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Sampling and Noise in Vision Networks

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This research is part of the Human Interface Research Branch-Vision Group's program to develop computable models of biological solutions to general vision system problems. Two problem areas are addressed: (1) effects of discrete sampling by receptors and (2) effects of visual system noise.

I. Image sampling

This research program originated as a collaboration with J. Yellott of UC Irvine on the question of why aliases are not seen in our normal vision as they are in images from other sampled systems. It has developed into a collaborative program with Yellott on the consequences of image sampling with the constrained sampling array disorder found in the retina.

A. Retinal cone arrangement models (Ahumada and Poirson, 1987). A hard disk packing algorithm with random variation in disk diameter can generate sampling arrays with the same sampling properties as the primate central fovea. 2. Peripheral cone positions (Yellott, 1983). The sampling properties of the peripheral cones are well represented by those of a Poisson hard disk process. 3. Red-green cone arrangement (Ahumada, 1987a). Simulated annealing allows models for the arrangement of the red and green cones to vary in disorder up to the maximum amount of order allowed by the cone array.

B. Receptor position learning models. Learning mechanisms can copy the detailed arrangement of receptor positions to higher levels of the visual system. 1. Weight adjustment models (Ahumada and Yellott, 1988a). Kohonen-like competitive learning models can construct topologically correct maps. 2. Position adjustment (Ahumada and Yellott, 1988b). Error-correcting position adjustment can generate maps with exact local position information and variable global magnification.

C. Interpolation network learning models. Interpolation of the sampled image allows further processing to ignore the details of the sampling. 1. Chen-Allenbach interpolation (Yellott, 1988). A generalization of their least squares interpolation works with both irregular spacing and variable density. 2. Network learning (Ahumada and Yellott, 1988b). A network implementable gradient descent learning algorithm allows the required matrix inverting network to be learned by spontaneous activity and self-generated feedback. 3. Related computational methods. Related algorithms can provide very efficient inversion of sparse matrices. They are also useful for inverting image encoding transformations.

II. Visual system noise limiting signal detection.

This research has been a collaboration with A. Watson and K. Nielsen at Ames, B. Wandell at Stanford, and D. Pelli at Syracuse. Matrix methods of signal processing are applied to visual models.

A. Equivalent noise of linear models 1. Spatial noise (Ahumada and Watson, 1985) Low contrast detection and recognition models can be represented either by a single filter with white noise or by an equivalent image noise. 2. Temporal noise (Watson, 1988) This concept is extended to the continuous temporal domain to provide a rational definition of neuronal signal detectibility.

B. Equivalent spatial noise of a nonlinear model (Ahumada, 1987b) For high contrast signals, masking dominates which can be represented as nonlinear signal compression or as stimulus-induced visual system noise.

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