Lab Meeting
-Experiment and Simulation on Temporal Prediction in the Retina-

20161024
Kevin
“Story Line”

- Omitted Stimulus Response (OSR)
- Entrainment under complex intervals
- Prediction in stationary process (predictive info.)
- An adaptive model for prediction
Probing Time Scales in OSR

Response latency (ms) vs. Stimulus period (ms)

Firing rate (Hz) vs. Time after stimuli (sec)

N=12
Predictive Information (PI)
Measurement under Stochastic Input

• Can signatures of prediction be seen under stationary predictable stochastic process?
Time Scale Dependency of PI

\[ I_{\text{pred}}(T) = \log_2 \left( \frac{P(X_{\text{future}}, X_{\text{past}})}{P(X_{\text{future}})P(X_{\text{past}})} \right) \]

\[ = -\left\{ \log_2 P(X_{\text{future}}) \right\} - \left\{ \log_2 P(X_{\text{past}}) \right\} - \left\{ \log_2 P(X_{\text{future}}, X_{\text{past}}) \right\} \]
Adaptive FHN Model

- An adaptive excitable system spikes and oscillates under certain input, and adjusts the excitability or frequency depending on the input.

\[
C_m \frac{dV}{dt} = -g_K n^4(V) \\
\frac{dv}{dt} = v - \frac{v^3}{v} + w + I(t) \\
- g_L(V - V_L) + I_{appl} \\
\frac{dw}{dt} = \frac{1}{\tau}(v + a)
\]
Capturing Characteristics by the Adaptive FHN Model

\[ \frac{dv}{dt} = v - \frac{v^3}{v} + w + I(t) \]

\[ \frac{dw}{dt} = \frac{1}{\tau} (v + \alpha) \]

\[ \frac{da}{dt} = \frac{1}{\tau_a} (a_c - pw - a), \quad a_c = (1 - p) a_0 + p \frac{a_0^3}{3}. \]
**Introduction to PI**

\[ I_{\text{pred}}(T) = \left\langle \log_2 \left[ \frac{P(X_{\text{future}}, X_{\text{past}})}{P(X_{\text{future}})P(X_{\text{past}})} \right] \right\rangle \]

\[ = -\left\langle \log_2 P(X_{\text{future}}) \right\rangle - \left\langle \log_2 P(X_{\text{past}}) \right\rangle - \left[ -\left\langle \log_2 P(X_{\text{future}}, X_{\text{past}}) \right\rangle \right] . \]

\[
\begin{align*}
\lim_{T \to \infty} \frac{S(T)}{T} &= S_0 \\
\lim_{T \to \infty} \frac{S_1(T)}{T} &= 0.
\end{align*}
\]

\[ I_{\text{pred}}(T) = \lim_{T' \to \infty} I_{\text{pred}}(T, T') = S_1(T). \]

\[ \ell(N) = S(N + 1) - S(N) \approx \frac{\partial S(N)}{\partial N}. \]


Efficient Representation


Predictive Error in MMN/OSR

Future Plans (for the next 6 months)

• SfN poster and admission: Nov.-Dec.
  • https://networks.tir.tw/~kschen/web.html

• Thesis(!): Dec.-Mar.
  • Defense schedule?

• $2^{nd}$-order signal and spatiotemporal dynamics: Dec.-Apr.
  • Crucial proof for information process in the system
  • Hypothesis for “distributed” predictors
Prediction with High-order Information

- 2\textsuperscript{nd}-order OSR

- Hidden Markov process
  - Can we generate a processes with same mean, deviation, correlation, but with different predictability!?
HMM vs. O-U Process in Temporal Patterns (Preliminary!)

\[ x_{t+\Delta} = (1 - 1/\tau)x_t + \xi_t \]

\[ I(X_{t-1};X_t) = 1.5126 \text{ bits} \]
\[ I(X_{t-2};X_{t-1};X_t) = 0.3242 \text{ bits} \]

\[ \langle \text{ISI} \rangle = 200 \text{ms} \]
\[ \text{std(\text{ISI})} = 20 \text{ms} \]
\[ \tau_{\text{corr}} \sim 20 \text{steps} \]

\[ x_{t+\Delta\tau} = x_t + v_t \Delta\tau \]
\[ v_{t+\Delta\tau} = [1 - \Gamma \Delta\tau] v_t - \omega^2 x_t \Delta\tau + \xi_t \sqrt{D \Delta\tau} \]
Characteristics of Two Processes Seen in the MI Curve (?)
Spatiotemporal Information

• Double correlation matrix (DCM) method

\[ \dot{y}(t) = \hat{A}(x)y(t) + \Gamma(t), \]
\[ \hat{A} = \hat{B}\hat{C}^{-1}, \]
\[ C_{ij} = \frac{1}{L} \sum_{q=1}^{L} y_i(t_q)y_j(t_q), \quad B_{ij} = \frac{1}{L} \sum_{q=1}^{L} \dot{y}_i(t_q)y_j(t_q). \]

• Local active information storage (LAIS)

\[ a(x_t) = i(x_{t-1}; x_t) \]
\[ = \log \frac{p_t(x_t \mid x_{t-1})}{p_t(x_t)}. \]
