



NEURAL PREDICTION CHALLENGE

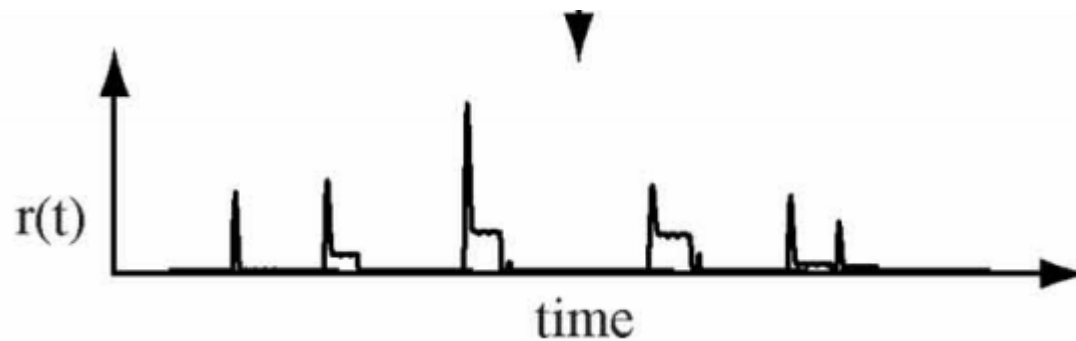
-Cognitive Science Project

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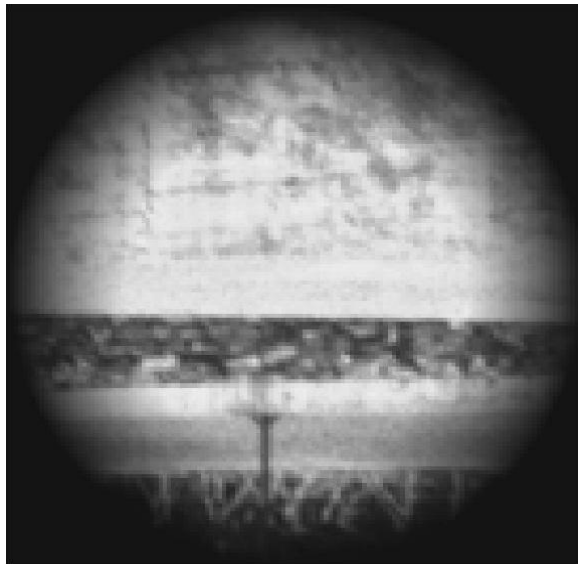
HOW DO NEURONS WORK

- Stimuli \rightarrow Neurons respond (Excite/Inhibit)
- ‘Electrical Signals’ called Spikes
- Spikes encode information !! (Many Models)



OUR CASE...

- Stimuli → Video of Natural Images
- Response of 12 V1 neurons → #Spikes



CHARACTERISTICS OF NEURONS

- Maximum fire rate (Need to discharge)
- Latency in response
- Concept of Receptive Field
 - Region of space where stimulus if present → alters neural activity
- Simple v/s Complex V1 neurons
 - Phase invariance: in complex



OUR DATA...

- A movie for each neuron
- Frames → Down sampled images (16x16)
- Each frame
 - Image spans twice the receptive field diameter
 - 16ms in duration
- Known: #Spikes/frame
- To build a model correlating stimulus and spike count.



SO, HOW TO DO IT ?

○ Problem: Stimulus

↓
Black Box

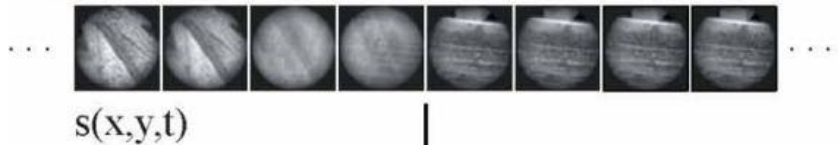
↓
Spike Rate

Concept of 'Filter'

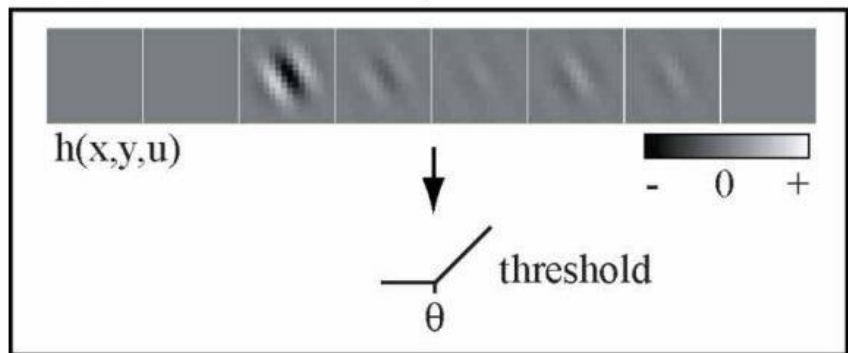
Space and Time both !
Latency !

A. Linear STRF

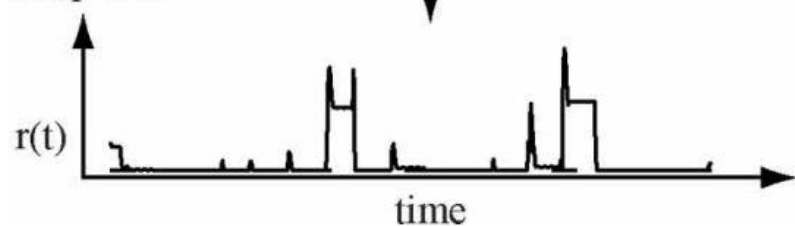
Stimulus



STRF

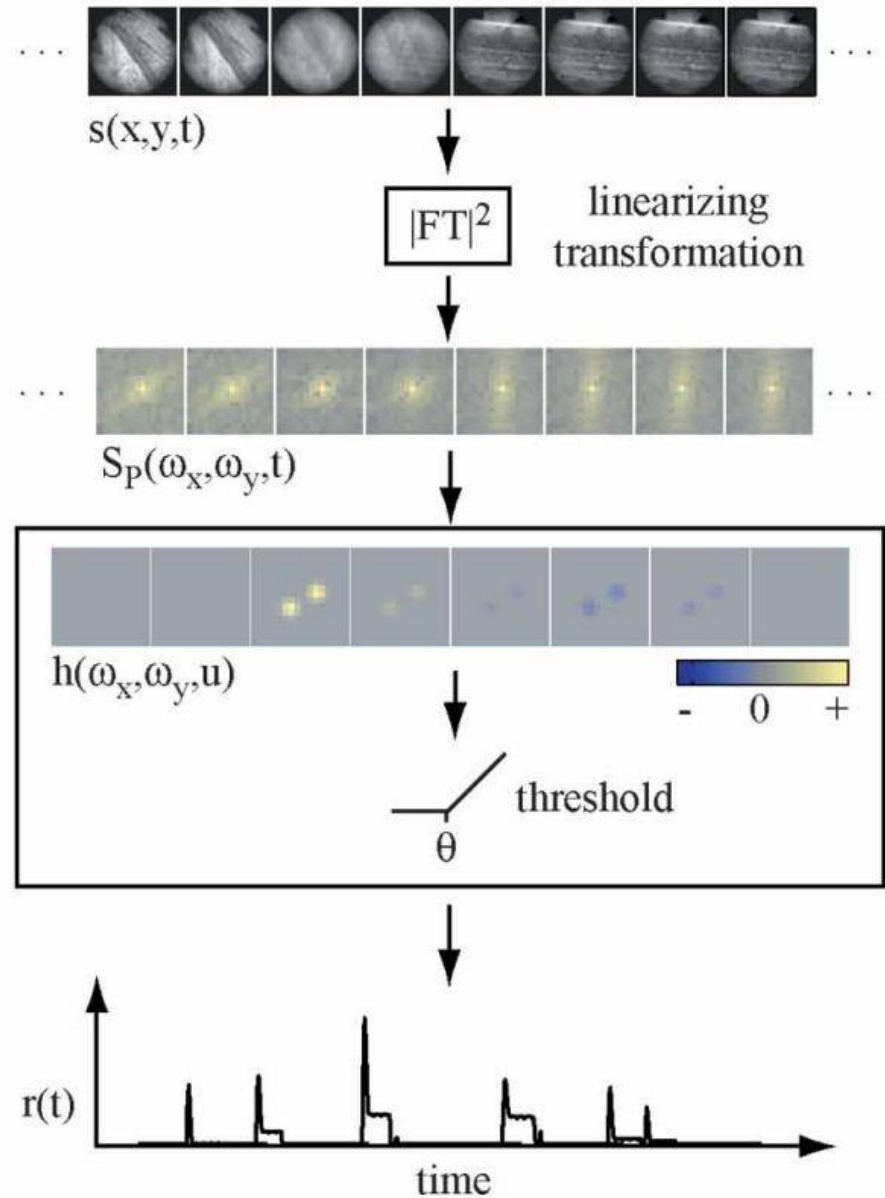


Response



PHASE INVARIANCE..

B. Linearized STRF



THE MATH OF ESTIMATION..

$$r(t) = \left| \sum_{i=1}^N \sum_{u=0}^U h(x_i, u) s(x_i, t - u) - \theta + \varepsilon(t) \right|^+$$

$$S_u = \begin{bmatrix} s(1, 1 - u) & s(2, 1 - u) & \cdots & s(N, 1 - u) \\ s(1, 2 - u) & s(2, 2 - u) & & s(N, 2 - u) \\ \vdots & & \ddots & \vdots \\ s(1, T - u) & s(2, T - u) & \cdots & s(N, T - u) \end{bmatrix}$$

$$S = [S_0 \quad S_1 \quad \cdots \quad S_U]$$

$$r = |Sh - \theta + \varepsilon|^+.$$

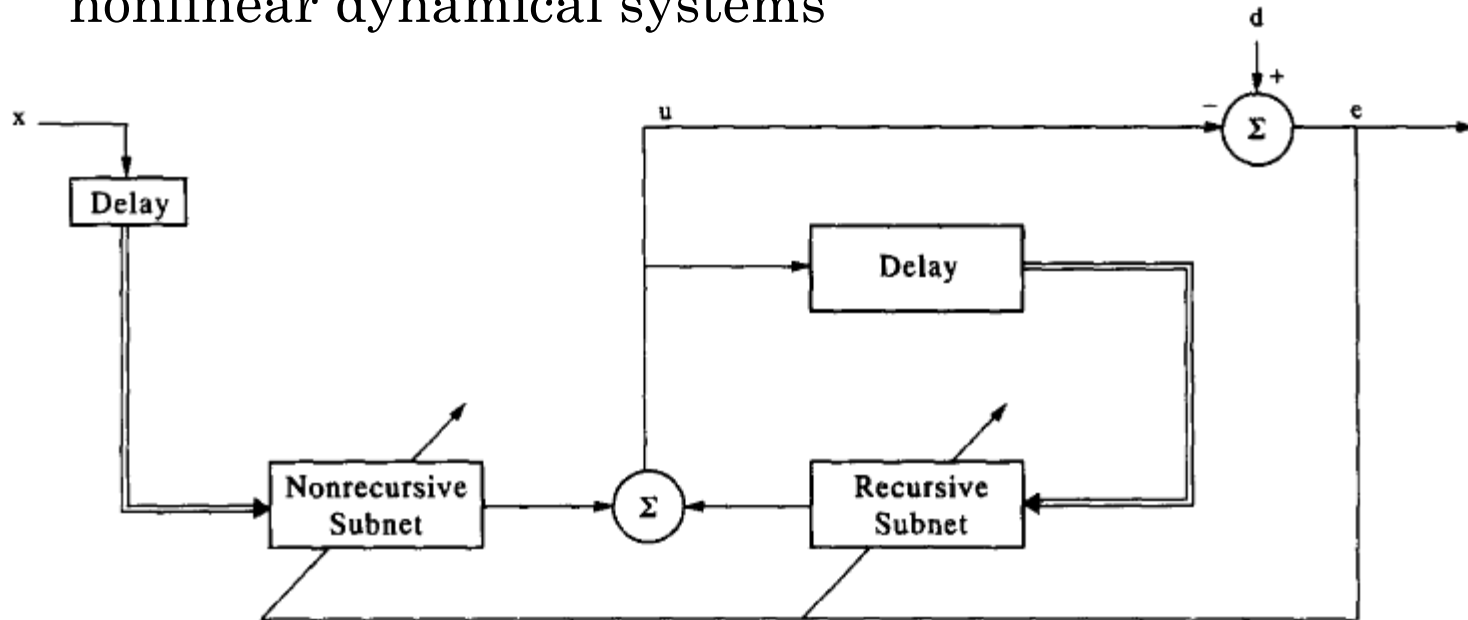
$$h = \frac{1}{T} C_{ss}^{-1} S^T r.$$



SECOND APPROACH: MACHINE LEARNING

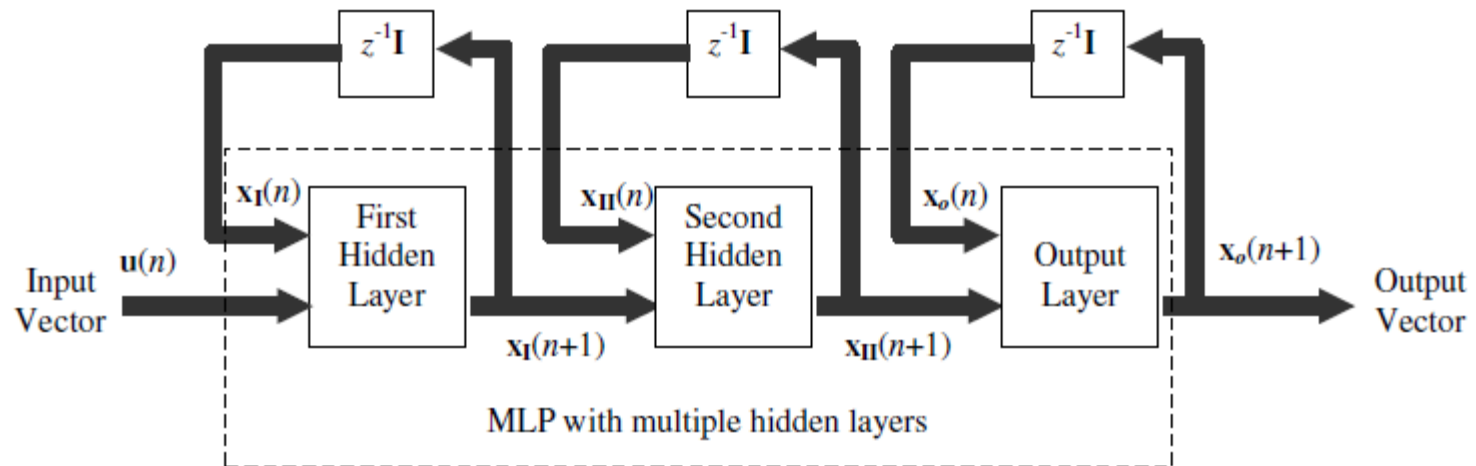
○ Recursive neural networks

- Composed of feed forward and feed back subnets.
- Were initially designed for the purpose of controlling nonlinear dynamical systems



Source: Hush et al. *The Recursive Neural Network and its Application in Control Theory*. Computers Elect. Engng. Vol. 19, No. 4, pp. 333-341, 1993

An exemplary recursive multi-layer perceptron:



$$x_I(n+1) = \varphi_I(\mathbf{w}_I \cdot \begin{bmatrix} x_I(n) \\ u(n) \end{bmatrix})$$

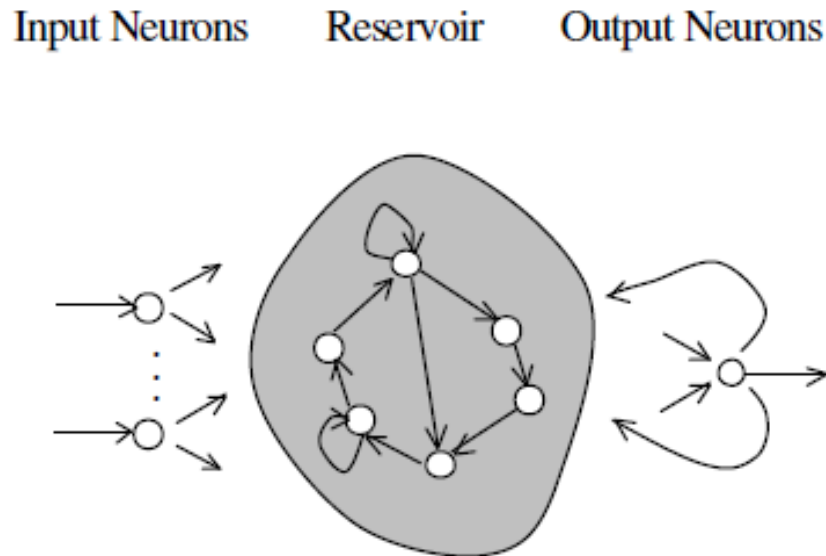
$$x_{II}(n+1) = \varphi_{II}(\mathbf{w}_{II} \cdot \begin{bmatrix} x_{II}(n) \\ x_I(n) \end{bmatrix})$$

$$x_o(n+1) = \varphi_o(\mathbf{w}_o \cdot \begin{bmatrix} x_o(n) \\ x_{II}(n) \end{bmatrix})$$



ECHO STATE NETWORKS

- Dynamic neural networks
- The hidden layer of ESN consists of a single large reservoir with neurons connected to each other randomly.



USING RNNs

- RNNs have been used for inverse modeling purposes
- Can handle time series data because of the presence of feed back and delay mechanisms
- May need to down sample data even further to keep network size manageable.



REFERENCES

- Predicting neural responses during natural vision, S. David, J.Gallant, Computation in neural systems 2005
- Wikipedia article on neural coding (http://en.wikipedia.org/wiki/Neural_coding)
- Theunissen et al., Estimating spatial temporal receptive field of auditory and visual neurons from their responses to natural stimuli .Network: Comp Neural Systems 12:289–316.
- Hush et al. *The Recursive Neural Network and its Application in Control Theory*. Computers Elect. Engng. Vol. 19, No. 4, pp. 333-341, 1993
- Le Yang, Yanbo Xue. *Development of A New Recurrent Neural Network Toolbox (RNN-Tool)* (http://soma.mcmaster.ca/~yxue/papers/RMLP_ESN_Report_Yang_Xue.pdf)

