

Noise Induced Memory in a 1D Excitable System

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Background & Objectives

Memory: The storage and retrieval of information by the brain.

Long-term memory is generally explained as a gradual modification of synaptic weights which can affect the firing patterns of neurons in the brain. But **short-term memory** cannot be explained in this way since its effected time window is too small to modify the synaptic strength.

We are Investigating a memory mechanism in excitable systems without synaptic learning.

Neuron cell:

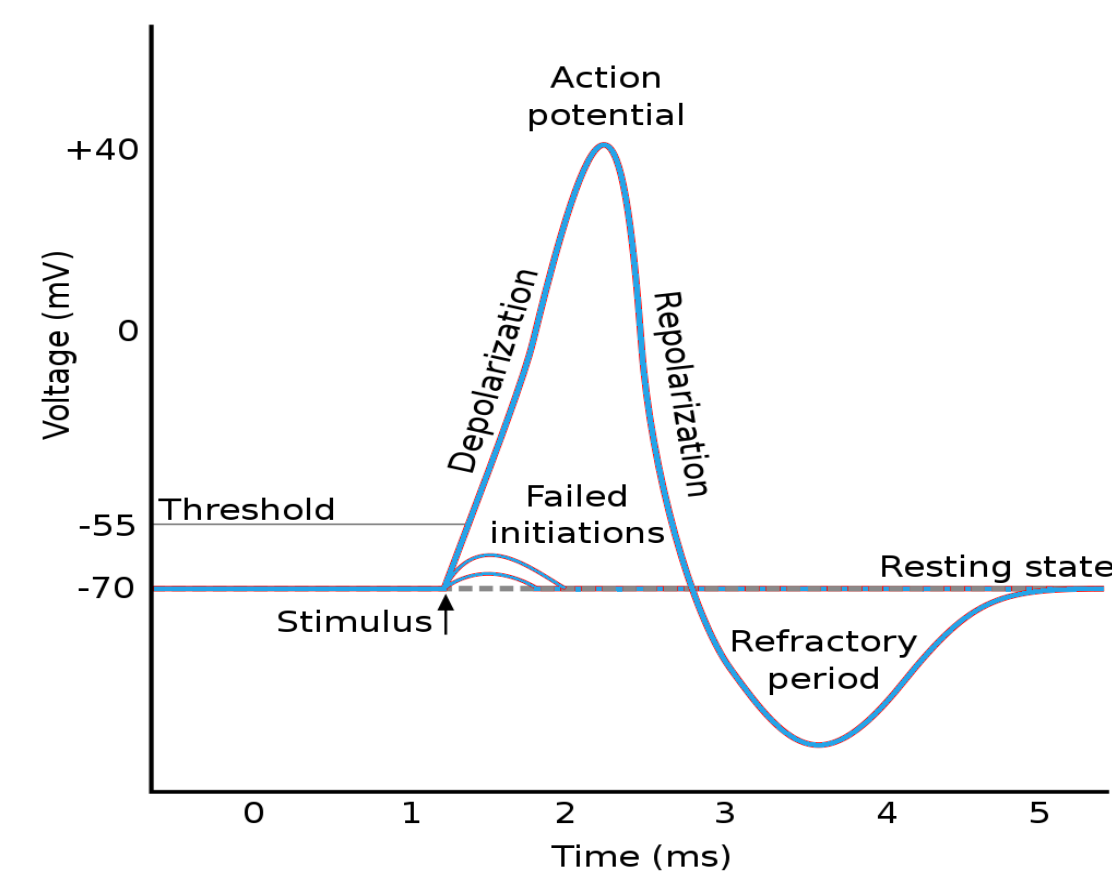


Fig. 1. Spike in action potential of neurons^[1]

Membrane potential of a cell

Rest: Synaptic inputs below the threshold value

Excited: Input above the threshold value, a neuron will fire an action potential

Refractory: After firing, the cell is unable to initiate another action potential in a specific time period

Objectives:

1. Generate the form of memory by stochastic excitation
2. Investigate the time period it can last and how much memory it can retain
3. Manipulate the model by changing its parameters
4. Investigate the effect of perturbation

Model

Greenberg-Hastings cellular automata model of excitable media:

At each time step, the cell can be in the 'Resting/Quiescent (Q)', 'Excited (E)', or 'Refractory (R)' state. We excite one cell at time $t=0$ (all others in resting state).

Evolutionary rules^[2]:

1. $E \rightarrow R$ at the next time step
2. $R \rightarrow Q$ state after r time steps (r is the refractory time period)
3. $Q \rightarrow E$ at the next time step with a probability p , or if at least one of its neighbours in E

Three parameters setup the system to generate waves:

1. lattice size l
2. spontaneous excitation probability (noise) p
3. refractory period r

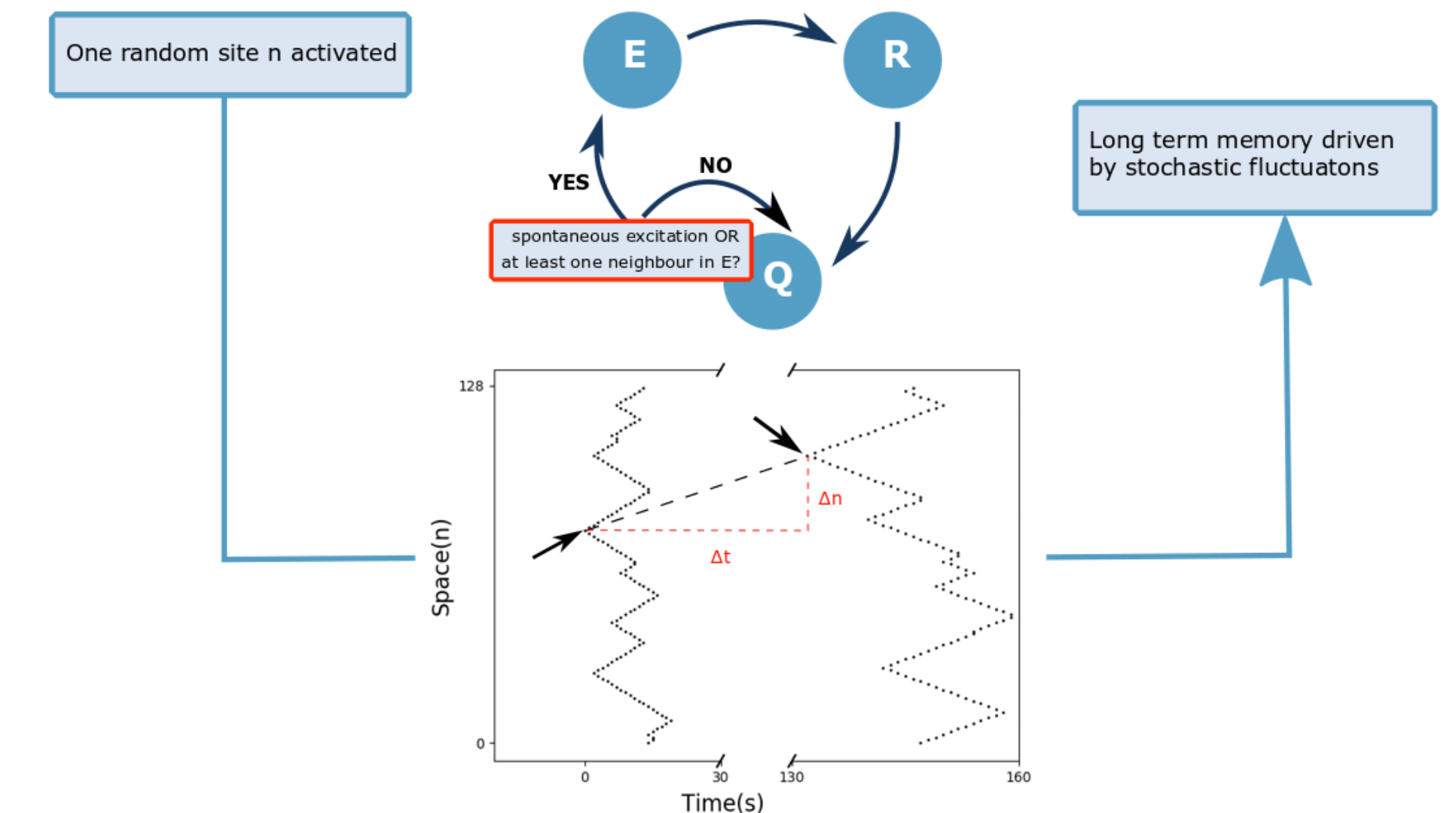


Fig. 2. Flow chart of the computational model

Preliminary Results

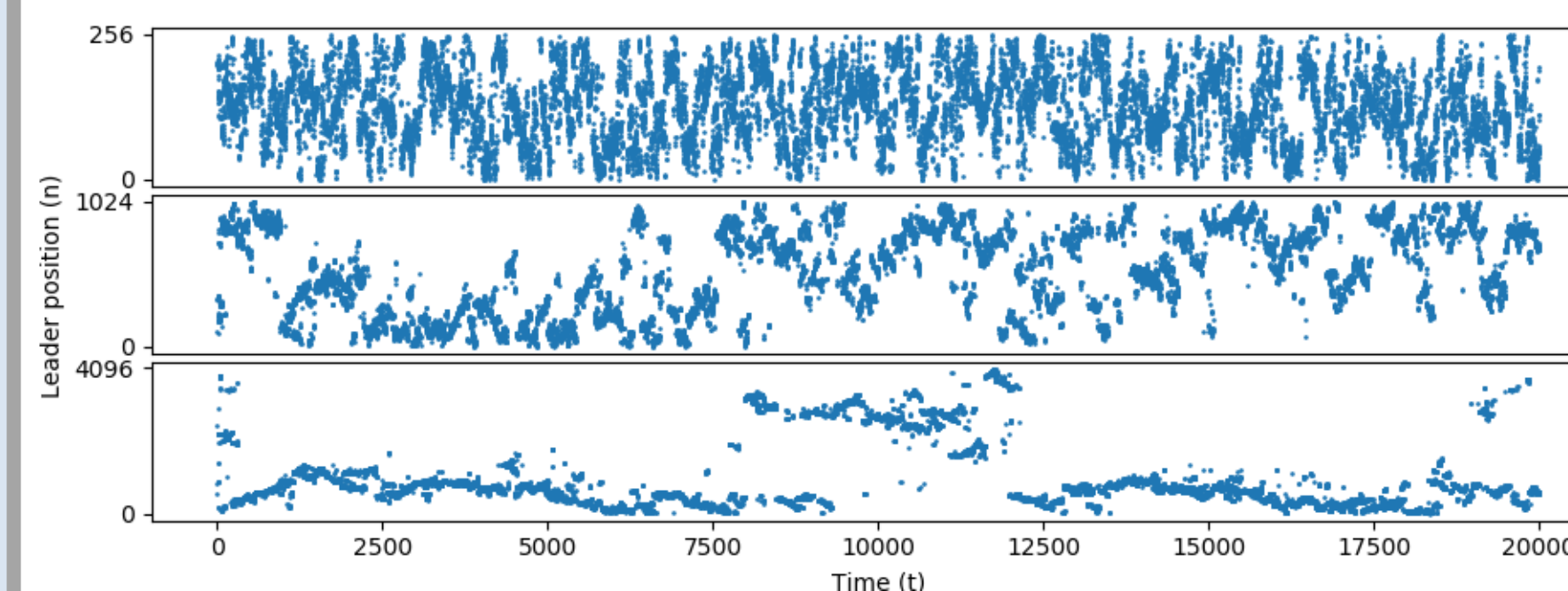


Fig. 3. Consecutive positions of leaders in each firing event over 20000 real time steps, for system sizes $N = 256, 1024, 4096$. The memory effect is more visible in large systems where leader of the next wave tend to stay close to that of the previous wave.

Fig. 4. Power law correlations for system sizes $N = 128, 256, 1024, 4096$ from bottom to top plots: (a) Distribution of shift in leader positions between two consecutive wavefronts, (b) mean shift in leader position as a function of time difference.

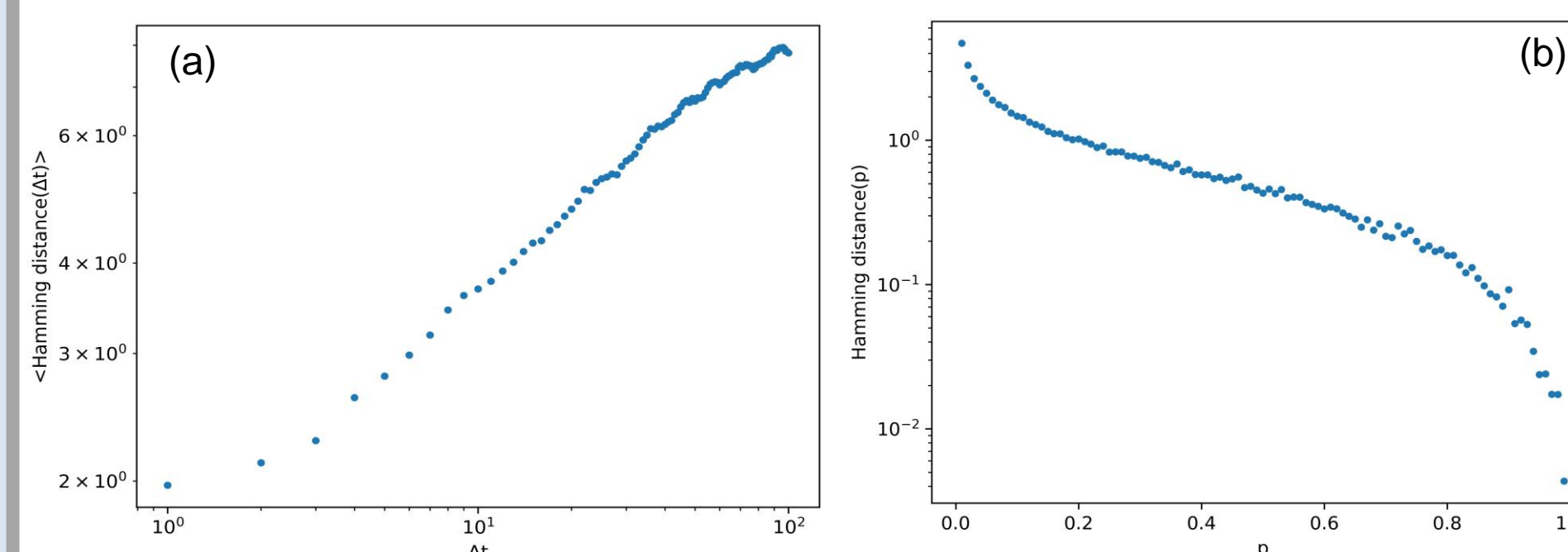
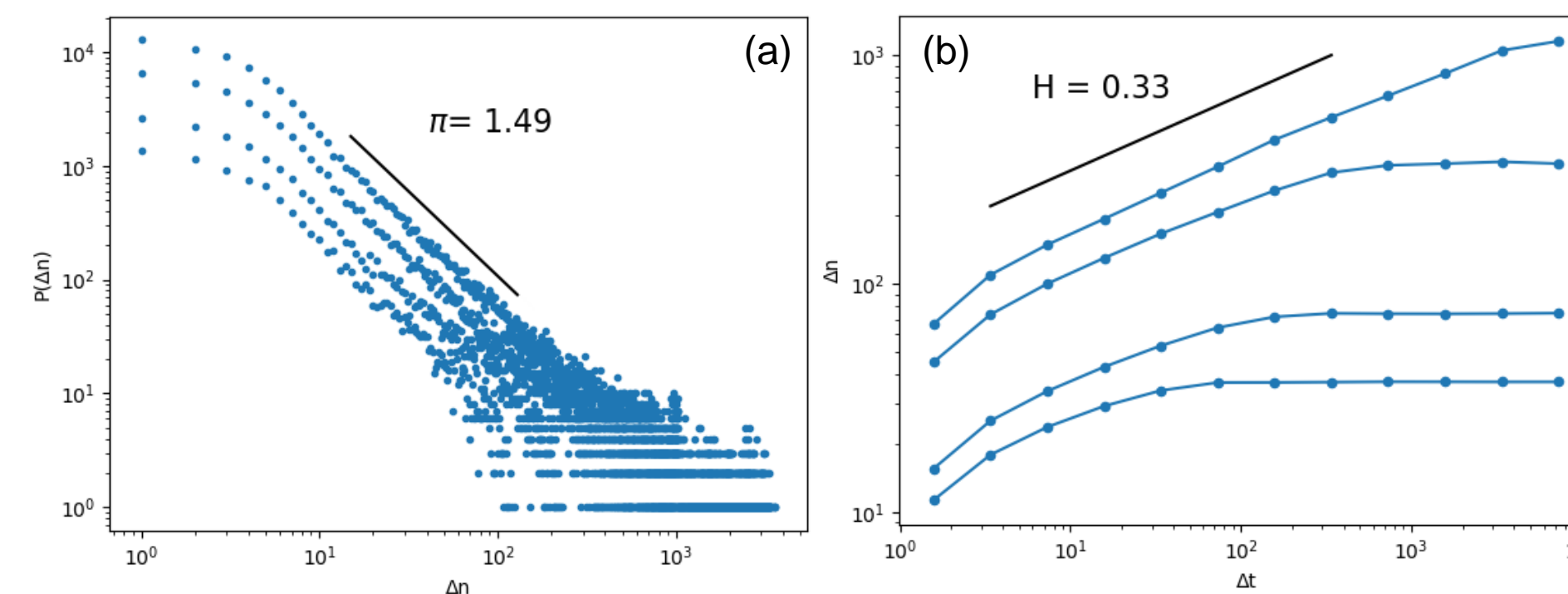


Fig. 5. The Hamming distance as a function of (a) time, and (b) noise for $N = 256$. The hamming distance decreases with noise p , shows a sign of long-term memory.

Conclusions

1. **Excitation in larger systems** – previous activation site is remembered by the subsequent waves.
2. **Power Law** - cutoffs are affected by the system size, the lack of characteristic scale has a similar form in the context of self-organized criticality^[3].
3. **Noise induced memory** – more noise gives longer memory.

This model simulates a condition that the neurons can remain correlated in a relatively lone time scale. We hope with more implications, we can draw links to neuroscience and brain plasticity.

References

- [1] Aarushi Khanna. Action potential - the resting membrane potential - generation of action potentials - teachmephysiology, Aug 2018
- [2] Greenberg J M, Hastings S P. Spatial patterns for discrete models of diffusion in excitable media[J]. SIAM Journal on Applied Mathematics, 1978, 34(3): 515-523.
- [3] Bak P, Tang C, Wiesenfeld K. Self-organized criticality: An explanation of the $1/f$ noise[J]. Physical review letters, 1987, 59(4): 381.