

and other application prototypes possible (Alex Malozemoff, American Superconductor). American Superconductor can produce 10 km of multi-filament BSCCO tape per month, in 1,000-m lengths. Critical current density (J_c) in these tapes can now exceed $44,000 \text{ A cm}^{-2}$. Malozemoff noted that, since 1990, BSCCO wire performance has followed a consistently linear upward trend with time.

Where will it stop? Small regions of BSCCO embedded in the tape, especially near the silver-cladding interface, have been observed magneto-optically to have $J_c > 10^5 \text{ A cm}^{-2}$ at 77 K (David Larbalestier, Univ. Wisconsin). Beyond this limit, and especially to service high-magnetic-field applications at liquid-nitrogen temperatures, a new technology will be needed.

One is already on the horizon (see my earlier News and Views article, *Nature* **375**, 107–108; 1995). Workers from the Los Alamos and Oak Ridge National Laboratories revealed their latest results for biaxially oriented coatings of YBCO (yttrium–barium–copper oxide) on flexible metal tape substrates. The Los Alamos group produces substrate texturization with an auxiliary ion gun during deposition of a buffer film between the metal tape and the YBCO, whereas Oak Ridge directly textures the metal tape using a combination of metallurgical deformation techniques. Texturization is important in producing low-angle grain boundaries and thus good inter-grain coupling. Los Alamos has now observed critical currents of 200 A at liquid-nitrogen temperatures in 2- μm -thick YBCO in short lengths 1 cm wide, a J_c of 10^6 A cm^{-2} .

The Oak Ridge group principally described the textural properties of their method, which at the time of the Houston meeting had produced a J_c of only around 10^5 A cm^{-2} . But while writing this review, I've heard that portions of their samples now have $J_c \approx 5 \times 10^5 \text{ A cm}^{-2}$, an important improvement given that metallurgical texturization may be scaled up to manufacturing processes more easily than ion beam bombardment.

In the meantime, the improving performance of 'first generation' BSCCO wire seems certainly enough to satisfy a number of anticipated applications in the next five years, especially transmission cable. The principal uncertainties are cost and market acceptance of this new technology. The generally acknowledged commercial target for cost/performance is $\$10 \text{ kA}^{-1} \text{ m}^{-1}$, but the latter factor, acceptance, is by far the greater challenge. If the next decade is to see deployment of HTSC wire in power applications, as much attention, if not more, needs to be given to this area as to improving the technology itself.

The workshop was a major event for all of us in the high- T_c trade. As a Hollywood columnist might have put it, it was a bash

where almost everybody who's anybody participated. The next great event will be the American Physical Society March Meeting in 1997 in Kansas City, bringing with it the tenth anniversary of our Woodstock. Unfortunately, this celebration will have to be held somewhere within the confines of a midwest conven-

tion centre, not in the Grand Ballroom of the New York Hilton where it all began. What a pity. □

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VISUAL PERCEPTION

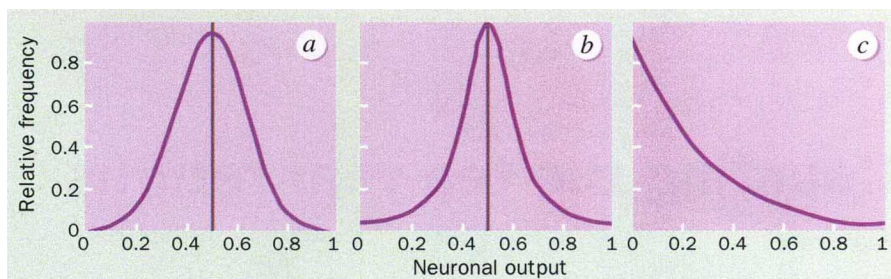
An efficient code in V1?

Roland Baddeley

THE primary visual cortex (V1) is the first cortical area to receive visual input from the eyes. For over 30 years it has been known that the neurons in this part of the brain are sensitive to bars of light of various orientations and sizes^{1,2}, and this phenomenon constitutes a common, crucial stage of visual perception in mammals. What has been far less clear is why neurons in V1 show such selectivity.

neighbouring measurements. Therefore, by using such a code, efficient transmission is achieved because the intensity information is preserved while allowing the minimization of some measure of neuronal output capacity such as total variance.

Several researchers have explored this notion of efficiency. By using estimates of the correlation in image intensity in natural scenes as a function of distance, character-



What is a sparse representation? For a system with binary outputs, sparsity can be simply equated with a low average firing probability. For a system with continuous outputs, a definition is more difficult. But one method is to define a measure of how 'peaked' the distribution of outputs is around its mean. Consider the distribution of outputs from a single 'filter' when presented with a large collection of natural images. If the filter has random spatial weightings, then by the central limit theorem we would expect the distribution of outputs to be gaussian (a). If, on the other hand, the weightings of the filter matched some nonrandom structure in the images, we may find a non-gaussian output distribution. One simple way a filter's output distribution could differ from gaussian is to be more concentrated around its mean value (b), and a representation with an output distribution that resembles b rather than a is called 'sparse' (see the paper under discussion³). Another reason for having such filters is that they minimize the output entropy for a fixed output variance³. Given the more biologically plausible constraint on the average firing rate of the neuron (and hence metabolic cost), one particular sparse output distribution (c) maximizes output entropy.

On page 607 of this issue³, Olshausen and Field describe some simulations that shed light on this question. They show that, for an appropriate definition of 'efficiency', the response properties of neurons in V1 qualitatively (and in some aspects quantitatively) resemble the most efficient linear representation of natural images possible.

Their definition of efficiency is probably best understood by reference to the coding performed by a more peripheral part of the visual system — the retinal ganglion cells that provide the output from the eye to the brain. Rather than simply signalling raw local image intensity, these cells appear to signal the difference between the intensity at a given location and that predicted from neighbouring locations. Image intensity in natural scenes is highly predictable from

izing potential sources of noise, and formalizing efficiency (for example using information theory), predictions of the precise form of processing can be made. Such an approach has led to accurate quantitative predictions of contrast sensitivity^{4,5}, colour sensitivity⁶ and the form of inhibition in fly retina⁷.

Unfortunately, early attempts to apply the same notion to the coding performed by cells in the primary visual cortex have been less successful. One method that has had some popularity is a form of factor analysis, known as principal components analysis (PCA), which finds the linear combinations of image intensities (components) that capture as much of the variation in natural images using as few components as possible. Although there

are some similarities between the neuronal properties predicted by this method and those observed empirically (the lower order components are well described as spatial and orientation derivatives of various orders⁸), it is far from adequate as a general model. The resulting spatial weightings only vaguely resemble those observed in V1 and, more importantly, PCA is only appropriate if the number of components is far less than the number of inputs (the number of neurons in V1 is much larger than the number of cells from the lateral geniculate nucleus providing input). Accounting for the variation in images alone is an insufficient constraint on coding to generate the properties of cells in V1.

What Olshausen and Field now show is that if, in addition to accounting for the variations in the image, representations are also constrained to be 'sparse' (a given image is represented by only a few 'active' cells out of a potentially much larger number — see figure), then the optimal representation of natural scenes possesses many similarities to the representation found in V1. The simulations reported provide an impressive existence proof that simple learning rules can be used to determine receptive-field-like structures. With an intuitive definition of efficiency, optimized using a simple neural-network learning rule, the representations generated share many qualitative similarities to those found in V1.

The question then becomes why these principles should underlie the processing performed. Olshausen and Field argue that there are two reasons: sparsity could be a signal that 'interesting' image structure has been identified; and sparse representations may be better suited for further processing, independent of whether or not they represent underlying input regularities, because they minimize output entropy for a given output variance.

Two comments seem appropriate. First, although use of characteristics of the output distribution (for example, sparsity) is an accepted statistical method for identifying structure⁹, and Olshausen and Field present three simulations showing that optimizing sparsity can indeed identify the desired structure, sparsity alone

does not necessarily identify 'interesting' structure because very sparse representations can be found for trivial reasons. Specifically, if the local intensity variance is not constant, then any filter with spatial weightings that sum to zero will generate a sparse representation¹⁰.

Second, it is not clear that output variance is an appropriate measure of neuronal channel capacity, as Olshausen and Field implicitly argue when they propose that sparse codes minimize output entropy. Rather, because the brain uses a large amount of energy, and V1 is the largest visual area in the brain, any strategy that would minimize energy use would be useful. Instead of constraining neurons by output variance, it seems more appropriate to

constrain their average firing rate. A code that maximizes output entropy when constrained by a given firing rate will be sparse — in fact the distribution of output states will be exponential¹¹. One of the proposed measures of 'sparsity' measured average firing rate ($|x|$), and this, it is claimed, will also generate V1-like receptive fields. So a potentially simpler explanation of Olshausen and Field's results is that the representations of the world found in V1 are 'efficient' simply because such representations will consume less energy. □

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GROWTH FACTORS

Mad connection to the nucleus

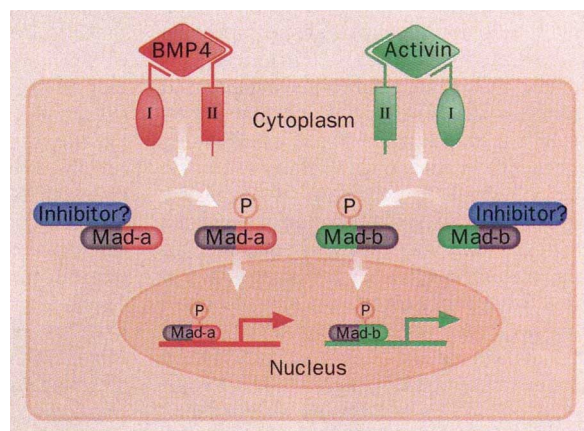
Christof Niehrs

MEMBERS of the transforming growth factor- β (TGF- β) family of proteins have a large part in cell signalling in animals. Expansion of genes encoding them was probably a milestone in vertebrate evolution, for they carry out such a wide variety of duties in development: they regulate the responses of some cells to other growth factors; they regulate cell growth and differentiation; and they act as inductive signals in the embryo. Very little is known about TGF- β signal transduction from the cell membrane to the nucleus, but three new papers present insights into the process. On page 620 of this issue¹, Liu *et al.* identify so-called *Mad* genes as encoding a previously unknown class of transcription factors which act downstream of TGF- β signals. And in *Cell*^{2,3}, two groups describe fruitful investigations into the regulation and specificity of *Mad* protein function.

About 40 members of the TGF- β gene superfamily are known to encode secreted proteins. These form homo- or heterodimers, so total TGF- β ligand diversity is high. The receptors for TGF- β ligands consist of complexes of a type I and a type II transmembrane serine/threonine kinase. There are a number of type I and type II isoforms that could by combination account for considerable receptor diversity⁴. Probably as a result of this

ligand/receptor variety, a single cell seems to respond differently when challenged with different concentrations or types of TGF- β proteins.

For example, the product of the TGF- β -type *Drosophila* gene *decapentaplegic* (*dpp*) acts as a morphogen in patterning of the embryonic wing, where it can elicit



Model of the *Mad* signal-transduction pathway in TGF- β signalling. A TGF- β ligand, here BMP4 and activin, binds and activates the transmembrane serine/threonine kinase of its corresponding type I/II receptor complex⁴. Either directly or by an unknown kinase cascade, this event activates the phosphorylation of a ligand-matched *Mad* protein in the cytoplasm. Phosphorylation enables *Mad* to move into the nucleus, which may also require dissociation of a hypothetical inhibitory protein interacting with the amino-terminal *Mad* domain (black) or direct unmasking of a nuclear localization signal. Once in the nucleus, *Mad* mediates transcriptional activation of specific genes.

various responses at various doses. Thus, an individual cell appears to distinguish different concentrations of *dpp* protein and respond accordingly (as discussed in News and Views last month⁵). Similar observations have been made in *Xenopus* embryos, where the animal cap system is

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