Input-Output Mapping Performance of Linear and Nonliner Models for Estimating Hand Trajectories from Cortical Neuronal Firing Patterns

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Goal

- Develop new real-time algorithms for predicting primate hand trajectories from neuronal ensemble recordings.
- Determine which model (linear or nonlinear) is best for producing accurate estimations during long excursions in hand trajectory and stationary positions.
- We continue the work of Nicolelis and colleagues by substituting the TDNN with a recurrent neural network (RNN) and compare the performance to the FIR and Gamma filters.

Motivation

- Brain Machine Interfaces (BMI) could restore motor functions in patients suffering from extensive body paralysis resulting from neurological disorders.
- As a consequence, BMIs could enable humans to use tools which are continuous extensions of the body
- Improve motor, sensory, and cognitive performance

This is an Input/Output Modeling Problem

- Adaptive systems are tools for modeling
- How do we choose models?
  - Parametric
    - Optimal model is selected from a set of mathematical functional forms which depend on a set of parameters
  - Nonparametric
    - No assumed functional forms for the model
    - Data driven (require large amounts for good performance)
- What is the complexity of the system being modeled?
- We must create a representation space which can map neuronal firing patterns to hand position

Nature of the Data

- Large input space – greater than 100 dimension
- Desired signal of dimension one or three
- Nonstationary

Tracking vs. Modeling

- Large stepsizes allow weights to change quickly and track trajectory changes
- Any adaptive system with a sufficiently large stepsize can track
- Modeling seeks to minimize error AND stabilize the weights
- Only a select number of topologies can model a system

Model Building Techniques

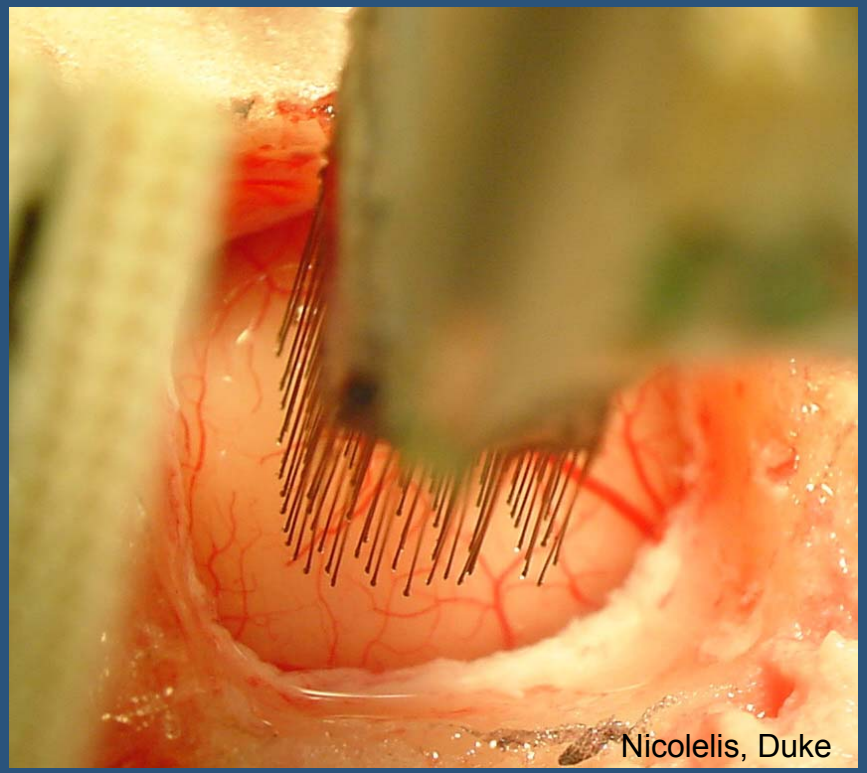
- Train the adaptive system while preserving generalization (minimize model output bias and variance).
- Freeze weights and present novel data.

Rationale

- Multiple interconnected cortical areas in the frontal and parietal lobes are involved in the selection of motor commands
- Each neuron in these areas is broadly tuned to motor parameters (position, force, etc.)
- Large populations of single neurons can be used to extract a particular parameter

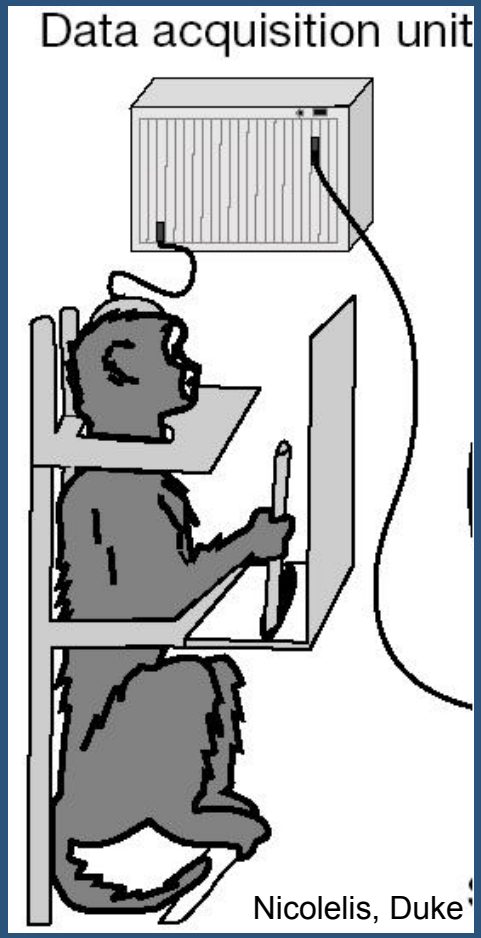
Collection Techniques

- Amplify, Filter, and A/D convert brain signals
- Multi-channel neural spike sorting (modified version of PCA)
- Spike detection resolution of 250μs.
- Up to 128 microwires (30-50μm in diameter)
- Total area of 15.7 mm

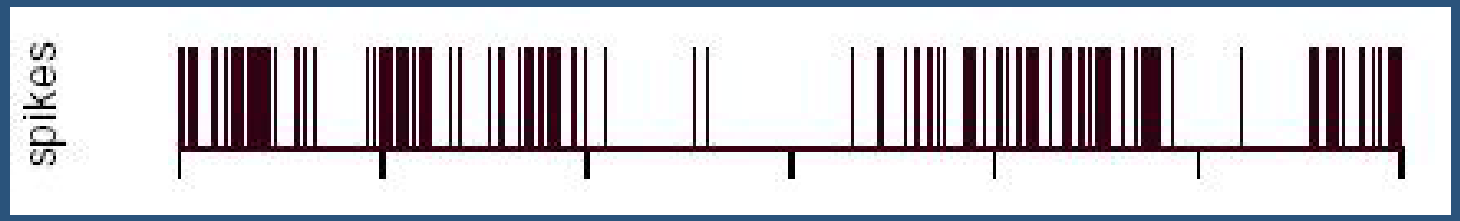


Experimental Setup

- Monkey cued to make 3-D movements
- Significant coupling between the spike data and had position for one second.
- 300ms movement planning period



Data Processing (Binning)

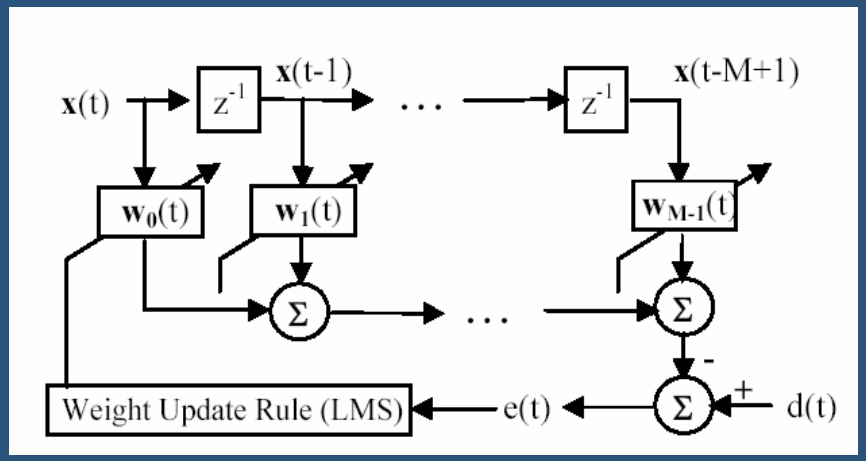


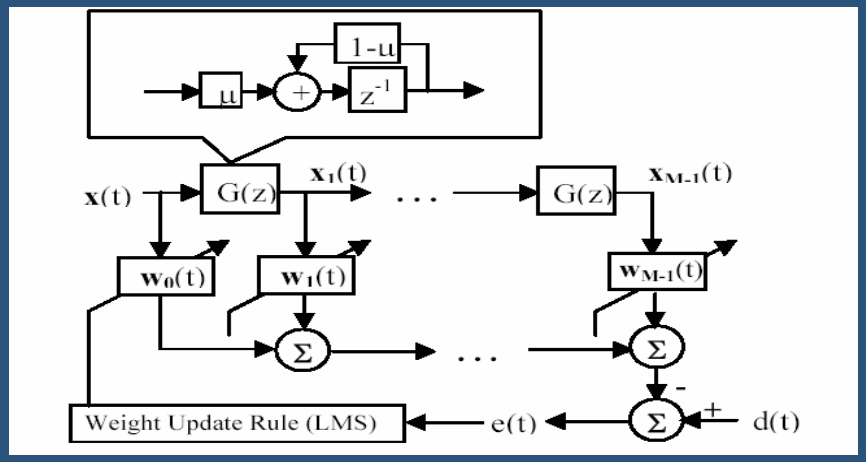
- To reduce the sparse nature of the data, neural spikes are grouped in 100 ms bins.
- A spike count for each bin is generated.

Population Statistics

- 90% of the data contains zeros.
- At all time instances in 104 channels at least one neuron is firing.
- Indicates that the brain is processing information for each hand position

Fir and Gamma Filters

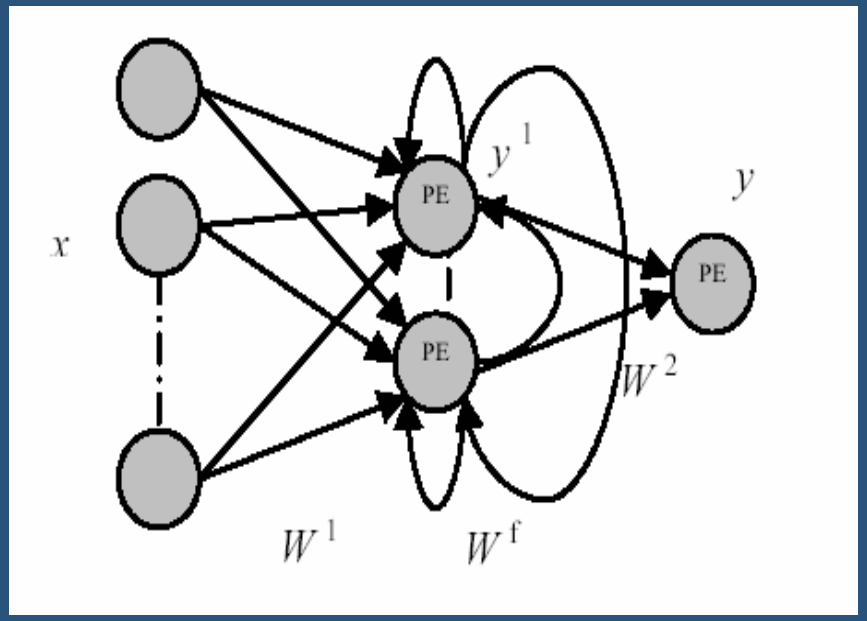




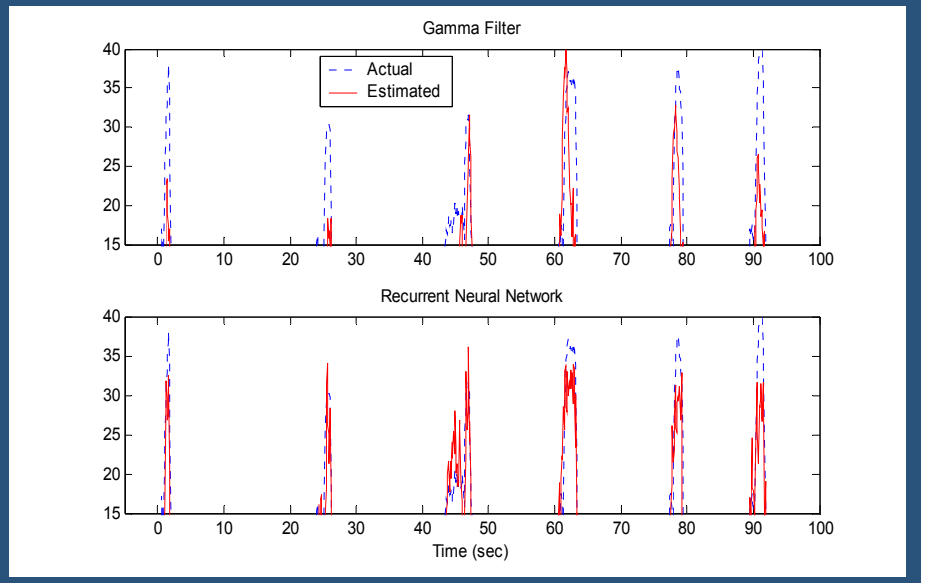
- Both approaches assume that there exists a linear mapping between the desired hand position and neuronal firing counts.
- The Gamma filter implements a restricted feedback architecture which uncouples memory depth from filter order.
- The Gamma filter structure allows for a reduction in number of free parameters for an equivalent FIR memory depth.
- This memory characteristic is especially useful for this problem since input data has a large dimensionality.
- Trained using the normalized LMS algorithm which can be used to avoid sensitivity to local amplitude and to set a time-varying learning rate that traces time-variant input statistics.

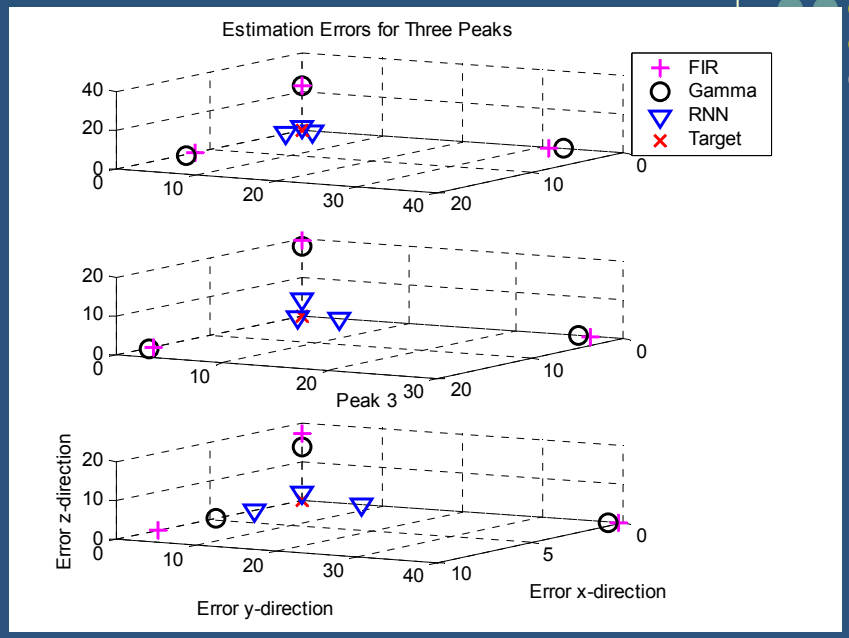
Recurrent Network

- Spatially recurrent dynamical systems in which PE output (state) is delayed and fed back to itself.
- Memory structure is moved to the hidden layer reducing the number of free parameters
- Trained with backpropagation through time
- Nonlinear mapper which requires much fewer parameters than the linear and TDNN models



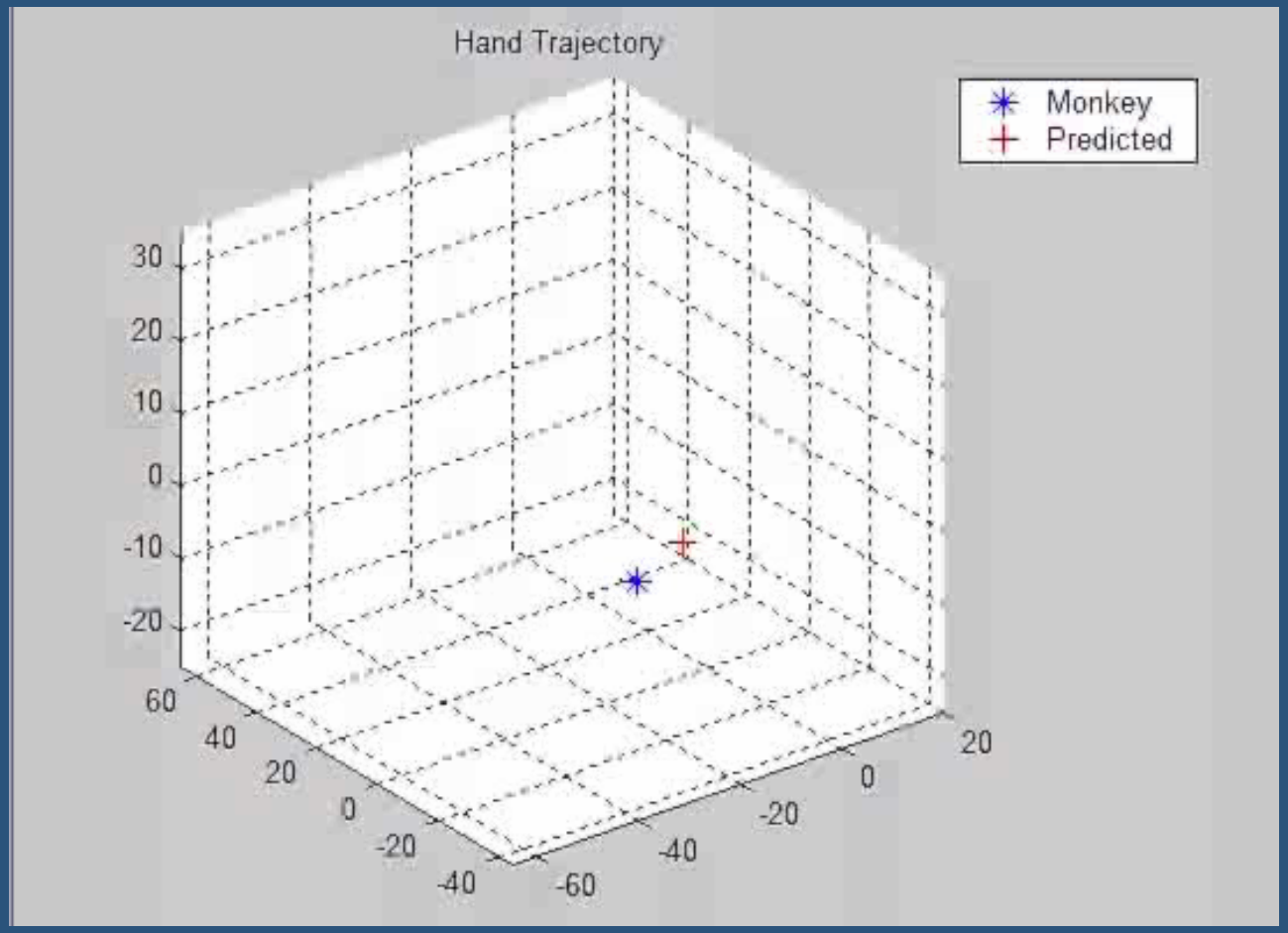
Results





	SER		Correlation Coefficient	
	(average)	(max)	(average)	(max)
FIR	0.8706	7.5097	0.6373	0.9528
Gamma	0.9002	8.5326	0.6446	0.9547
RNN	1.6101	32.3934	0.6483	0.9852

3-D Trajectory I/O Modeling Movie Using RNN (Fixed Parameters)



Conclusions

- CNEL has created a simple models which estimates hand position in 3-D space from a population of neuronal firing patterns.
- FIR
  - Longer memory depths result in more free parameters to train.
  - Training requires a low computational complexity.
  - The eigenvalue spread of the data causes long convergence times to multiple solutions at a single minima.
- Gamma
  - Outperformed the FIR filter.
  - Equivalent memory depths can be achieved with a fewer number of free parameters.
  - Gamma filter training is as computationally efficient as the FIR filter.
- RNN
  - The RNN repeatedly produced peak estimations better than FIR and Gamma with errors that formed tight clusters around the target.
  - The RNN implements an infinite memory depth on multiple timescales.
  - RNN is capable of constructing complex nonlinear I/O mappings.
  - BPTT is more computationally complex than standard LMS.
- We have performed estimation tasks for the trained (fixed-parameter) RNN for long periods of testing data (over 15 minutes).

Acknowledgments

- Justin Sanchez
- Sung-Phil Kim
- Deniz Erdogmus
- Yadunandana Rao