Learning sequence disambiguation with synaptic traces in associative neural networks

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Summary. Sequence disambiguation in an associative neural network with meta-stable sequential attractors and learning capabilities is investigated. We present a neural network that is capable of both learning and correctly recall sequences with the associative Bayesian Confidence Propagation Neural Network (BCPNN) learning rule through the use of synaptic z-traces. The problem of sequence disambiguation is parameterized in this work by the number of previous states required for the network to correctly disambiguate between two competing possibilities. The network disambiguation power is discussed here in terms of its dynamical and structure parameters. The sensitivity of the system to noise under various regimes is also tested.

Central question. The disambiguation of sequences with overlapping states of activity using contextual information is a long standing problem in systems neuroscience [3] (see Fig. 2A-B for examples of sequence disambiguation). Although different neural mechanisms have been proposed in computational modeling, they suffer from either poor disambiguation capabilities, high computational overhead or excessive suceptibility to noise. Following previous work [1, 2] we propose here an extension of the attractor memory model that learns the sequential structure of the input through the associative BCPNN learning rule and examine its disambiguation capabilities.

Approach. The topological structure of the network is presented in Fig. 1A. Recurrent connectivity tends to fix patterns of activation in place whereas feed-forward connectivity coupled with adaptation dynamics together with competition initiate pattern transition (meta-stable attractor states). The dynamics of the network are described in detail by the rate-model in Eq. 1 which contains an adaptation term and binary activation units whose sequential dynamics we illustrate in top of Fig. 2B. The short term dynamical history of the system is preserved in the z-filters (shown in Fig. 1B, middle) which are low-passed versions of the activation characterized by a time constant τ_z. The z-filters are responsible for both unit activation through the current and learning. Learning works by accumulating evidence of independent and correlated activity of unit activation ($\vec{p}$ and $\mathbf{P}$ respectively) and weighting them against each other to calculate the connectivity matrix as show in Eq. 2. The sequential binding of attractors in accomplished by the z-traces (Fig.1C) where contiguously active units developed excitatory connectivity between themselves.
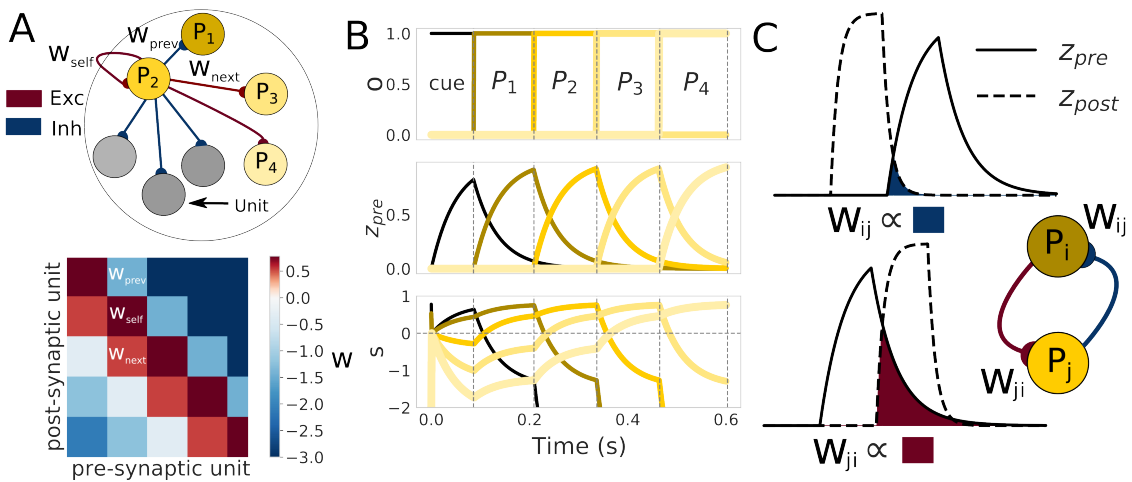

Figure 1: Network: (A) topology (only connections emanating from P_2) and weight matrix, (B) dynamics, (C) learning scheme. Overlap of z-traces (red and blue) leads to temporal binding of units.

$$\tau_s \frac{d\vec{s}}{dt} = \mathbf{W} \cdot \vec{z}_{pre} - g_a \vec{a} - \vec{s} + \sigma d\vec{\xi}(t) \qquad \tau_a \frac{d\vec{a}}{dt} = \vec{o} - \vec{a} \qquad o_i = \begin{cases} 1, & s_i = \max_{hypercolumn} (\vec{s}), \\ 0, & \text{otherwise} \end{cases} \qquad (1)$$

$$\tau_{z_{pre}}\frac{d\vec{\mathbf{z}}_{pre}}{dt} = \vec{\mathbf{o}} - \vec{\mathbf{z}}_{pre} \qquad \tau_{z_{post}}\frac{d\vec{\mathbf{z}}_{post}}{dt} = \vec{\mathbf{o}} - \vec{\mathbf{z}}_{post} \qquad t\frac{d\vec{\mathbf{p}}_{pre}}{dt} = \vec{\mathbf{z}}_{pre} - \vec{\mathbf{p}}_{pre}$$

$$t\frac{d\mathbf{P}}{dt} = \vec{\mathbf{p}}_{pre} \otimes \vec{\mathbf{p}}_{post} - \mathbf{P} \qquad t\frac{d\vec{\mathbf{p}}_{post}}{dt} = \vec{\mathbf{z}}_{post} - \vec{\mathbf{p}}_{post} \qquad \mathbf{W} = \log\left(\frac{\mathbf{P}}{\vec{\mathbf{p}}_{pre} \otimes \vec{\mathbf{p}}_{post}}\right) \qquad (2)$$

Results As can be expected, the success rate (successful trials over total trials) depends on the length of the disambiguation window (the number of overlapping sequence components) across different synaptic time constants, $\tau_{z_{pre}}$ (Fig. 2E). Interestingly, the network's capability to disambiguate sequences with increasing overlap at least with 0.8 success rate does not monotonically grow with $\tau_{z_{pre}}$(Fig. 2) but shows an U-shape with a limited value of optimal conditions for sequence disambiguation. This stems from the interaction of two competing mechanisms: 1) for low values of $\tau_{z_{pre}}$ the z-traces are not active long enough to bridge the required sequence overlap whereas longer values of $\tau_{z_{pre}}$ lead to non-differentiating learning among the sequence (homogeneous weights structure).
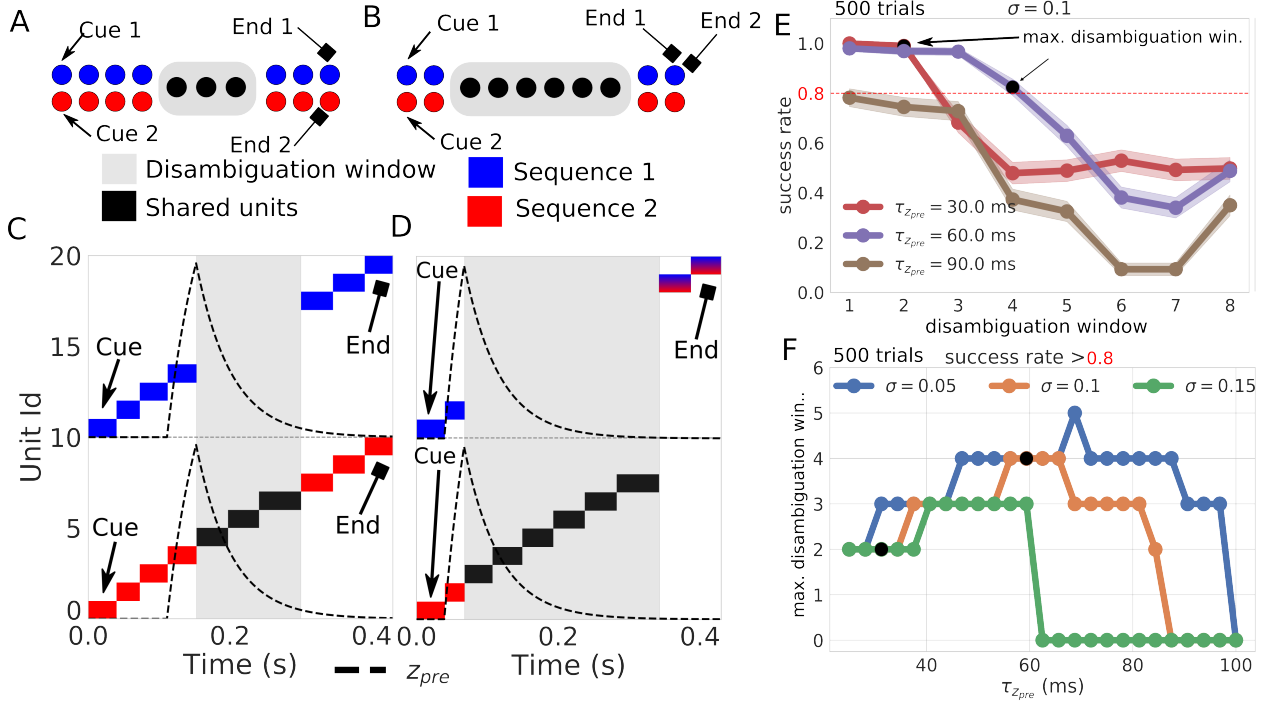

Figure 2: Schematic of the sequence disambiguation problem with either short (A) or long (B) overlap. Short overlap is successfully bridged by the synaptic trace resulting from the unit activation prior to the overlapping component resulting in successful recall of the correct sequence (C). The longer overlap cannot be bridged, which results in unsuccessful sequence disambiguation (D). (E) Success rate of disambiguation (over 500 trials) for varying size of sequence overlap and $\tau_{z_{pre}}$ under noise corresponding to $\sigma = 0.1$. (F) The effect of $\tau_{z_{pre}}$ on the max sequence overlap in a disambiguation task allowing for at least 0.8 success rate under varying noise conditions.

Conclusions. The proposed synaptic trace based BCPNN learning in an attractor network model allows for encoding and successful recall of largely overlapping sequences even in noisy conditions. The upper limit of the overlap window length for successful disambiguation is non-linearly dependent on the time constant of the synaptic traces and monotonically decreases with rising noise levels

References

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