Chapter 1
Introduction to Holonomic–Compatible Models for Vision

1.1 STARTING REMARKS

The purpose of this book is to research possibilities for complementing neural models of early vision with the new preliminary quantum models of consciousness in order to construct a model of human image processing.

Contents. The contents of this book are the following. In the first chapter, a comprehensive introduction to the problem and the basic "tools" for tackling it will be presented and extended. These are the holonomic brain model and some computational models like the Independent Component Analysis (ICA) and quantum-implementable associative networks of coupled oscillators with phase-encoding. In the second chapter, the *Holonomic Brain Theory* of Karl Pribram, especially its part on vision, will be presented. In the third chapter, computational information-

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maximization models like the version of Independent Component Analysis (ICA) of Bell and Sejnowski and the sparseness-maximization net of Olshausen and Field will be presented and discussed in the context of Holonomic Brain Theory and related models. In the fourth chapter, the models of image processing are summarized and integrated into a complete, partially hypothetic, global picture. Some speculations about higher associative, attractor-based and quantum-rooted, visual processing, which gives results (images, episodes) that we are conscious of, are presented. For this purpose, models of dendritic image-processing in V1 and hypotheses on subcellular (e.g., microtubular) and quantum brain processing and binding are reviewed. Consciousness, in particular visual consciousness, and its neural correlates are discussed at the end.

The *second part* of the book provides additional or detailed information – auxiliary to the chapters of the first, main part. In the first auxiliary chapter, no. 6, information processing along visual pathways from retina to cortical areas will be presented as described by the modern main-stream experimental neuroscience (including neurophysiology, neuropsychology, cognitive neuroscience). The neuropsychology of image processing and related processes (like early vision, figure/ground segmentation, visual memory, object perception, visual attention and binding) will be presented. Recognition of edges and other features using contrast- and color-processing will be especially discussed. A comparison with the holonomic alternative will be made.

The majority of so-called auxiliary chapters mainly review neural-net-like quantum associative processing, starting from my list of neuro-quantum analogies which is then used for translation of a neural information-processing "algorithm" to quantum formalism. Some essential improvements where quantum associative processing transcends the neural-net basis are highlighted. These improvements are mainly based on holography-like phase-relationship processing.

Auxil. Chapter 6 can be skipped by neuroscience experts. The mathematical auxiliary chapters and appendices are complements to the main text and to the Auxil. Chapter 6 which, however, alone incorporate *all* the relevant neuropsychology. Mathematical Auxiliary Chapters provide theoretical and computational details mathematically and physically more rigorously, but are *not essential* for understanding of the main text (or of Auxil. Ch. 6).

Computer-implementable core. The central part of this work is to provide a global (rough) mathematically-supported, computer-implementable model, i.e. a "skeleton" of an information-processing "algorithm", for image processing giving a conscious result – a consciously perceived image. We will start with a "skeleton" based on neural-net models, enrich it with holography-like phase-dynamics, and embed it into quantum dynamics.

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Here I will use the term *neural networks* for those *real (biological) networks or circuits of neural cells which are optimally modeled by computer simulations*, i.e. *we take into account as much experimental biological data as possible* in the model.

That is to say, we do not know very well how the real visual brain looks like. But, anatomical research shows that there are a lot of densely-connected cells. Our mathematical models transformed into computer simulations try to imitate as much physiological findings as possible. Such models become our metaphor or our "internal image" of the brain. Everybody of us has an optimal "image" of it which she/he uses for her/his research purposes. When I will talk about neural networks here, I will have in mind this optimal "map" of the brain interior at the level of more or less large neural circuits (many cells connected in a web). I do not know how much we share such a "virtual image" in its details, but I will try to increase agreement by occasionally providing a more detailed specification of my "image".

Beyond neural nets. Neural networks[1] realize the basis for automatic behavior and are good in processes like pattern recognition and associative memory. On the other hand, they do not explain awareness. Therefore the question remains how much are neural networks responsible for real brain functioning which is (also) essentially related to the phenomenon of (self)consciousness. I consider awareness as for all practical purposes synonymous (identical in our model) to self-consciousness (i.e., phenomenal auto-reflective consciousness). And I also suppose, following arguments by Gennaro (1995), that consciousness entails self-consciousness.

Neural networks surely are very important, but our hypothesis is that they also essentially exploit relatively more microscopic (i.e., sub-cellular) processes. I will take into account that such sub-neuronal processes might be of different, but essentially interdependent, types or levels: dendritic (Savtchenko & Korogod, 1997), microtubular, quantum-biological, sub-quantum (Globus, Hiley in Pylkkänen & Pylkkö, 1995). This means that I will consider different, but hopefully approximately compatible, models which subjectively put the center of scientific attention to a particular level, not entirely neglecting the others. I believe that the "objective truth" is a sort of "combination" of these specialized views. However, in particular I will follow the holonomic[2] brain model of Pribram (1986, 1991-1998). Namely, it seems presently to have more experimental support, regarding the question of consciousness, than "neighboring" models like *neural network models* (for example, by Churchland & Sejnowski (1992), Crick, J.G. Taylor), the *microtubular model* (by Hameroff with quantum extensions by Penrose – see Hameroff *et al.* (1996, 1998; in Pribram, 1993)), and *quantum-biological models* – i.e., models with some relatively-purely quantum ingredients: by Vitiello (2001, 1996), Alfinito & Vitiello (2000) and Pessa & Vitiello (1999, and refs. within), Jibu & Yasue (1995, 1997; in Pribram, 1991, 1993) and other quantum field physicists[3]. Of course, almost everybody of the above-mentioned agrees that beside their preferred level also (all)

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"neighboring" levels are important, therefore the "names" of the models refer just to the center of attention of the model. My hypothesis is that too specialized models (devoted to a particular level only) are irrelevant for conscious experience which seems to be an essentially global, multi-level and holistic phenomenon.

Pribram's holonomic model, using the *holographic metaphor* (Pribram, 1971), gives the center of attention to *synapto-dendritic networks* (therefore I added it among dendritic models). Webs of dendrites with their synaptic connections are embedded in dense interactive polarization fields. Dendritic junctional microprocesses[4] have background in quantum coherent states (Fröhlich, 1968; cf., Matsuno, 2002), according to Pribram's hypothesis (later shared and extended to quantum domain with Jibu and Yasue) (Pribram, 1991, 1993). Hypothetically, peri-membranous[5] ordered water dynamics and Bose condensates[6] (Marshall; *et al*. in Hameroff *et al*., 1996) realize ultimate perceptual binding.

Note that Karl Pribram's original views will be presented under keyword "holonomic theory". My extensions of the holonomic theory will be presented usually in separated sections or paragraphs with first-person statements.

1.2 THE HOLONOMIC MODEL OF VISUAL PERCEPTION

Aims. Pribram expresses a hypothesis, with serious theoretical reasons and with experimental support, that holonomic principles govern several parts of the cortex, especially visual, auditory and somatosensory. Discussion will from now on be confined to the visual cortex which is central in the holonomic theory. According to my knowledge, Pribram's Holonomic Brain Theory provides, among all theories, the most global physiological experimental data and holistic theoretical interpretation for modeling visual perception – therefore such a choice. I combine this theory with own observation (orig. Peruš in Wang *et al*., 1998) how holography-like information-processing principles are implementable in quantum systems also. Holonomic Brain Theory seems to provide a firm framework for such quantum–neural complementary and comparative studies.

V1 and surround. The *striate cortex* (i.e., V1 area of the visual cortex)[7] is the most important one for image processing, although for higher-order visual and synthetic or synesthetic perceptions the extrastriate cortices (V2 and higher) seem to be very relevant also. It is debatable which of the above-mentioned visual cortices is the central one for *conscious* visual perception. V1 is *necessary* for conscious image processing, because if V1 is damaged, eye-inputs are processed unconsciously (Baars, 1997). However, Koch and Crick claim that primates might *be aware of* processing in extrastriate cortices, but *not directly* of those in the striate cortex (Koch in Hameroff *et al*., 1996).

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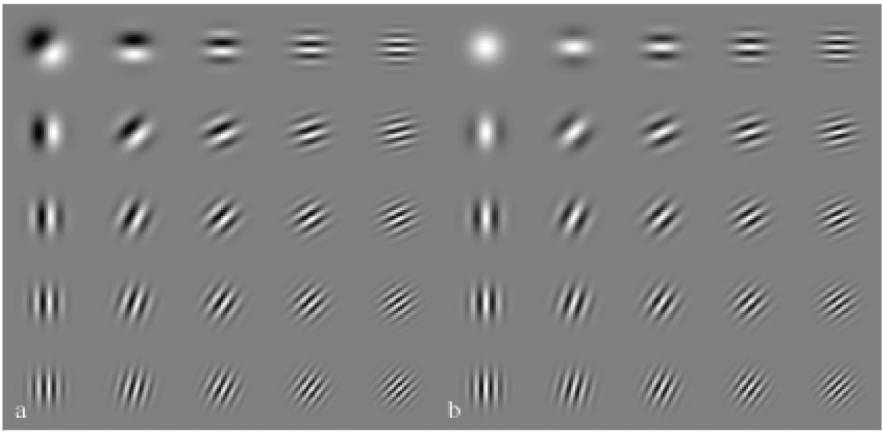
Figure 1. Each sub-figure depicts a Gabor wavelet. Wavelets have different orientations and spatial frequencies (i.e., "densities of waves"). (From Lee, 1996, fig. 1)



The aim of this introductive presentation is to provide a biocybernetic framework for a computer-implementable model which attempts to take into account as much significant neuropsychological and psychophysical evidence as possible, as reviewed in the book "Brain and Perception" (Pribram, 1991). Following this reference, the form of receptive fields[8] of the striate-cortex neurons are *Gabor wavelets* (Figure 1). They minimize the uncertainty in the so-called phase-space of space-time and spatial and temporal frequencies, and thus maximize information. Gabor wavelets serve as "patterns" which interfere in order to realize a Hebb-like memory-storage (presented in sec. 6.8). We propose a hypothesis that *holography-like image-processing and related Gabor transforms are implementable in synapto-dendritic and/or quantum substrates*. Because holonomic principles seem to be to a significant extend level-invariant, somewhat similarly to fractals[9], their synapto-dendritic and quantum-biological implementations could coexist and cooperate.

Convolutions. The Holonomic Brain Theory (henceforth: holonomic theory) provides a macroscopic as well as microscopic view on brain processes. At the *macroscopic* level, the theory suggests biologically-plausible computational mechanisms for a triple convolution-process[10] along the visual pathway. The visual pathway is: *retina — lateral geniculate nucleus (LGN) — striate cortex*. At each of these three stages, inputs from the previous stage are convoluted with the receptive fields of neurons receiving those input at the present stage. For example, signals from many retinal neurons (retina – first stage) arrive into a LGN neuron (LGN – second stage). These retinal neurons constitute the *receptive field* of the LGN neuron.

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The first convolution process is executed by the optics of the eye: Pupillary input (optical image) is convoluted with activities of retinal receptors. The second convolution is the following: Retinal signals are convoluted with the receptive fields of the signal-receiving LGN-neurons, and this "overall weighted sum" (such a sum is convolution!) of signals now determines the states of the LGN neurons. Similar signal-summation process, involving Gabor transforms, is realized by a striate-cortex neuron (striate cortex – third stage) while receiving signals from many LGN neurons (These LGN neurons constitute the receptive field of the striate neuron.). (Pribram, 1991)

Roughly the same or at least similar processes continue inside the visual cortex, at its various hierarchical levels (Perret & Oram, 1998).

Dendritic implementation. At the *microscopic* level, the holonomic theory considers synapto-dendritic networks (where synapses and dendrites belong to neurons at the above-mentioned three stages of the visual pathway, especially V1) as the most relevant information-processing executive level.[11] So, image processing in the striate cortex using Gabor wavelets may be implemented by interacting dendritic polarization-fields[12] arising from spine-produced[13] oriented electrical dipoles.[14] In retina and LGN a similar image *pre*-processing is done. The difference is that such pre-processing is realized using "Mexican-hat"-shaped "filters" corresponding to receptive fields of retinal neurons and later, at the second stage, of LGN neurons. On the other hand, cortical neurons have receptive fields described by Gabor wavelets. This means that along the visual pathway between retina (or, better to put, LGN) and striate cortex, a "transformation" to Hilbert space[15] is realized (Pribram & Carlton, 1986). In the striate cortex, the image is then processed "to a full extent" in a (quantum)-holography-like way.

Why does the holonomic theory consider processes at the synapto-dendritic-network[16] level more relevant than processes at the usual neural-network level (or neural-circuit level[17], respectively)? The reason is that dendritic processes are more flexible, faster, realize a higher rate of connectivity, or interaction, and greater parallelism than conventional nerve-signal processing. Dendritic processes are also "more directly connected" with quantum holism and unity – over the citoskeleton, especially microtubules (sec. 4.7). That is to say, as everybody agrees, nerve impulses between somas propagate through dendrites and axons, and over synaptic clefts between them, but the usual neural-network theories consider just the out-of-soma axonal signal propagation, without adding the sub-cellular microstructure of interactional processes in dendrites and their webs[18] into account. These dendritic microprocesses can modulate the macroscopical nerve-signal propagation and are thus relevant.

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It has been observed that the duration of awareness is proportional to the delay in dendritic-network processing (Pribram, 1991). Especially relevant seem dendritic networks to be because they could be essentially influenced by underlying quantum processes (AuxLit 21). Quantum holism is needed, we believe, for explaining subjective unity and "envelopal" stability[19] of bound-together multi-modal conscious experience. Classical binding models using synchronous neuronal oscillations (e.g., Gray *et al*., 1989; Roelfsema, 1998) are probably not sufficient.

Thus, the holonomic theory postulates quantum-rooted dendritic processes realizing *conscious* perception, not merely information dynamics. The "involvement" of consciousness starts (or to say alternatively: conscious experience emerges) probably not earlier than in the visual cortex.[20]

The holonomic theory is optimally experiment-fitted (Pribram, 1995) (as will be shown later) and allows at least approximative mathematical and computational modeling of visual perception up to a semi-phenomenal (pre-qualitative) level. Conventional neural-net models (LeCun & Bengio, Fukushima in Arbib, 1995; ASSC, 1998; Gupta & Knopf, 1994) do not come so far, I would like to argue. We will pay our interest to quantum-neural holographic processes, like Fourier decomposition, optimal correlation-matrix memory-storage and associative recall, which explicitly include phase-information.

Gabor wavelet transforms. According to the holonomic theory, the task of primary visual cortex (or its simulation) is to determine the Gabor coefficients *s* corresponding to elementary Gabor functions (also called Gabor wavelets) *g* which together constitute a superposition, the Gabor field *γ*, describing the cortical receptive fields: $\gamma = \sum_k s_k g_k$.

Following Pribram & Carlton (1986), let us make an approximation of the visual-pathway processing and concentrate on the main part of its multi-stage convolutional mechanism, that is on the retina-cortex-convolution process. It is described by the following integral over the 2-dimensional area of retinal cells:

$$Gf(p,u) = \iint_{retina} g(p,u;x) f(x) dx_1 dx_2 \ . \tag{1.1}$$

Gf is the Gabor transform of the instantaneous retinal image *f*. Coordinates *x* and *p* correspond to points on retina (*p* falls into the center of the Gabor wavelet *g(p,u)*) measured in distance units from the origin at retinal foveola[21]; *u* corresponds to spatial frequency.[22] They are all two-dimensional coordinates, as the retina is. The response of the striate-cortex neuron to stimulation with signals from retina, described by *f(x)*, is determined by such a Gabor transform. The above convolution

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integral sums all contributions from retinal neurons weighted by the elementary Gabor function or wavelet *g(p,u)* having the following form:

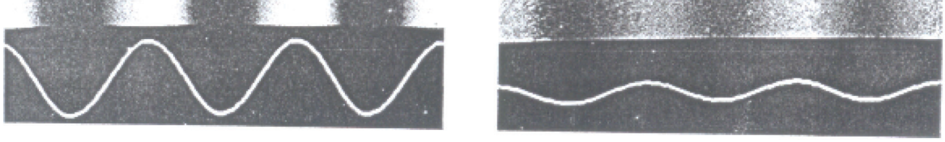
$$g(p,u;x) = \exp\left(-\frac{(x-p)^2}{\sigma^2}\right)\exp\left(-iu(x+p)\right). \tag{1.2}$$

Such a *Gabor wavelet* or wave-packet (details in Lee, 1996) describes the form of the receptive field of a striate cell. It has a gaussian bell-shaped envelope, centered at *p,* (first exponential factor) and a sinusoid "interior" (second exponential term). The wavelet has sinusoidal excitatory and inhibitory regions (seen from above: "stripes"; with "density of stripes per wavelet" *u*) which are a result of lateral inhibition.[23] It ensures maximal selectivity to spatial frequency *u* (R. & K. DeValois, 1990) and consequently to stimulus-orientation angle given by $\arctan\frac{u_y}{u_x}$.

V1 columns. Each component *Gf(p,u)* of the Gabor transform *Gf*, made by the network of striate neurons as anatomically connected with groups of retinal neurons while receiving retinal input *f,* represents the activity in a *cortical column* tuned to spatial frequency *u* and responding maximally to an input from the retinal position *p.* So, columns of the striate cortex are specialized, local neural-net structures which respond maximally to a stimulus which has a particular orientation and arrives from a particular origin as detected by retina.

Outputs from striate (V1) columns project to peri-striate (V2) neurons. It is probably there that retinal image *f* is recovered in the inverted form (turned upside-down): *F = f(-p)*, where *F* corresponds to the V2 image-reconstruction. This happens after a new, inverse, Gabor transform has been made. (Pribram & Carlton, 1986)

Figure 2. Examples of two different groups of "spatial plain-waves" (above) with the same spatial frequency, but different amplitudes (or also intensity-contrasts). By comparing the upper with the bottom parts of both sub-figures, one can understand the origin of the term "spatial frequency". (From Stillings et al., 1995, fig. 12.6)



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1.3 SEARCH FOR QUANTUM NEURAL SUBSTRATES OF VISION AND THEIR MODELS

The question of biological implementation of holonomic principles in various sub-cellular environments remains the central problem. Due to enormous complexity and interdependence of brain structures, experimental evidence is often poor in many respects, but there was some relatively reliable and precious experimental work done. Constraints, which a mathematical or/and computational model should satisfy as much as possible while realizing image processing, are being derived from experimental reports.

The multi-stage convolution of advancing input-signals with the Gabor "filters" is, in principle, equivalent to a special[24] *multi-layer perceptron*-like artificial neural network (ANN) with an important exception. ANN (Haykin, 1994; AuxLit 10) usually incorporate only "amplitude"-information which is quantified using real-valued numbers.[25] Such ANN do not incorporate phase-information, because they do not contain wave-dynamics. There are some new ANN-models which incorporate wave-dynamics and wavelet processing using complex-valued numbers and phase-information (in the Euler exponents).[26] If the wavelets are Gabor wavelets, then such ANN come quite close to the holonomic model. (This is no wonder if that imitation followed results of the same psychophysical research which lead Marčelja[27] to describe receptive fields by the Gabor elementary functions.)

Phase models. To proceed with modeling of image processing, it is thus useful to incorporate phase-information into amplitude-correlation (second-order statistics) models like the model of Hopfield (1982) or *Principal Component Analysis* (PCA) (see Appendix A). Such associative-memory models use correlation-matrices (Hebb memory-storage matrices).[28] There are some modern models which successfully exploit *phase-information* in addition to amplitude-information. Some of them are very interesting in our holonomic context, because they share many features with the holonomic theory and may complement it. These models are:

- **Independent Component Analysis** (ICA): a perspective method (e.g., Comon, 1994) brought to vision research by Anthony Bell and Terrence Sejnowski (1995, 1996, 1997);
- **field computation** model by Bruce MacLennan (1990, 1991, 1994; in Pribram, 1993; in Wang *et al.*, 1998; Wolpert & MacLennan, 1993) which also uses Gabor wavelets and many physics-inspired techniques;
- **Holographic Neural Technology** (HNeT)[29] by John Sutherland (1990): an application-effective neurobiology- and holography-inspired artificial model[30] (in other words, simulated holography-based neurocomputation) which was recently renamed to **Holographic / Quantum Neural Technology**, because

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analogies between mathematical models of holography, associative neural networks and quantum fields were recently systematically listed and discussed (Gould, Peruš in Pylkkänen & Pylkkö, 1995; Peruš, 1996, 1998a; Schempp in Pribram, 1993; Marcer & Schempp, 1998);

- **Quantum neurodynamics** by Mari Jibu and Kunio Yasue (in Pribram, 1991, 1993);
- **Quantum associative network** model by Peruš (2000b,c; in Wang, 1998): a quantum information-processing "algorithm", inspired by the Hopfield associative neural-net model (Hopfield, 1982), and partly by the Haken synergetic-computer model (Haken, 1991), rewritten to quantum-mathematical formalism.

1.4 QUANTUM ASSOCIATIVE NETWORK

Origins. My model, the Quantum Associative Network, is deliberately "shockingly"-simple and fundamental (Peruš, 2000b,c; Peruš in Wang, 1998). It bases on observations that the mathematical formalism of associative-neural-network theory, as usually simulated, and the mathematical formalism of quantum theory are very similar (Peruš, 1997a, 1998). To construct the quantum associative net[31] from Hopfield-like simulated ANN, the real-valued "neural" variables have been translated to analogous quantum complex-valued (phase-information-carrying) variables (Peruš, 1997a). The translation to quantum formalism was deliberately and purposely done in the most "natural" way, i.e. so that the neural-net-like associative information-processing can be *implemented in a usual quantum-physical system, not necessarily in some artificial quantum-based device*. This characteristic distinguishes the quantum associative net from all similar quantum-computer models (Ezhov *et al*., 2000, 2001; Berman *et al.*, 1998; Ventura, 1999; Bonnell & Papini, 1997; Behrman *et al*., Ventura in Wang *et al*., 1998; Chrisley in Pylkkänen & Pylkkö, 1995) which are, at least in part, hypothetically-implementable only using some artificial quantum devices or procedures.

Significance. The quantum associative net is the *simplest* or the *basic* quantum model which realizes content-addressable associative memory and pattern recognition. It uses fundamental and completely-natural quantum characteristics as described in the first chapters of any basic textbook on quantum mechanics (e.g., Messiah, 1965; AuxLit 16). I believe that many more advanced, more complicated, but also more effective quantum information-processing implementations will be found in the near future – natural, artificial, or hybrid. But the purpose of the quantum associative net is to serve as a *primitive prototype* for all future quantum associative PDP-models[32] which will necessarily be advanced extensions of the present model. They will probably exploit "deeper" (e.g., quantum-field-based) or/and more artifi-

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cial, technological ingredients, e.g. NMR.[33] (For purposes like the present one, i.e. modeling human vision, artificial models are, of course, not directly acceptable.)

Furthermore, I argue that the quantum associative net processing suggests that *any quantum-physical system is a potential associative-information-processing system if properly manipulated*.[34] With proper manipulation I mean that something or somebody, usually an intelligent being, interacts with the system, triggers its transformations, and gives interpretations to its initial and final states. *By giving such an interpretation or meaning to system's states, physical dynamics "transforms" into information-processing dynamics.* So, the (quantum) system has to be open and flexible enough that we can force it to manifest specific states, and we must be able to attribute specific meaning to these states (Peruš & Dey, 2000). Brain is such a system, but not only brain. Brain is a system which even interprets its own states and even more (exhibits conscious experience etc.). Usual quantum systems could also be harnessed for associative information processing after we give interpretations to their states.

"Algorithm". I will now present briefly the core of processing of the *Quantum Associative Network* as a Hopfield-like "algorithm":

STEP 1: **encoding images into a quantum system**

Quantum eigen-waves are given the role of encoding our patterns or images. Their number shall be *P*. Eigen-waves will be denoted by Ψ with index *k* (in contrast to Ψ which shall denote the current quantum state):

$$\psi_k(\vec{r},t) = A_k(\vec{r},t)\exp(i\phi_k(\vec{r},t)) \quad . \tag{1.3}$$

STEP 2: **quantum memory construction**

Hebb-like quantum interference pattern is produced, e.g. by performing a holography-like interference of (quantum) image-modulating waves. **G** is the matrix of all Green functions *G* which describe the response of the system to perturbations (in our case, "inputs of data"). Global result of this interaction is the emergence of interference-pattern. **G** describes the interference-pattern which encodes the *quantum associative memory*.[35]**G** is thus the direct analogue to the Hebb memory-storage matrix from ANN-models. **G**, like the Hebb memory matrix, has a form of a correlation (which is similar to convolution!) matrix, but additionally implicitly encodes local phase-differences (in the exponent of the bottom part of equation below). The elements of **G** are given by:

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$$G(\vec{r}_1, t_1, \vec{r}_2, t_2) = \sum_{k=1}^{P} \psi_k(\vec{r}_1, t_1)^* \psi_k(\vec{r}_2, t_2) = \\ = \sum_{k=1}^{P} A_k(\vec{r}_1, t_1) A_k(\vec{r}_2, t_2) \exp\Big(i(\phi_k(\vec{r}_2, t_2) - \phi_k(\vec{r}_1, t_1))\Big) \quad . \tag{1.4}$$

STEP 3: **quantum associative computing**

G also serves as so-called quantum propagator, therefore the usual quantum propagation can be harnessed as a quantum associator (but only if **G** has the form given in STEP 2; in fact it has!). Such quantum computation is best described by the Feynman interpretation of the Schrödinger equation:

$$\Psi(\vec{r}_2, t_2) = \iint G(\vec{r}_1, t_1, \vec{r}_2 . t_2) \Psi(\vec{r}_1, t_1) d\vec{r}_1 dt_1 \ . \tag{1.5}$$

STEP 4: **quantum memory recall or image recognition**

G has one more capability: it is a projection-operator: It projects to a subspace which corresponds to those eigen-image which is the most similar to the newly-presented "input" Ψ'. For such a quantum image-recall process, the celebrated *wave-function "collapse"* is used:

$$\Psi(\vec{r}_2, t_2 = t_1 + \delta t) = \int G(\vec{r}_1, \vec{r}_2) \Psi'(\vec{r}_1, t_1) d\vec{r}_1 = \int \Big(\sum_{k=1}^{P} \psi_k(\vec{r}_1) \psi_k(\vec{r}_2) \Big) \Psi'(\vec{r}_1, t_1) d\vec{r}_1 = \\ = \Big(\int \psi_1(\vec{r}_1)^* \Psi'(\vec{r}_1, t_1) \, d\vec{r}_1 \Big) \psi_1(\vec{r}_2) + \ldots + \Big(\int \psi_P(\vec{r}_1)^* \Psi'(\vec{r}_1, t_1) \, d\vec{r}_1 \Big) \psi_P(\vec{r}_2) = A \psi_1(\vec{r}_2) + B \tag{1.6}$$

where $A \approx 1$ ("extracted image") and $B \approx 0$ ("noise").

Thus, those eigen-image is recalled from memory (i.e., from the interference-pattern of all images) which has the highest correlation with the current input Ψ'. This is because one of the terms in the series goes to 1 (constructive interference), all the others decay to 0 (destructive interference). For details see Auxil. Chapter 10 and Peruš (2000b,c) or Peruš & Dey (2000).

The quantum associative memory-storage and pattern recognition are essentially nothing else but the most fundamental quantum feature — in the simplest way described (in Dirac notation, in three equivalent versions, the third one being the most suited for our purposes) by

$$\left| \Psi \right\rangle = \left| \Psi \right\rangle \left\langle \Psi \right| \left| \Psi \right\rangle = \sum\nolimits_k \left| \psi_k \right\rangle \left\langle \psi_k \right| \left| \Psi \right\rangle = \Big(\sum\nolimits_k \left| \psi_k \right\rangle \left\langle \psi_k \right| \Big) \left| \Psi \right\rangle . \tag{1.7}$$

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1.5 TRYING TO INTEGRATE THE MODELS

I have already listed some models of visual perception which have, in my opinion, potentials for tackling the problem of visual conscious experience, not merely the early vision analysis (like "feature detecting"[36], orientation selectivity) and automatic image processing (Stillings *et al*., 1995). Because I share the belief that the future models of conscious vision have to be compatible with quantum-biological models, I concentrated on the holonomic theory by Pribram and its compatible models (listed in sec. 1.3). A sketch of the main specific purpose of this book is given here, i.e. search for a potential unified framework of these models, which all seem to have some merit for modeling conscious vision, and the potential role of the quantum associative net as a "primitive prototype" model (as sketched in sec. 1.4) in this context.

ICA. The model of Independent Component Analysis (ICA) is a relatively new (Comon, 1994), but perspective one. Pribram believes[37] that it is very relevant for the holonomic theory of vision, because it may provide an experimentally-supported solution to the problem of *edges* of perceived objects (which has not been well solved by classical neural models). Namely, the ICA-filters resemble the receptive fields of so-called simple cells in the primary visual cortex (Bell & Sejnowski, 1997; van Hateren & Ruderman, 1998). The "independent components", selected by ICA-filters, are localized and oriented, as was also experimentally found for those simple cells which were denoted as edge-filters. Furthermore, the unsupervised ICA learning algorithm, based on information-maximization (*"infomax"*), provides maximal statistical independence of resulting neural states (outputs). This happens when their probability-distribution gets factorized. This is equivalent to getting mutual information between the output-states zero (details in: Bell & Sejnowski, 1995, 1996, 1997; McKeown *et al*., 1998).

Maximization of information (and minimization of mutual information) is a characteristic of Gabor wavelets. Gabor wavelets are a possible connection between ICA and the holonomic theory. Another connection is the fact that ICA as well as the holonomic theory encode and exploit the phase-information in addition to the amplitude-information. Actually, as ICA-simulations show, the amplitude-information is less necessary for good image-recall than the phase-information. This is similar to HNeT-processing and to findings by MacLennan (in Wang, 1998) for some Gabor-based field-computation models. In HNeT phases are considered as the main output; amplitudes merely measure the rate of importance, confidence (or reliability, accuracy, respectively) or urgency of the phase-output.

Phase-information is necessary for edge detection, because edges are situations where many sine-waves of different spatial frequencies "get in phase", i.e. they are all aligned in phase and sum together precisely where the edge lies. Such a coherent

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constructive interference is not realizable without wavelets, so the usual Hebbian amplitude-correlation methods (without phase-differences incorporated) cannot be successful for edge detection. Without detection of edges the image-processing capability of the system can be severely impaired.

Comparison. ICA, HNeT and field computation are not necessarily quantum-implemented, but are classical (partially holography-like) computational models. However, quantum ideas might improve them all, and might also make them relevant for modeling conscious vision. The basic core of HNeT is mathematically almost identical to the quantum associative net, as shown by Peruš (in Wang, 1998), although they were developed independently – the HNeT model from classical (holographic) foundations, but the quantum associative net from quantum ones (although ANN-inspired). The relations between ICA, HNeT and the quantum associative net will be explored and put into the context of vision research in my following chapters. However, although effective computationally and having biologically-plausible *results* (outputs), the ICA algorithm does not have any biologically-plausible *mechanism* to support it as a brain procedure. That is to say, up to now it has not been found where and how the nonlinear ICA "infomax"-algorithm could be implemented in brain tissue. But this is a possibility which will be explored.

Table 1 compares characteristics of chosen models in the context of vision problem.

My hypothesis. Since holography is an universal process, the microstructure of junctional slow-wave potentials, attributed to polarization-fields in dendritic nets (Pribram, 1971, 1991), may have various implementations, but the basic one would

Table 1.

	HNeT	Quan.Assoc.Net	ICA	field computing
effectiveness	very effective	effective, potentially very effective	very effective	a general model with potentially very effective "sub-branches"
biological plausibility	biol. plausible at the fundamental level only	biol. plausible at the fundamental level only	biol. implausible mechanism, but plausible output	biol. plausible at the fundamental level only
possible quantum implementation	indirect, similar core as Q.A.N.	direct	not yet known	indirect, partially direct
main strength	very applicative and developed	fundamentally quantum, "natural"	fits experiments on receptive field profiles	a general model with a concrete vision sub-model
main weakness	a mixture of natural and artificial features	limited to assoc. memory and pattern recognit.	algorithm's biol. implementation unknown	(consciousness still missing)

Note: With "fundamental" I mean "fundamental (bio)physical implementation" – without specific macroscopic biological characteristics (structural and functional), although compatible with them.

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be quantum. The quantum associative net could realize it *if Gabor wavelets would be used as quantum associative-net's eigenstates* Ψ to be processed as in section 1.4.[38] If this is the case, then *the neural brain serves as an encoder and decoder into and out of the Gabor representation*, and such Gabor wave-packets are processed in quantum interference dynamics as in section 1.4. Detailed biological structures and processes (ICA-like?) which maximize *(de)coding* performance (as ICA does) remain to be researched. The *core* of information processing would be of quantum nature (and therefore ultimately conscious?).

ENDNOTES

1. Artificial neural net (ANN) models are overviewed in Haykin (1994) and Peretto (1992). Details see in AuxLit 10.
2. In simplified terms, holonomic refers to holography-like, spectral (additionally to space-time), but law-full (constrained with biological laws), and bio-dynamic (in contrast to invariant, unconstrained optical holograms). Spectral here refers to description in terms of distribution (spectrum) of wave characteristics, like frequency.
3. Here we must not forget that they do not have intention to present a self-standing brain model, but collaborate in this respect with neuroscientists.
4. With the term "junctions", all those interaction-sites are meant which can implement the associative (i.e., correlational / convolutional) processing as will be described later. These sites, collective carriers of the interference-pattern ("hologram"), could be various synapses (especially between dendrites), or any more microscopical or less materialized *mediators of interaction*.
5. Peri-membranous means near to or along the membrane.
6. Bose-(Einstein) condensates are quantum structures where bosons (quantum particles with integer spin) behave collectively as a coherent whole – they enter into a state where they all have the same quantum numbers (i.e., characteristic parameters describing a quantum state).
7. Striate cortex, primary visual cortex, V1 and area 17 (which must not be confused with the citoarchitectonic Brodmann area 17) are synonymous expressions for the earliest cortical vision center.
8. Let's begin with the most general definition; its variations will be precised later. A receptive field of a neuron is everything that influences its output *after* inputs from its environment have entered it, i.e. all transformations of all inputs along its own arborization (dendritic tree). With the term "receptive field", one might mean the whole surrounding space or network where stimuli effect the neuron from, or a mathematical function describing the effect of transforma-

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tions upon neuron's inputs (the "weights" of inputs) before the axonal output is "calculated".

9 Fractals are self-similar structures emerging from recursive, collective dynamics, usually in complex systems.

10 Before giving a more precise mathematical definition later, i.e. in Equation (1.1), let us describe convolution $g*f$ as a sum of all inputs f, where each input f gets its own "weight" g (i.e., the "amplifying factor" for each particular input signal) (details in MacLennan, 1990).

11 When we will talk about activity of a *neuron*, we will mainly mean the activity of its body (*soma*) and its nerve impulses sent along its *axon*. (Processing in its dendrites will usually be considered separately.)

12 (Electric) polarization is the strength of the electric field between a group of positive charges and a group of negative charges. It may constrain the electromagnetic waves to oscillate in specific directions only.

13 Spines are small excrescences on dendrites.

14 Electric dipoles are structures, usually molecules, with two opposite endings carrying positive and negative electric charge. Magnetic dipoles (related term: spins) are small "magnetic needles" (which have two poles).

15 Hilbert space is the characteristic mathematical framework of quantum mechanics (e.g., Messiah, 1965). States in Hilbert space (here: images) can be described as a superposition, i.e. as a weighted sum of elementary so-called eigen-states (eigen-images).

16 In dendrites, a signal-summation process is performed (a sub-cellular one). It is similar to summation in neural bodies (i.e., somas) (an inter-cellular one) – "a fractal-like replica" of the summation process in somas.

17 Here we mean the level of neural bodies (somas) and signal-summation within somas (or, to be more precise, in axon hillocks).

18 Meant are dendritic signals before they reach the soma of the neuron.

19 By "envelopal" stability I mean that although there is a lot of hidden dynamics inside the process, e.g. as consciousness, also a stable overall aspect (i.e., the "envelope" – a term from wave analysis) of the process emerges.

20 As mentioned before, it is still open whether consciousness starts at the level of striate cortex (V1) or at some later extrastriate cortex level (V2 and above), if such localization attempts are relevant at all.

21 Central fovea coincides with the yellow spot in the (most sensitive) center of retina.

22 Spatial frequency is a measure of frequency or density of periodic events (e.g., lines, waves) across space (receptive field) in a given direction (Figure 2).

23 Lateral inhibition is a suppressing influence of neighbouring neurons onto a particular neuron.

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24 Here "special" means that the Gabor elementary functions replace Mexican-hat functions or radial basis functions (RBF) which are more usual in perceptrons (a sort of hierarchical artificial neural net). Mexican-hat "filters" are used as models for receptive fields of retinal and LGN neurons, but Gabor "filters" are appropriate as models for receptive fields of cortical neurons. For some other possibilities, like Hermite, Fresnel, Fourier or Walsh transforms, see Aleksenko & Kirvelis *et al.* (1987).

25 Amplitude is the highest value or intensity (height) that a wave can reach. The word "amplitude" is in quotes, because in non-wave ANN there is computation using just "intensities of signals", or just some numerical values (integers or reals), respectively.

26 Wave phenomena are conveniently described by complex numbers: Real components are cosines and imaginary components are sines (Both function-types, sines and cosines, look like "waves".). After the Euler formula $exp\ (ix) = sin\ x + i\ cos\ x$ (where i is the square-root of –1), the exponent (here ix) incorporates the *phase* x. Phases are delays between peaks of waves. They are measured as angles (in degrees), due to a mathematical observation that the waving process can be geometrically projected to an analogous pendulum-like oscillating process. Waves are thus mathematically described by expressions like $A\ exp\ (ix)$, where A is the amplitude and x is the phase.

27 S. Marčelja (1980): *J. Opt. Soc. Amer*. **70**, 1297-1300.

28 I have presented these well-known second-order-statistics models, supported by own computer simulations, in several previous works (Peruš, 1995a,b, 1997d, 2002; Peruš & Ečimovič, 1998), therefore they will not be discussed here. Hebbian learning is briefly presented in Auxil. Section 6.8.

29 HNeT has been developed by AND Corporation, Toronto, Canada. (Now renamed to HQNeT.)

30 In this context, see also Prideaux (1996) and Psaltis *et al.* (1990).

31 This name will henceforth be used for *my model* which is here presented in detail in Auxil. Ch. 8 (and also 10).

32 PDP = parallel-distributed processing (like in networks where many interacting units process in parallel).

33 Some attempts in this direction, beside those mentioned in the previous paragraph, see in: Cory et al. (1997); Gershenfeld & Chuang (1997); Pessa & Vitiello (1999); Fatmi & Resconi (1988). NMR is nuclear magnetic resonance.

34 Similar views see in Chapline (1999), Cahill (2001) and Landauer (1991 – especially p. 29). Here are relevant citations from Chapline (1999). "Quantum mechanics can be regarded as a fundamental theory of distributed parallel information processing and pattern recognition." (p. 97) "It appears that our [Chapline's] holographic formulation of quantum mechanics may indeed be

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pointing us in the direction of a fundamental structure of theoretical physics." (p. 103) "We are led to suggest that the fundamental connecting link between mathematics and theoretical physics is the pattern recognition capabilities of the human brain." (p. 104)

[35] Memory and associations could be realized also using the *quantum density-matrix* description (Auxil. Ch. 7, paragraph no. 7; Peruš, 1997a, and references within; Robertson, 1966; basic theory in Ballentine, 1970).

[36] The term (a not-up-to-date name, but still used in practice) is in quotes, because neurons do not really behave as feature detectors. There is no one-to-one correspondence between a stimulus feature and the firing of a specific neuron, or its spike train, respectively (Pribram, 1991).

[37] Personal communication.

[38] For quantum associative nets, as a general associative-information-processing model, it is not necessary that eigenstates are Gabor wavelets. But without Gabor wavelets, quantum associative nets would be biologically implausible; they would only be physical.

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