A Neural Implementation of Predictive Coding

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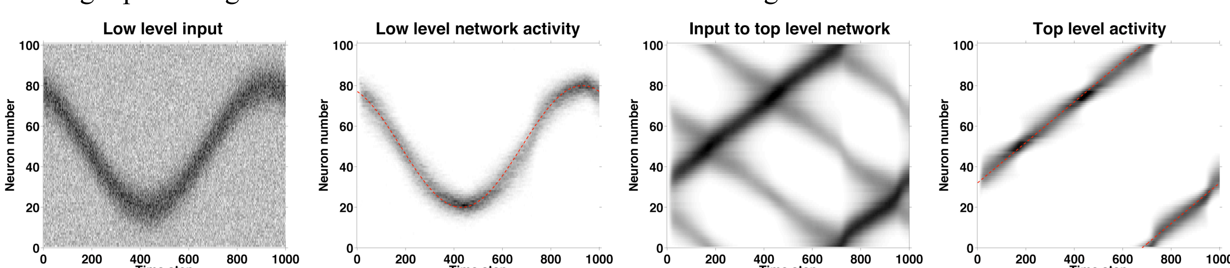
The world is an ever-changing place. To make sense of it, the brain must be able to process a constant stream of noisy input data in real time and in an (apparently) optimal manner in order to be able to direct behavior. Formally, to achieve optimality, the brain *ought* to be performing some sort of Bayesian filtering; yet how such computations can be performed in neural networks is still an open question [1, 2]. In a previous abstract to this conference [3] we extended the work of Deneve et al. [4] to allow optimal decoding of a single moving stimulus with divisive normalization neural networks; and in this work we extend it still further to handle the case of more complex moving stimuli.

For concreteness, we use the example of gait recognition and tracking, in particular the case where we wish to track several different joint angles simultaneously. The approach we take is to build a causal model for the generation of joint angle data, where each joint angle configuration is a function of both the type of gait and the current phase through the gait cycle.

Such a hierarchical scheme maps readily onto a neural network. In particular we encode each joint angle as a bump of activity in a low level network (one per joint angle), and the phase angle in a high level network, with one high level network for each gait. Feedforward connections from low to high level networks implement an inverse model of the system, connecting effect to possible cause; while feedback connections propagate predictions of the causal model back to the input layer. Recurrent connections in both layers perform two functions. The first is to make a 'within layer' prediction; while the second is to try to explain away inputs by providing inhibition to the places where input (either from below or above) is expected to appear at the next time step. The resulting network can be shown to be approximating predictive coding [5].

The figure illustrates some of the properties of the network. On the left is a noisy input signal corresponding to one of the time varying joint angles. Next, the low level network decodes this input with the help of top-down signaling to produce a much cleaner signal. All of the low level networks input into the top-level network. Since each joint angle is associated with two high-level phase angles (i.e. on the forward and reverse parts of the motion), this input is not a single bump, but many. However, the high level network, with the help of inhibitory recurrent connections, is able to decode this input to reveal the single phase angle that can be fed back to inform the decoding in the low level networks.



References
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