Critical subnetworks for feature integration

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For understanding complex visual scenes, our brain has to integrate local, distributed information into global, coherent percepts. This computational process is fundamental for important functions such as contour integration, figure-ground segregation and, ultimately, object recognition (e.g. [1-2]). In our contribution, we propose that feature integration can be performed most efficiently when the neural dynamics of "figure"-encoding networks is close to a critical state [3]. In such a regime, avalanches of spiking events are observed on all length scales, thus rendering figures in a scene "visible" for coincidence detectors in higher visual areas.

We consider the analytically tractable network model of Eurich-Herrmann-Ernst (EHE) units [4] and we simulate a large network embedded with N_e subnetworks of recurrently, excitatorily coupled units, each representing a "figure". Each subnetwork of N_s units is poised at the critical state and competes with other subnetworks through inhibitory connections. We then present the network with semi-realistic stimulus pairs, mimicking a 2-AFC task: one containing a complete figure and K random background elements, and one without a figure, consisting purely of random elements. When a figure is present, the units belonging to the corresponding subnetwork are externally driven and the avalanche statistics of this subpopulation is critical while the rest of the network remains subcritical. When no figure is present, critical dynamics are not observed. We take advantage of this knowledge to conceive a read-out mechanism based on detecting avalanches above a threshold size s_0 and quantify the 2-AFC task performance.

In our simulations, we observe robustness of feature integration against increasing numbers K of activated background units. For a fixed observation time interval T, we find an optimal threshold s_0 for maximizing detection performance. Furthermore, we compute phase diagrams delineating regions in parameter space where detecting coincidences performs better than using rate detection schemes, and vice versa. Moreover, the use of the EHE model allows to analyze the observed dynamics in a simplified setting with purely excitatory couplings. As can be expected, feature integration without inhibition is less stable, but the analytical treatment reveals closed-form expressions for avalanche distributions, thus enabling a comprehensive understanding of our numerical observations.

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