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Bio-computational model of object-recognition: Quantum Hebbian processing with neurally shaped Gabor wavelets

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Abstract

Theoretical and simulational evidence, as well as experimental indications, are accumulating that quantum associative memory and imaging are possible. We compare these data with biological evidence, since we find them to a significant extent compatible. This paper presents a computationally implementable integrative model of appearance-based viewpoint-invariant recognition of objects. The neuro-quantum hybrid model incorporates neural processing up to *V*1 and quantum associative processing in *V*1, achieving together an object-recognition result in *V*2 and ITC. Results of our simulation of the central quantum-like parts of the bio-model, receiving neurally pre-processed inputs, are presented. This part contains our original simulated storage by multiple quantum interference of image-encoding Gabor wavelets done in a Hebbian way, especially using the Griniasty et al. pose-sequence learning rule.

Keywords: Vision; Object-recognition; Quantum; Gabor wavelets; Griniasty et al.; Temporal sequences; Holography; ICA

1. Introduction

It is reasonable to make a model of human conscious visual experience (Lamme et al., 2000) that incorporates quantum information-processing parts where they outperform purely neural dynamics and better fit neuropsychological phenomenology. The reasons were presented in Peruš (2001b, in press) and Woolf and Hameroff (2001). For a broader context of hypotheses on possible quantum basis or backgrounds of brain processes and consciousness see also Pribram (1993), Hameroff et al. (2002), Matsuno and Paton (2000), and references within these six publications. Some recent hypothetical hints see in Rocha et al. (2001, 2004), Vitiello (2001), Khrennikov (2003), Alfinito and Vitiello (2000) and Xi and Ma (1999).

The aim of this paper is to present an outline of an integrative model of human recognition of objects which optimally obeys biological experimental data and is articulated mathematically in order to allow computational implementation. The paper discusses mainly a combination of two processing phases: the

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first phase is natural production of Gabor-like receptive fields by an information-preserving ("infomax") procedure. The second phase is a Hebbian-like multiple self-interference of the resulting quantum-implemented Gabor wavelets,[1] i.e., a Hopfield-net-like processing of quantum Gabor wavelets as eigen-vectors (which act as attractors). We have implemented and successfully tested the quantum core of the model (the second phase) (Peruš et al., 2004; cf., Loo et al., 2005a,b).

In Section 2, Gabor wavelets and models of their bio-production are presented. In Section 3, three sorts of image representation are discussed. After reviewing biological findings in Section 4, computational models of object-recognition are overviewed in Section 5. Section 6 presents how Gabor wavelets are hypothetically processed in a quantum net to recognize objects. A temporal sequence-based generalization of the Hebb learning rule by Griniasty et al. is presented, in Section 7, as the core of our Gabor wavelet holography. Details on Gabor wavelets used in our simulation are in Appendix A.

2. Output of pre-processing: Gabor wavelets

It is one of the rare detailed agreements of natural vision research (Palmer, 1999; Buser and Imbert, 1992) and computer vision practice that Gabor wavelets (Navarro et al., 1996) are the best descriptors of *V*1 receptive fields and computationally efficient (cf., Wundrich et al., 2002). Gabor wavelets representation is approximately affine transformation invariant, i.e., a Gabor-encoded object is recognized also if translated, rotated, dilated, skewed, scaled (or combined) (Kyrki et al., 2004; Khalil and Bayoumi, 2002). Gabor wavelets (orig. Gabor, 1946) are very similar to quantum-wave-packets or Heisenberg-Weyl coherent states (Lee, 1996; Segman and Schempp, 1993; Feichtinger and Gröchenig in Chui, 1992).[2] Lee (1996) derives conditions under which Gabor wavelets, which are in general non-orthogonal, behave as if they were orthogonal (one says that they form tight frame). This allows good reconstruction of, e.g., high-resolution images from low-precision neural codes. There is physiological evidence (listed in Lee, 1996, Section 6 end; De Valois and De Valois, 1990; cf., King et al., 2000) on an overcomplete (much redundant) and even almost tight-frame Gabor image representation obtained through significant oversampling by the primate visual system. Non-orthogonality and non-compact support of Gabor wavelets is thus no obstacle neither for natural nor artificial object-recognition, since they can be made almost/effectively orthogonal and mainly compact (i.e., with negligible "tails") (e.g., Krüger and Sommer, 2002, Section 2.2; Resconi and van der Wal, 2002, Section 5.3).

Peruš (2001a,b) summarize the bio-evidence on the retino-geniculo-striate pathway. Two simulation-models are relevant for studying its role. The first model is presented in Bell and Sejnowski (1995, 1997). It is based on independent component analysis (ICA) (details: Hyvärinen et al., 2001, 2000).[3] The second model is by Olshausen and Field (1996, 1997). Visual processing along the retino-geniculo-striate pathway seems to maximally preserve information ("infomax") and leads to sparse coding of approximately statistically independent image-components. Sparse coding means that information is encoded by a net having a small ratio of active versus passive neurons. Statistical independence means that the probability distribution of the scene-data is describable as a multiple product of component-factors belonging roughly to objects of the scene.

Both Bell and Sejnowski's ICA net and Olshausen and Field's sparseness–maximization net produce Gabor wavelet outputs as such sparse codes of "statistically separated" scene-components (objects). The produced outputs of the net are biologically plausible, but the (bio)net implementation of the Bell and Sejnowski and Olshausen and Field "algorithms" is not. Peruš (2001a) analyzed that the sparseness-enforcing Olshausen and Field net is more brain-like (according to present limited physiological knowledge) than infomax-enforcing Bell and Sejnowski net, although no bio-counterpart of global top–down enforcing of sparseness has been found (yet). MacLennan's (in Pribram, 1993, Chaper 6 and 7) dendritic field computing model, based on Daugman's, is similar to Bell and Sejnowski's model, except having no explicit sparseness-enforcing (cf., Zhao, 2004).

[1] If you need explanation of these terms, see Peruš (2001c).

[2] Cf. Lie groups (Kanatani, 1990; orig. Hoffman).

[3] On ICA–PCA recognition comparison: Draper et al. (2003). On Gabor–ICA–PCA combination: Liu and Wechsler (2003).