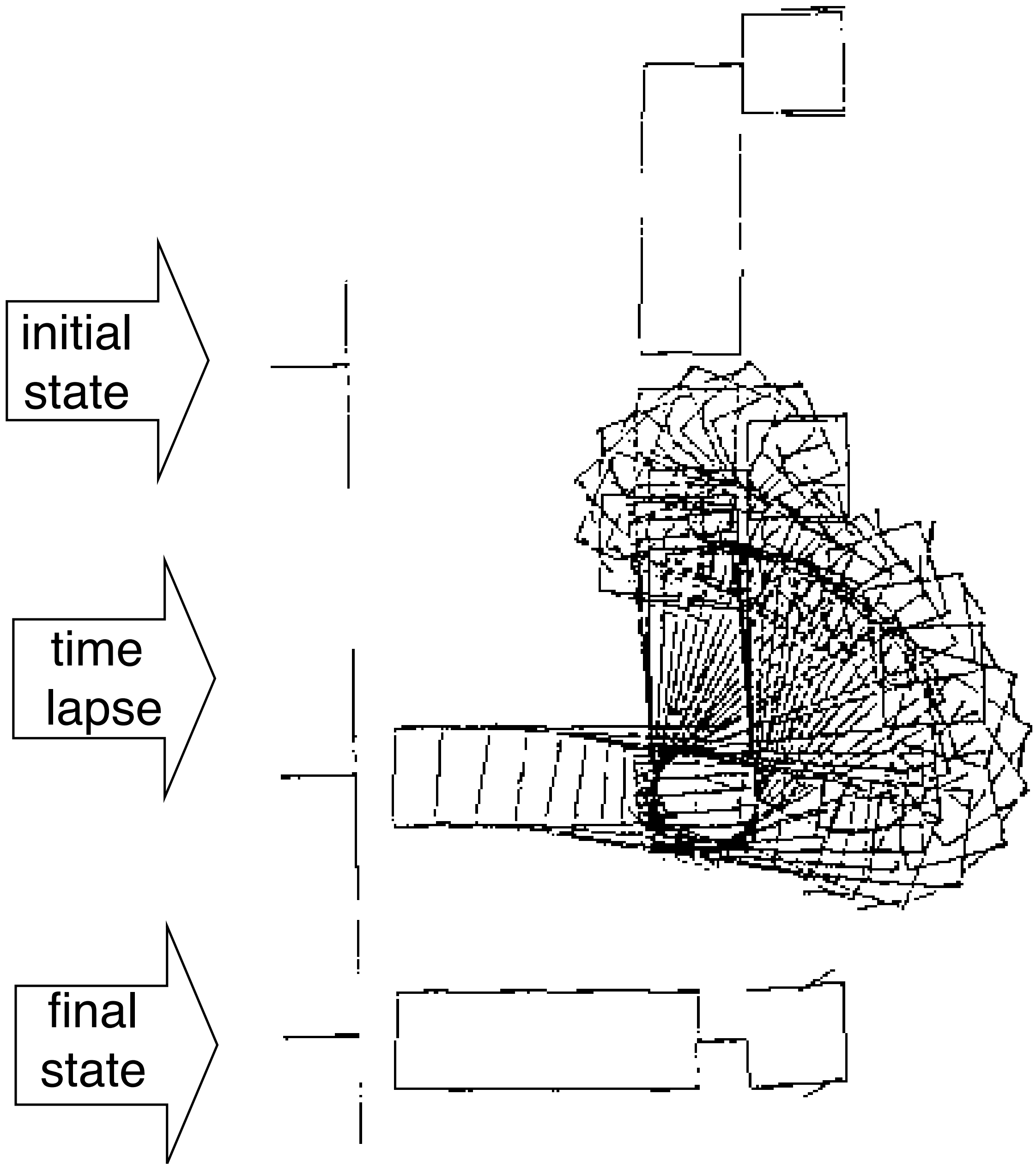
- 20,000 trials required to train
  - 16 lessons of 1000-2000 each
- Initially truck positioned very close to dock and in a nearly-correct position, so controller could **learn easy tasks first**.
- Final MSE was 3% of truck length, angle 7 degrees

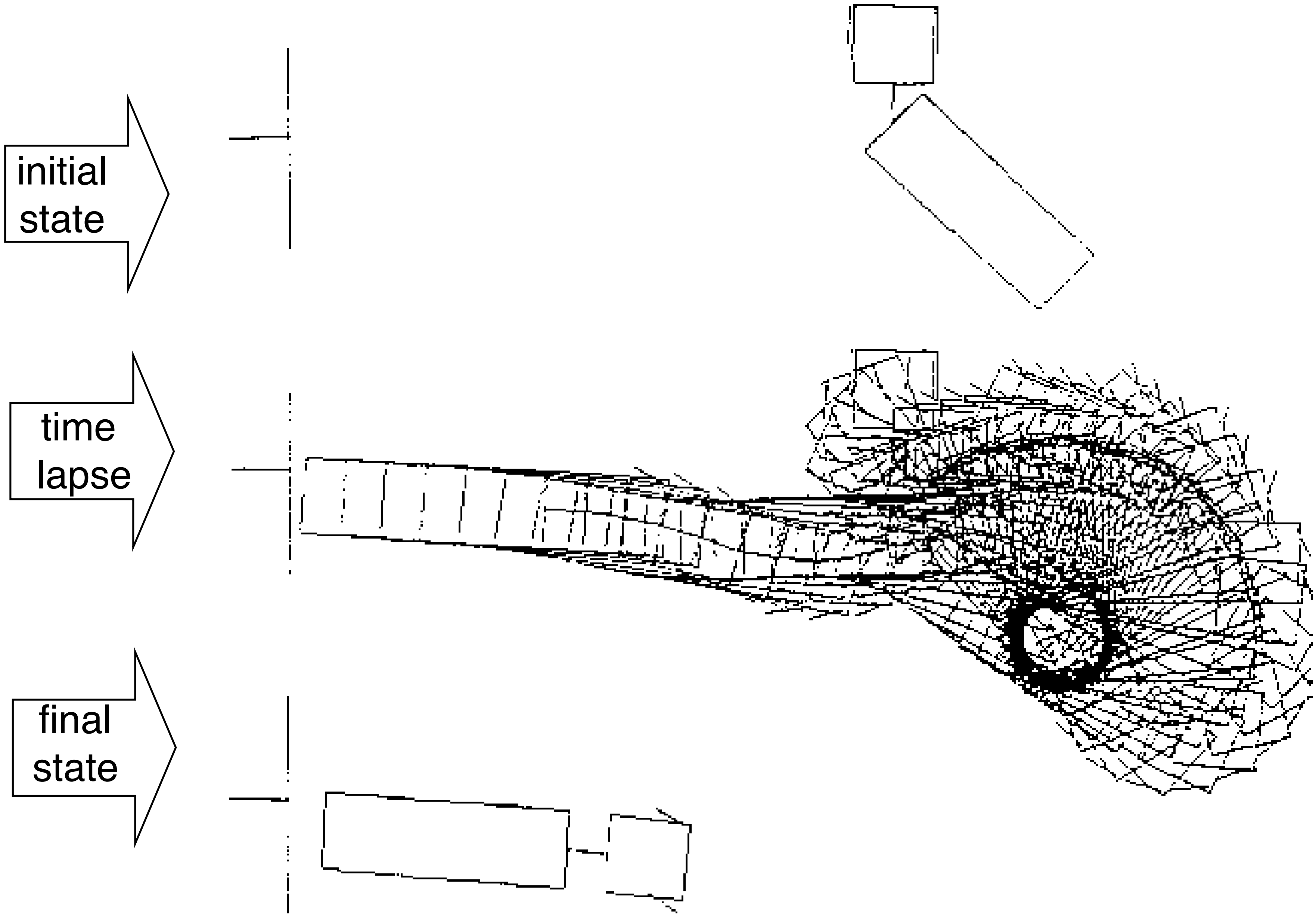
# Simulations



# Simulations




initial state
time lapse
final state


initial state
time lapse
final state