Dynamic Features of Neural Activities in The Lamprey's Brainstem: A Study With A Neuro-robotic System

A. Karniel*[1], K.M. Fleming[1], V.Sanguineti[2], S.T.Alford[3], and F.A.Mussa-ivaldi[1], [1]Physiology, Northwestern University Medical School, Chicago, Illinois, USA 60611
[2]Informatica Sistemistica E Telematica, Università di Genova, Genova, ITALY [3]Biological Sciences, University of Illinois at Chicago, Chicago, Illinois, USA 60607

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INTRODUCTION

- In order to study learning mechanisms, we developed a research tool that included the reticular formation of an *in vitro* lamprey brainstem preparation and a two-wheeled robot, interconnected in a closed loop (Reger et al 2000).
- Under normal circumstances, vestibular signals and motor commands are used to stabilize the orientation of the lamprey during swimming (Deliagina 1997).
- We exploited this system, using light intensity signals in place of vestibular signals. The resulting behavior was the tendency of the robot to track the source of light.

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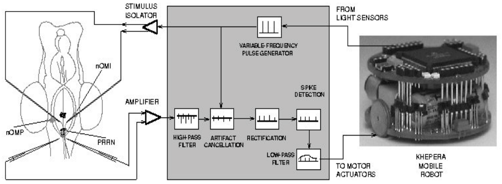
Robot setup and Schematic diagram of the neuro-robotic system.
Top: Using a pattern of colored circles, the overhead camera tracked the robot.

Bottom: The neural interface translated the light sensor data from the robot into a pattern of stimulation for the neural preparation; neural recordings were converted into motor signals for the robot.



- To induce plastic changes in the neural connections we electrically "blinded" the left side of the robot and let it move about the workspace with random stimulation for 20 min.
- After "un-blinding," we observed a tendency to move to the left, which reflected neuronal change.
- We explored the neuronal basis for the observed behavior and adaptation by considering various two-input/two-output neural network models.

METHODS

- In anesthetized larvae of Sea lamprey (Petromyzon marinus), the whole brain was dissected and maintained in Ringer's solution (9-11°C). Two stimulating electrodes were placed in the axons of nOMI and nOMP (200µS monophasic in variable rate). Two recording electrodes were placed in left and right PRRN axons (Alfrod et al. 1995).
- On a Khepera (K-Team) mobile robot, three light sensors from each side were combined to provide light levels on the left and right "eyes". Eight lights mounted at 45° increments around a 50-cm diameter circle comprised the workspace. A LabVIEW interface converted between neural and robot signals.
- To explore the possibility that the spinal cord was responsible for the dynamic properties, the spinal cord was cut in four preparations.

Modeling

- To approximate the behavior, a static polynomial model was fitted and the simulated behavior was compared to the measured for each preparation (Fig. 2, left).
- To further explore the best model for the neural tissue, the input and output set of data for each trajectory was fitted with a polynomial function of the input (static model).
- To check the capability of the model to generalize, part of the data from each set of trajectories was not used for the fitting and was kept for testing. The mean error over the fitted data and over the test data (generalization) was calculated over 27 preparations (Fig. 2, right, Fig. 4 Bottom).

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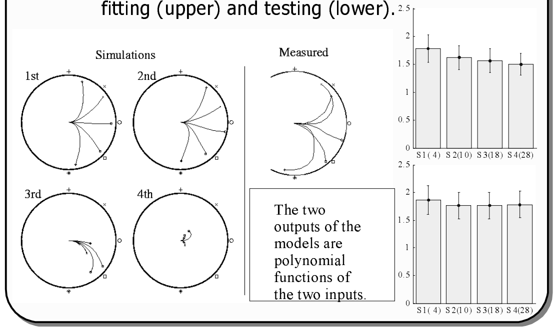
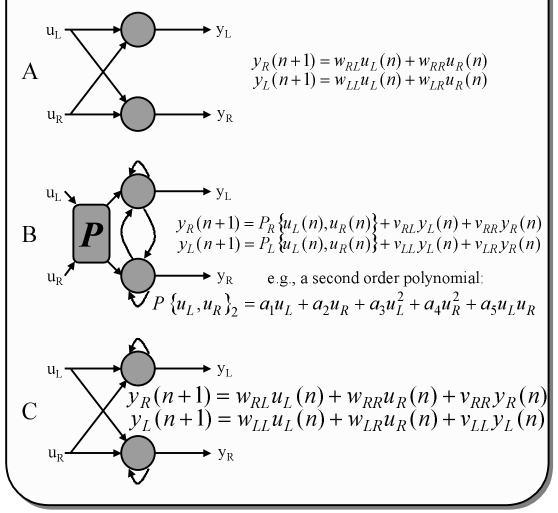
Approximation of behavior and Neural models. Left: Comparison of measured data and simulations of increasing model order for one preparation. Right: RMS errors (n=27) fitting (upper) and testing (lower).



- We also considered dynamic models where the output was also a function of the previous output and not only of the previous input (Fig. 3).

3

Neural Models: A. Static linear model. Braitenberg (1984) used this kind of model to described the elementary properties of two wheeled robots' behavior. B. We considered a family of models that included nonlinear input function and dynamic connections. C. Among these possibilities, our results support a linear model with ipsilateral dynamic connections.



A

$$y_R(n+1) = w_{RL}u_L(n) + w_{RR}u_R(n)$$
$$y_L(n+1) = w_{LL}u_L(n) + w_{LR}u_R(n)$$

B

$$y_R(n+1) = P_R\{u_L(n),u_R(n)\} + v_{RL}y_L(n) + v_{RR}y_R(n)$$
$$y_L(n+1) = P_L\{u_L(n),u_R(n)\} + v_{LL}y_L(n) + v_{LR}y_R(n)$$

e.g., a second order polynomial:

$$P\{u_L,u_R\}_2 = a_1u_L + a_2u_R + a_3u_L^2 + a_4u_R^2 + a_5u_Lu_R$$

C

$$y_R(n+1) = w_{RL}u_L(n) + w_{RR}u_R(n) + v_{RR}y_R(n)$$
$$y_L(n+1) = w_{LL}u_L(n) + w_{LR}u_R(n) + v_{LL}y_L(n)$$

Results

- The linear static model (Fig. 3A) provided a qualitative description of the behavior type. In extending the accuracy and the number of parameters, the simplest dynamic model was significantly superior to any static model. (Fig. 4).
- Ipsilateral connections (Fig. 4, Di) were much more important than contralateral connections (Fig. 4, Dx) in the model. This was expected from the anatomy of the brain.
- Four preparations with transected spinal cord exhibited similar behavior and similar testing errors (as in Fig. 4). This refutes the hypothesis that recurrent connections in the model represent the pathways to the spinal cord and back.
- In an experiment designed to induce adaptation, the change in the weight of a recurrent connection was most significant (Fig. 5).

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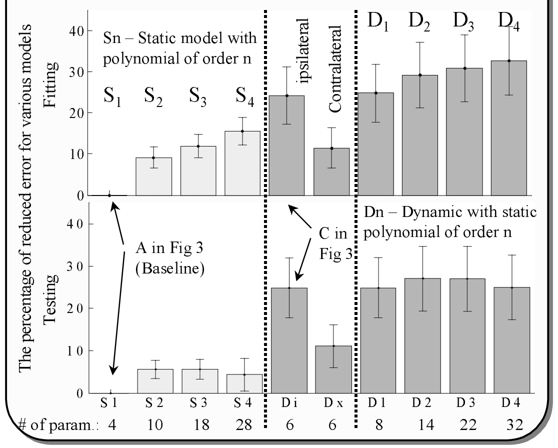
The error reduction by various neural models, compared to the static linear model. Fitting (top), Testing (bottom)



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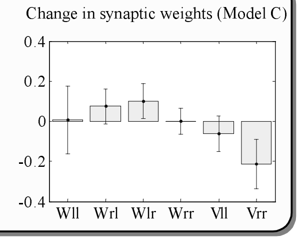
Adaptation analysis

Change in weights (Fig. 3C) after the procedure of artificial blinding with 20 minutes of random stimulation (n=9).



DISCUSSION

- The neuro-robotic system allows us to simultaneously study the behavior, network, and cellular level in a controlled environment.
- We demonstrated the significant role of the dynamic properties of the network.
- We narrowed the physiological possibilities for the origin of these properties and demonstrated plastic changes of these dynamic properties.

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