



Fig. 6. Two re-drawings of the ice-cube model, emphasizing (top) the functional anatomy and (bottom) the processing. A retinotopic array (the tilted plane) and a sampling of superficial-layer cells drawn (scale not included) on fibres representing hypercolumns. (Top left) Inter-columnar connections are not only between iso-orientation cells. (Top right) Notation for a game theoretic interpretation of inter-columnar processing; see text for details. (Bottom) Here cells are drawn as oriented segments to show their orientation preference. The thickness of the orientated bars denotes activity of cells; initial values in time (bottom left) and then later (bottom right) denote processing in time, which may be viewed as a selection process along each fibre. Dynamics are not shown.

curvature in particular, is necessary to understand why co-aligned facilitation is dominant but not unique; there are an important (and predictable) number of non-co-aligned facilitatory influences that play key processing roles.

2. The columnar machine

We begin by re-drawing the ice-cube model to illustrate the possibility of geometric information processing. We focus on columns with the same monocular specificity and drop deep layers. We depict the orientation hypercolumns as vertical fibres distributed over a retinotopic array (the tilted plane) and we display the orientation preference of cells within each hypercolumn as oriented segments (Fig. 6). When organized in this fashion, a geometric view of processing emerges, in which the fibre of orientations at each position in the retinotopic array abstracts the orientation hypercolumn, and the arrangement of neighbouring fibres suggests an architecture that is specialized to support interaction between orientations. All orientations in nearby columns are clearly in a position to interact.

Mathematically we conceptualize this interaction by thinking of the different orientations at each position as “labels” and the measure of activity of each neuron as the probability that the neuron is signaling the correct

orientation for that retinotopic position. Interactions are modeled as a compatibility function ($r_{ij}(\lambda_1, \lambda')$ in the top right of Fig. 6) between orientation λ' at position j with orientation λ_1 at nearby position i . In game-theoretic terms, one can think of this function as representing the *payoff* that player i gets by choosing strategy (label) λ_1 when player j plays strategy λ' . The goal is to seek an equilibrium for this game. Diagrammatically we illustrate this with the thickness of the orientated bars, with thicker bars denoting more activity or higher probability (bottom of Fig. 6). Note that this can be viewed as a selection process. The initial values are spread out along each fibre (bottom left, Fig. 6), but the final values concentrate on a single, or a small number, of distinct orientations (bottom right, Fig. 6).

Dynamics are not shown in this diagram, but are key to specifying the manner in which abstract computations map onto networks of real neurons. We have developed one way to do this, which is consistent with biophysics at least to low-order. Imagine neurons as players in the above game, with pure strategies being whether the neuron should depolarize (spike) or hyperpolarize [36,37]. Modeling neurons as piecewise-linear amplifiers, synapses (compatibilities) as conductances, etc., they can be placed in the above form. The key idea behind our model is to consider groups of tightly interconnected excitatory neurons capable of bringing themselves to saturation feedback response following a modest initial