Chapter 5

Computational neuroscience

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5.1 Advances in statistical generative models

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In this project, various extensions to the theory of independent component analysis and blind source separation were developed.

First, we developed different methods of performing blind source separation using other information than that used by ordinary ICA. These new methods exploit the temporal structure of the signals.

The first method [1] models signals using nongaussian autoregressive models. As in basic ICA, nongaussianity is paramount here, but in this case it is not directly the nongaussianity of the signal, but of the noise (innovation) signal that drives the autoregressive process. This can also be understood as finding those projections of the data that are the most "interesting": Those projections that are the most structured are considered as the most interesting. This is reminiscent of the basic ICA estimation principle: Find those projections that are the most structured in the sense of being the most nongaussian.

A second method [2] in the same vein considers signals that have nonstationary variance. This is a very different form of time structure from the one above. We showed how such a structure can be interpreted simply using cumulants, which also provide an efficient algorithm in the same way as FastICA.

What these two methods have in common is the extension of the separation ability to gaussian signals. Whereas ordinary ICA can only separate nongaussian signals, these two methods can separate gaussian signals if other properties of the signals match those used in the underlying models. An example of a gaussian signal that can be separated by the latter method is given in Fig. 5.1.

All commonly used methods for ICA assume that the number of independent components is not larger than the number of observed signals. If there are more independent components, estimation becomes much more complicated. This case, called the case of "overcomplete bases" requires new estimation methods. Previously proposed methods are computationally very demanding, so we attempted to find algorithms that can do the computations needed for the estimation with reasonable computational load. The methods we found [3] are based on rather heuristic extensions of some well-known ICA estimation principles.

Also, we investigated a very interesting and surprising connection between ICA and the well-known nonlinear regression method of backpropagation using multi-layer perceptrons. We showed [4] that if the data is modelled by ICA, the theoretically optimal nonlinear regression is very closely approximated by a multi-layer preceptron whose weight vectors are given by the elements of the ICA mixing matrix

Finally, we developed a method [5] for using prior information in ICA estimation. We argued that the most interesting form of prior information that one can use in this context is the information on the sparseness of the mixing matrix, i.e. most elements of the mixing matrix are practically zero. Such a prior can easily be incorporated in ICA estimation because it is a conjugate prior, thus no new algorithms need to be developed because the prior information can be expressed in the form of a virtual sample, i.e. addition of artificial data to the sample.

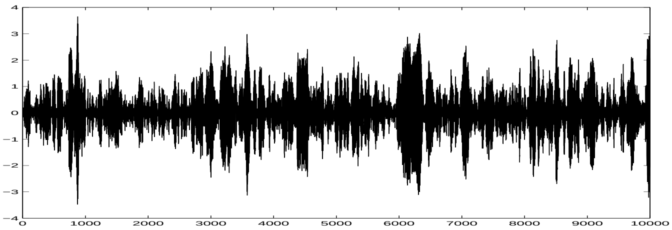

Figure 5.1: A signal that is gaussian, i.e. cannot be separated by ICA from linear mixtures. Our new method [2] can separate this kind of signals, however.

References

[1] A. Hyvärinen. Complexity pursuit: Separating interesting components from time-series. *Neural Computation*, 13(4):883–898, 2001.

[2] A. Hyvärinen. Blind source separation by nonstationarity of variance: A cumulant-based approach. *IEEE Trans. on Neural Networks*, 12(6):1471–1474, 2001.

[3] M. Inki and A. Hyvärinen. Two methods for estimating overcomplete independent component bases. In *Proc. Int. Workshop on Independent Component Analysis and Blind Signal Separation (ICA2001)*, San Diego, California, 2001.

[4] A. Hyvärinen and E. Bingham. Connection between multilayer perceptrons and regression using independent component analysis. *Neurocomputing.* in press.

[5] A. Hyvärinen and R. Karthikesh. Imposing sparsity on the mixing matrix in independent component analysis. *Neurocomputing.* in press.

5.2 Statistical models of visual processing

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Our research concentrates on modelling visual perception using statistical models. We build models of the statistical structure of the typical input that the perceptual system receives, and estimate the parameters of the model from realistic input, such as digital photographs of wild-life scenes. We then describe the function of parts of the visual cortex as statistical estimation and inference in such models.

Our modelling has been largely based on independent component analysis (ICA), a statistical technique that has recently gained widespread attention in neurocomputing and signal processing. The goal is to transform a data vector into components that are statistically independent. In [1,9] it was shown that ICA applied to natural image input yielded features closely resembling the spatial receptive fields of simple cells in the mammalian primary visual cortex. We have extended this result by showing that ICA can also explain chromatic and binocular properties of simple cell receptive fields. This was done by applying the method to natural colour and stereo images and comparing the learned features (see Figure 5.2) with known receptive field properties [3].

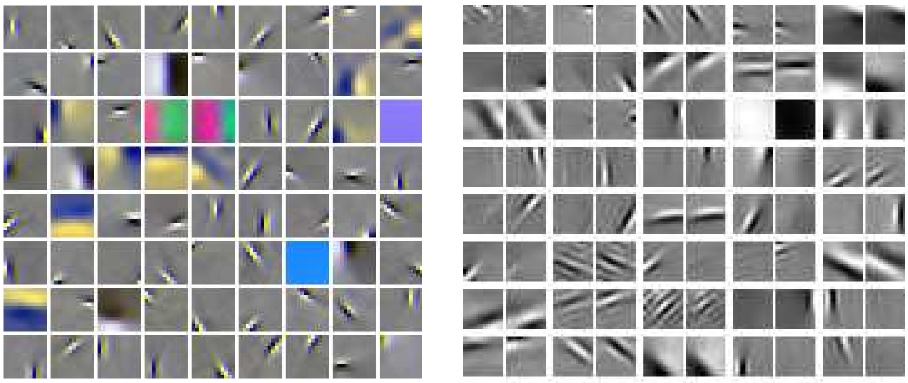

Figure 5.2: ICA features from colour and stereo image data. Left, a small subset of features estimated from colour images. Right, features from stereo images (each pair of patches depicts one binocular feature).

We have also developed extensions of ICA to model further properties of the primary visual cortex. Specifically, we wanted to additionally explain the response properties complex cells (the second major functional class of cells in the primary visual cortex) as well as the columnar structure of the cortex. For this purpose, we have developed a model called *topographic independent component analysis* [8], that applied to natural image data yields both simple and complex cell receptive fields and a topography like that observed in the visual cortex [6,7]. Figure 5.3 shows an estimated basis for image data.

Can further properties of the visual system be explained by this information-theoretic approach? We have considered how the responses (to natural images) of complex cells could be sparsely represented by a higher-order neural layer [2]. Essentially, we filtered our images with a widely accepted complex-cell model (see Figure 5.4) and performed ICA on this data. This leads to an interesting kind of contour coding, where units are selective to the contour length. A subset of the learned components is shown in Figure 5.5. In addition, the model can explain certain extra-classical receptive field effects of neurons in the visual cortex.

We have also started to explore the statistical structure of natural image sequences,

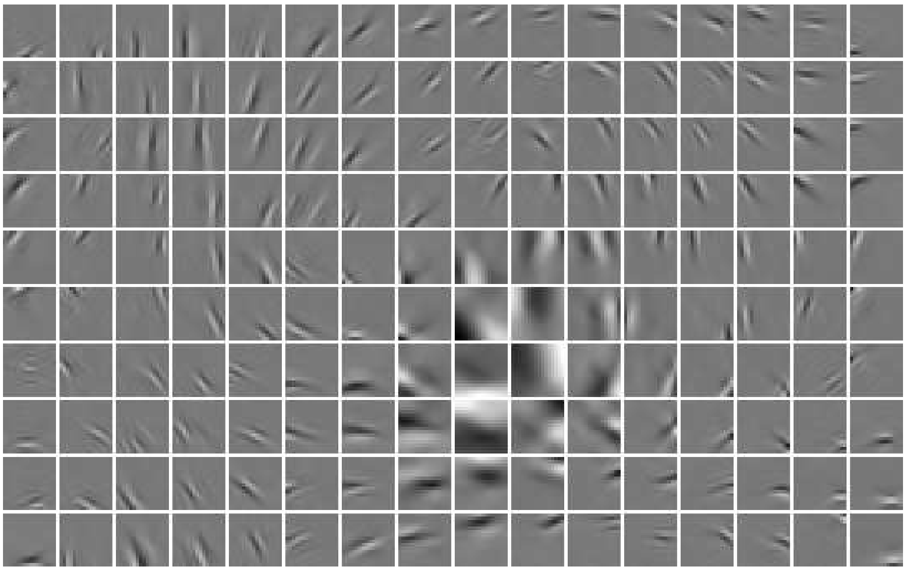

Figure 5.3: Topographic independent component basis estimated from natural image data. Each patch corresponds to the receptive field of a simple cell, whereas the responses of the model complex cells are given by locally pooled responses of the simple cells. Note that neighboring units tend to have similar location, orientation and spatial scale, making the topography very similar to the one found in the visual cortex.

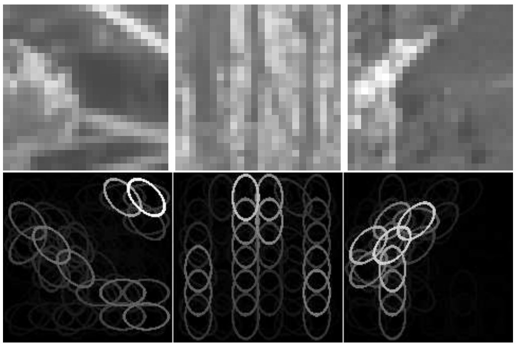

Figure 5.4: Illustration of the complex-cell responses to natural image patches. Top row: Three patches from our set of natural images. Bottom row: Corresponding responses of the model complex cells to the patches. The ellipses show the orientation and approximate extent of the individual complex cells. The brightness of the different ellipses indicate the response strengths.

that is, natural video. We have developed a simple model of the temporal structure of linear filter outputs based on a nonlinear form of autocorrelation. This approach leads to the emergence of simple cell properties as well [4]. Thus, we have an alternative approach to sparse coding or independent component analysis. The advantages of this alternative approach are a problem that we will investigate in the future.

In addition to these experiments regarding natural image statistics, we have also investigated the theoretical foundations of independent component analysis, as related to the neurobiological principle of maximum information transfer (infomax). In [5] it was shown that the standard formulation of nonlinear infomax is very sensitive to the assumed nonlinearity, but that an alternative formulation based on a non-Gaussian noise model gives similar predictions but is much more robust.

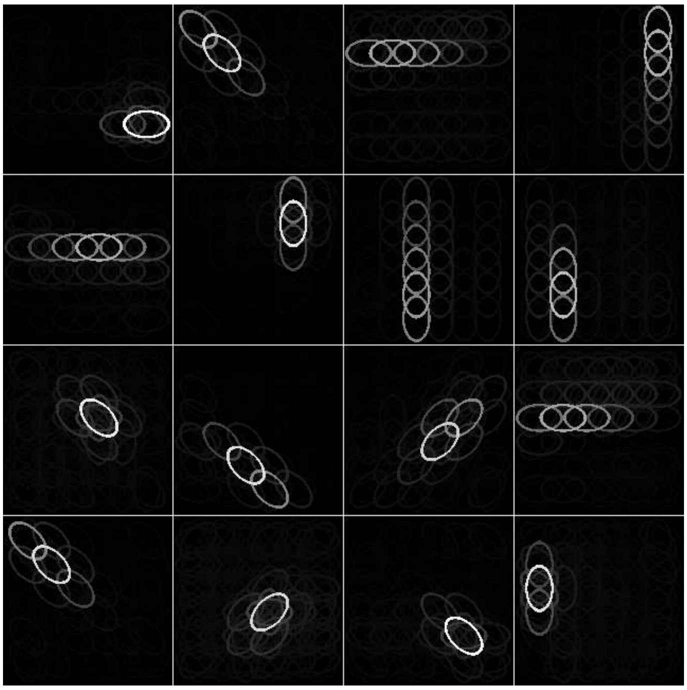

Figure 5.5: A subset of the learned higher-order features. The features code for *collinear* active complex cells, representing contours of varying length in the images.

References

[1] A. J. Bell and T. J. Sejnowski. The 'independent components' of natural scenes are edge filters. *Vision Research*, 37:3327–3338, 1997.

[2] P. O. Hoyer and A. Hyvärinen. A multi-layer sparse coding network learns contour coding from natural images. *Vision Research*. In press.

[3] P. O. Hoyer and A. Hyvärinen. Independent component analysis applied to feature extraction from colour and stereo images. *Network: Computation in Neural Systems*, 11(3):191–210, 2000.

[4] J. Hurri and A. Hyvärinen. Simple-cell-like receptive fields maximize temporal coherence in natural video. Submitted.

[5] A. Hyvärinen. An alternative approach to infomax and independent component analysis. *Neurocomputing*. In press.

[6] A. Hyvärinen and P. O. Hoyer. Emergence of topography and complex cell properties from natural images using extensions of ICA. In *Advances in Neural Information Processing Systems*, volume 12, pages 827–833. MIT Press, 2000.

[7] A. Hyvärinen and P. O. Hoyer. A two-layer sparse coding model learns simple and complex cell receptive fields and topography from natural images. *Vision Research*, 41(18):2413–2423, 2001.

[8] A. Hyvärinen, P. O. Hoyer, and M. Inki. Topographic independent component analysis. *Neural Computation*, 13(7):1527–1558, 2001.

[9] B. A. Olshausen and D. J. Field. Emergence of simple-cell receptive field properties by learning a sparse code for natural images. *Nature*, 381:607–609, 1996.