PSYCHOPHYSICS.

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ABSTRACT

In the XIX century and earlier such physicists as Newton, Mayer, Hooke, Helmholtz and Mach were actively engaged in the research on psychophysics, trying to relate psychological sensations to intensities of physical stimuli. Computational physics allows to simulate complex neural processes giving a chance to answer not only the original psychophysical questions but also to create models of mind. These lecture notes review relevant fields of science sketching the path from the brain, or computational neurosciences, to the mind, or cognitive sciences.

I. INTRODUCTION TO PSYCHOPHYSICS

Basic concepts of physics, such as energy, mass, time, temperature or strangeness are highly abstract metaphors useful in constructing models of reality. These models relate observations and measurements to other observations and measurements. In the early history of physics results of the measurements were directly related to sensory experiences. In Galileo times confirmation of two independent senses was required to acknowledge a new phenomenon and to avoid self-deception (telescope, giving only optical measurements, was therefore highly suspect). Understanding the relation of objective measurements to psychological sensations was very important. Newton tried to model spectral hues by points on a circle, Helmholtz and later Schrödinger [1] by curved Riemannian manifolds. Psychological spaces for representation of pure tones, odors and tastes were also proposed.

Creation of good models to relate various features of sensory perception proved to be much more difficult than creation of models based on objective measurements of physical quantities. Methods of measuring the strength of psychological sensations in relation to the intensity of physical stimuli were developed by E.H. Weber (1834, 1846) and G.T. Fechner, whose classic book *Elements of psychophysics* was published in 1860. This book had strong influence on Ernst Mach, who developed measurement theory and wrote that "a psychophysical measurement formula assigns numbers to sensations in the same way a thermometer assigns the temperature to a state of heat."

Psychophysics has another important aspect, even more difficult than quantification and description of psychological sensations. "Psychophysical problem", also know as the mind-body problem, concerns the very relations between the mental and the physical. Thus psychophysics should be placed on the crossroads of psychology, physics and philosophy. Problems rised in XIX century are still not resolved, as the recent review of the history of psychophysics has showed [2]. Psychophysics has been of marginal interest to physicists (with notable exception of acoustics and optics communities concerned with tone, speech and visual perception). This situation may change since it became recently clear that the way to understand the mind leads through modeling of neural processes at many levels, from biophysical to the systems level [3]. Computational physicists will undoubtedly play a major role in these modeling attempts. The final goal - understanding the brain and building artificial mind - encompasses much more than the original goals of psychophysics. In a sense it may prove to be the last goal of science as we know it.

I will present here a sketch of a path that leads from computational models of brain functions to models of the mind, a path from *physis* to *psyche*, something that Wofgang Pauli always wanted to achieve. In 1952 he wrote [4]: "It would be most satisfactory if *physics* and *psyche* could be seen as complementary aspects of the same reality". We are slowly reaching this point.

II. COMPUTATIONAL BRAIN

Psychophysics in a broad sense must be based on computational physics of brain processes. Mind is an emergent property of the brain, a very complex, modular dynamical system. Some physicist argue that incorporation of mind or mental processes to natural sciences is possible only using quantum mechanics [5]. The long time scales of higher cognitive processes associated with conscious perception, requiring from tenth to several seconds, are in agreement with the typical times of cooperation of assemblies of noisy neurons via electrical excitations, slowed by the synaptic processes mediated by biochemical neurotransmitters. It is hard to imagine quantum processes that would be so slow.

Penrose [6] has argued that cognitive processes are non-computational in nature since formal systems are not able to answer some Gödel-type questions related to their own specification. These arguments have been discussed already by Gödel himself and repeated many times by Turing, Lucas and other philosophers (for a discussion see Penrose [6]). Human brain is too complex to contemplate any questions of Gödel type requiring full formal specification of neural machinery, therefore claims that humans are able to answer such questions and computational systems are not able are greatly ex-

aggerated. It is not possible to create computational equivalent of God, a system that will have a perfect knowledge of everything, but humans do not posses such knowledge either. From the Gödel argument Penrose concludes that completely new physics is required to understand human mind, physics that should be based on noncomputable processes, but fails to find any clues how such processes could look like. This is an example of extremely speculative approach, lacking precise definition of the problem and certainly not directed at understanding of the human cognition.

Another common misunderstanding is the computational power of the brain. With a total of about 40 billion neurons (including about 10 billion neurons in the neocortex) and 10^{14} synapses operating with the speed of about 100 times per second and a resolution of about 7 bits there is enough adaptive parameters to account for various aspects of human memory and cognition. The problem is not in the complexity or speed of information processing, as some authors looking for faster computational processes in cellular microtubules suggest [6], but with organization. The brain contains dozens of large structures with rather different neuroanatomy and functions, and even neurocortex has modular structure. Some proponents of the quantum mechanical approach to mind [5] try to understand "thoughts" as some philosophical entities. Empirical Theory of Mind is much more precise and ambitious. It should explain: basic facts about perception, e.g. stereoscopic vision and psychophysical data; dynamical optical illusions such as color phi, metacontrast, Stroop interference, tachistoscope results [7]; thousands of facts from cognitive psychology, such as the typing skills or the power law of learning [8]; stages of development, from infancy to adulthood, such as learning to walk, learning basic perceptual categories and knowledge structures [9]; various types of memory and amnesia; conscious and subconscious perception, relation of perception to brain events; qualia, mental content, meaning of symbols; states of consciousness, such as the dream states, daydreaming, hypnotic and other unusual states of mind; formation of ego, personality, Multiple Personality Disorder (MPD); intuition and immediate response behavior; linguistic competence, thinking and reasoning; psychiatric disorders, from anxiety and dyslexia to schizophrenia, blindsight, hysterical blindness; exceptional abilities, e.g.: "idiot savants" syndrome and many other cognitive phenomena. Great advances have been made recently in most of these areas.

Cognitive processes performed by the brain allow for construction of an internal model of reality from the sensory data. A natural approach to models of mind should therefore start with models inspired by the brain, models capable of learning, categorization and internal representation of the sensory data. The task may be roughly divided into two parts: low-level cognition, or preliminary analysis and preprocessing of the incoming sensory signals in the sensory reception and higher-level cognition, where the internal representations are manipulated during perception, thinking and problem solving. The low-level processing of sensory data by computational maps is modeled by self-organizing, unsupervised neural networks.

The central problem remains: how to bridge the gap between the mind and the brain? How to link the mental and the physical? In the following sections I will sketch the solution to this problem. A short review of cognitive modeling will be given first, followed by some remarks on self-organization and topographical maps and concluded by a section on resources for neural modeling.

III. NEURAL AND COGNITIVE MODELING

Neural-network FAQ [10] defines an artificial neural network as "a processing device, either an algorithm, or actual hardware, whose design was motivated by the design and functioning of human brains and components thereof." Since neural networks are popular and almost every approximation or classification algorithm may be presented in a network form there is a tendency to add the adjective "neural" in cases where no biological motivations are justifiable. In such cases a name "adaptive system" should be preferable to "neural network". Adaptive system A_W is a system with internal adjustable parameters W performing vector mappings from the space of inputs X to the space of outputs $Y = A_W(X)$. Neural networks are certainly the best adaptive systems for all kinds of approximation problems [11].

In these notes I will not write on general neural network algorithms, only on those that are useful in elucidation of brain's function. One of the first attempts to model psychophysics of perception at a neural level was published by Rashevsky in 1938. His book was republished in 1960 [12] and pioneered the continuous neural models based on the dynamical systems or differential equations, known as neurodynamics. The paper of McCulloch and Pitts in 1943 (reprinted in Vol 2 of [13]) was very influential and Rashevsky came to the conclusion that "the proper mathematical tool for representing the observed discontinuous interaction between neurons was not differential equation but the Boolean Algebra of Logical Calculus" [12]. Soon it became apparent that the relation of reaction times to stimulus intensities modeled by differential equations are not easily reproduced by logical calculus. Rashevsky came to the conclusion that his differential equations describe average activity of a very large number of neurons. He developed a number of highly specific models for psychophysical and neurophysiological phenomena and this line of research is continued [14].

Although it is not clear how to divide the gray matter into functional units over which one could average neuronal activity one idea is based on the concept of neural cell assemblies (NCAs), advocated in the classical book of Hebb [15]. Some neural modelers argue that the microcolumns of neurocortex are the required functional units [16]. These microcolumns, distinguishable using neuroanatomical techniques, contain between $10^4 - 10^5$ neurons in a $1 - 2$ mm high column spanning six layers of neurocortex, within the cortical area of a fraction of mm^2. Vertical connections inside the column are excitatory and their density is of an order of magnitude higher than the

connections with neurons outside of the column. Axons of some NCA neurons spread horizontally on several milimeters enabling mutual excitation of different NCAs. Small (about 100 neurons) functional groups of neurons with inhibitory connections were also considered [16]. Although such NCAs should play important role in brain models they require rather complex dynamical models themselves. Neurons integrate the incoming signals and, if the potential on their body in a short time exceeds a threshold value, they send a series of spikes. To simplify the models the average firing frequency of the neuron is taken as a measure of its activity. To determine the output from a given neuron its activation is computed as the weighted sum of the incoming signals (average firing frequencies) of the neurons connected with it:

$$I(t) = \sum_i W_i x_i(t) \qquad (1)$$

where the coefficients W_i represent different couplings (due to synaptic conductivities) and are positive for excitatory and negative for inhibitory connections. If this total activation is larger than some threshold value the neuron outputs a signal with strength $f(I(t))$ that is a monotonic function of I. If in an assembly of stochastic neurons the distribution of the thresholds for firing is normal (Gaussian) with some mean θ then the probability of firing is described by a sigmoidal function, i.e. a function growing sharply above the threshold and reaching saturation for large values of the argument. The most common type of function with the sigmoidal shape is:

$$\sigma(I) = (1 + e^{-(I-\theta)/T})^{-1} \qquad (2)$$

The constant T determines the slope of the sigmoidal function around the linear part and θ is the inflection point. It should be stressed that the use of such neuron transfer function is based on rather unrealistic assumptions and neural models useful in modeling neurophysiology phenomena on a single neuron level are based on very complex models of neurons provided by biophysicists.

Sigmoidal functions have non-local behavior, i.e. they are non-zero in infinite domain. The decision regions during classification – i.e. if the output of the network of neural elements is checked for non-zero values – are formed by cutting the input space x_i piecewise with hyperplanes (combinations of sigmoidal functions). There are a few disadvantages of such classification: there are no regions of indecision, the system "pretends" that it knows everything, which is quite false especially far from the sample data regions where hyperplanes, extending to infinity, enforce arbitrary classifications. If the network is large and the training data is small the positions of the hyperplanes is to a large extent undetermined, depending on the initial state of the network. The accuracy of approximation grows with the number of adaptive parameters (weights W_{ij} in neural networks), but if the training data set is finite the network may change into a look-up table and may not generalize smoothly on the test set (similarly as in the "overfitting" case). For sigmoidal processing nodes powerful mathematical results exist showing that if there is enough data for training a

universal approximator may be built from only a single layer of processing elements [17].

Another class of powerful functions used in the approximation theory is called the radial basis functions (RBFs). Some of these functions are non-local while some, such as the Gaussian functions, are localized. RBF networks are also universal approximators [18]. One may argue that processing functions localized in the input space are biologically plausible since some neurons act in a very selective way as feature detectors. In the network of spiking neurons not only the value of signals but also the timing or the phases of the incoming trains of impulses are important, leading to high activations $I(t)$ only for a very specific combinations of the incoming signals. Most networks use averaged values of the incoming signals instead of the spikes and it seems justified that the model neurons should use localized functions [17].

Neurodynamical models pioneered by Rashevsky had random and recursive connections (cf. review article on the early models [19]). Models with excitatory connections (positive weights only) tend to the maximal or minimal values of activity but models with excitatory and inhibitory connections show a rich and interesting stable behavior. Another style of neural modeling based on stochastic approach to neurons was inspired by statistical mechanics [20] and nonequilibrium thermodynamic [21] instead of classical dynamical systems. This line explored the fruitful connections with the Ising and spin glass models [22] and has lead to a number of interesting applications in modeling brain functions [23]. In the real brain random organization in the small scale is combined with highly specific organization of groups of neurons. Many groups of randomly connected cells, called netlets, were used for simulations showing interesting cooperative effects, including cyclic attractors [24]. Deterministic models try to get rid of the randomness by some kind of averaging procedures. However, there is experimental evidence that some groups of neurons behave in a chaotic way, for example in the olfactory bulb [25] chaotic EEG behavior is observed in the absence of stimuli and synchronized behavior when odorant is present.

One of the most interesting early attempts to create a computational theory of brain's functions was made by Caianiello [26]. His guiding principle was the conviction that dynamical laws obeyed by the brain concern large neuronal assemblies and are not necessarily very complicated. Caianiello proposed to divide the dynamics of the brain neural network according to the time scale. Fast dynamics, related to the retrieval of information, is described by the neuronic equations. Slow dynamics, related to the synaptic plasticity and learning, is described by the mnemonic equations. This "adiabatic" approximation is well justified for the long-term memory, although there are some fast learning processes, such as LTP [27]. The neuronic equations may be written as:

$$a_i(t + \tau) = \Theta \left[\sum_{k,j} W_{ij}^{(k)} a_j(t - k\tau) - \theta_i \right] \qquad (3)$$

where Θ is a step function (neurons are either active $a_i = 1$ or nonactive $a_i = 0$), τ is the time step, W_{ij} is the strength of

synaptic connection between neurons i and j; θ_i is the threshold of excitation of the neuron i and k numbers previous times steps that can influence new activity $a_i(t+\tau)$. In the absence of learning the dynamics of this system, identified with the "thought processes", has stable states of activity, described by the vector $a = (a_i)$ determined by the W_{ij} matrix.

The mnemonic equations used by Caianiello are rather complicated:

$$\frac{dW_{ij}^{(k)}(t)}{dt} = \tag{4}$$
$$\left[\alpha^{(k)}a_i(t)a_j(t-\tau) - \beta^{(k)}\Theta\left(W_{ij}^{(k)}(t) - W_{ij}^{(k)}(0)\right)\right]$$
$$\times W_{ij}^{(k)}(t)\Theta\left(A_{ij}^{(k)} - W_{ij}^{(k)}(t)\right) + \text{inhibition}$$

The inhibitory terms are quite similar to the excitatory ones. The first term in these equations is of the Hebbian type [15], i.e. it is proportional to the product of the pre- and post-synaptic activities. The last term restricts the connection strenght to maximum values preventing their unbounded growth. Networks of processing elements operating in accordance with the neuronic and mnemonic equations were used by Caianiello to study learning, forgetting, conditioning, analysis and spontaneous formation of patterns of reverberations. Logic plays a role of constraints on the type of behavior of the dynamical system. One may expect all kinds of effects in such complex system, including chaotic and quasi-periodic attractors and nonlinear rezonances. Characterization of this system requires determination of spontaneous modes of reverberation from neuronic equations. Short reverberations appear with the frequency of 10 Hz (assuming realistic time quantization connected with the average firing rate of biological neurons), in agreement with the observed EEG recordings. In the brain stable reverberations of a few neurons were observed lasting for minutes [26]. Epileptic seizures are one possible form of catastrophic instabilities in the network. Analyzing the mnemonic equations Caianiello points out that more realistic description of the brain should contain at least two additional structures: reticular activation system necessary for attention and thalamic structures controlling emotions.

Many other models of neural networks have been developed, for example perceptrons and the multilayered versions of perceptrons that are so popular in applications [13], but these models are not too interesting for cognitive modeling. In fact the model of Caianiello, although quite successful for qualitative explanations, is not specific enough to explain quantitatively experimental data. The book by D.S. Levine [28] reviewing various cognitive models does not even mention his model. More specific models of associative learning, sensory representation, lateral inhibition, competitive learning, conditioning, attention, reinforcement, coding and categorization, control, optimization and knowledge representation are discussed.

Experimental data on neural mechanisms leading to a formation of orientation and ocular dominance maps in the primary visual cortex are quite detailed. More than 10 computational models have been proposed [29] and compared with experimental data. Competitive Hebbian models describe the development of visual system on the mesoscopic level close to the resolution of neurobiological experimental data. In orientation and ocular dominance maps these models predict global disorder and anisotropies, singularities and fractures, simulate learning under exposure to a restricted set of oriented visual features, including monocular deprivation. Correlations between the two type of maps are also well reproduced. Such models are based on the self-organizing feature maps of Kohonen [30]. Response properties of cortical cell groups located at position $\mathbf{r}$ in the visual neurocortex involve the retinal location $(x(\mathbf{r}), y(\mathbf{r}))$, the degree of preference for orientation $q(\mathbf{r})sin(2\phi(\mathbf{r})), q(\mathbf{r})cos(2\phi(\mathbf{r}))$ (orientation maps code for 180 degree periodic orientation), and the ocular dominance $z(\mathbf{r})$. Feature vector $\Phi_t(\mathbf{r})$ composed from these five features evolves according to:

$$\Phi_{t+1}(\mathbf{r}) = \Phi_t(\mathbf{r}) + \alpha h_S(\mathbf{r},\mathbf{r}')[\mathbf{V}_{t+1} - \Phi_t(\mathbf{r})] \tag{5}$$

$0 < \alpha < 1$ and the stimulus $\mathbf{V}_{t+1}$ is chosen at random using some probability distribution. The local neighborhood function

$$h_S(\mathbf{r},\mathbf{r}') = \exp(-||\mathbf{r} - \mathbf{r}'||/2\sigma^2) \tag{6}$$
$$\mathbf{r}'(\mathbf{V},\Phi(\mathbf{r})) = \min_r ||\mathbf{V} - \Phi(\mathbf{r})||$$

Each presentation of a stimulus leads to a change of features around $\mathbf{r}'$, i.e. features coded by the group of neurons that are already most similar to the stimulus itself.

IV. FROM BRAIN TO MIND

The ambitious model of Caianiello has not influenced the mainstream of neural models of cognition because it lacked the modularity and specificity of different structures of the brain. Some of the insights offered by this model may ultimately prove to be true. It is clear that stable reverberations in the brain are connected with thoughts and perceptions. Direct observation of neural activity during such cognitive tasks as smelling [25], hearing words and meaningless sounds [31] or watching the pictures by monkeys [32] shows that global reverberations, interpreted as synchronized activity of a number of neural cell assemblies, correspond to perceptions and thoughts. Synchronization of oscillations of groups of neurons in the gamma band of EEG has been observed in many areas of neocortex as a result of visual stimulation [33]. Attractor character of the neural dynamics [23] has been demonstrated already in the experiments performed on cats by John *et.al.* [34]. Cats were trained to react to two different frequencies of pulsating light. Intermediate frequencies were leading to one of the two dynamics of the visual neurons and to the corresponding behavior of the animal.

Unfortunately neural systems showing interesting behavior are complex and difficult to analyze. Dynamical systems in physics are usually analyzed in a low dimensional space,

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rarely higher than five dimensional. Networks showing interesting properties may have hundreds or thousands of neurons and such large number of parameters makes them difficult to control. One way to simplify these models is to observe that the most important information about brain states is in the structure of attractors and transition probabilities of different attractor states. How are these attractors formed? Stable reverberations of neural cell assemblies, identified with determination of categories, thoughts and perceptions, arise because slow learning processes ("mnemonic equations" of Caianiello) make synaptic changes creating appropriate conditions for them. Due to the evolutionary selection processes the brain has learned basic categorization of lines, colors, shapes, visual objects, sounds, smells and other sensations. The low-level processing, developed in an unsupervised way by the computational topographical maps in the brain, provide the stimuli for the cell assemblies and some of these NCAs start to respond by reaching an attractor while the others stay in a chaotic state. In psychological terms this means that in the space of internal features of representation a particular combination of these features, corresponding to a category of perception, has been recognized and is kept active for some time. Such feature spaces (mental spaces, conceptual spaces or mind spaces) were used in psychology since a long time [35]. The correspondence of categories in feature spaces and attractors in the dynamics of the brain is the bridge between the mental and the physical [36].

This approach solves the neurons vs. symbols debate [37] defining the language useful in description of the cognitive, mind events and relation of these events to the dynamics of the brain. The problem of mind modeling is reduced from the problem of neural dynamics to a problem of finding the best approximation for this dynamics, for example by a geometrical representation of objects in the mind spaces. From a technical point of view one can do it in many ways, depending on the particular interest. Models of cognitive systems based on the mind space concept are realized in a natural way by neurofuzzy systems, combining neural optimization of adaptive parameters (learning) with symbolic representation based on fuzzy logics [17]. Learning and categorization is presented in such systems as a problem of constructing an appropriate geometrical model of the data in feature spaces of much lower dimension than the number of parameters necessary to describe the dynamics of the underlying network.

At present we have considered several ways to approach the problem of simplified description of feature spaces. First, the functional approach leads to a generalization of the Radial Basis Function model [18], especially in its constructivist form, where the network grows with the incoming data while the clusters in the feature space are constructed. This approach has been generalized in the Feature Space Mapping (FSM) system [17] where learning is presented from the geometrical point of view as finding the best possible description of "mind objects" in the feature spaces. From this point of view the best neural processing functions should have small number of parameters and should allow for great flexibility in defining regions of non-vanishing density in the feature space. Recogni-

tion is identified with the local maximum of density in which information about the object is stored. The input is composed from distorted or partially known vector of features pointing to a region in the feature space where the search for the object (local maximum of density) is made. Some applications to the "naive physics" and qualitative physics problems, i.e. mind models of understanding the basic ideas of physics, applications to recognition of the molecular or stellar spectra of the functional approach have been presented [17].

Another way of describing the mind space based on functional approach is to use Hilbert space formalism defining transition probabilities by overlaps of the densities representing different attractors, i.e. states and categories. Field computation in the brain based on a continua of microfeatures were developed into a model of a *simulacrum*, a continuous representation of information [38]. Other connections worth exploring are deterministic finite automata (DFA) and their stochastic versions, which may be used to model transitions between different attractors in dynamical systems and vice versa [39]. A theory of conceptual mental spaces has been developed in cognitive linguistics [40]. A rather different approach is based on the local coordinate transformations. Instead of functional description of mind objects the topology of the mind space is described by a local, noneuclidean coordinate systems parametrized in a non-linear way. In both cases network realization of systems describing feature spaces is natural.

Psychophysics should lead from Artificial Intelligence to models of Artificial Minds. Concepts of the mind space, mind function and mind states, the role of fuzzy logic and the dynamics of mind states, associations as coupling of attractors, adaptive resonances and descriptions of the mind space based on analogies with quantum mechanical formalism seem to be fruitful in establishing the bridge between neurosciences and cognitive psychology.

V. RESOURCES FOR NEURAL MODELING

Some resources that can be found in the Internet for developing neural models are listed here. WWW entry to the neural network Frequently Asked Questions is very useful [10]. In the same catalog FAQs of the comp.ai Usenet groups on evolutionary computation, fuzzy logic and artificial intelligence may be found. Neural network FAQ lists, among other things, free and commercial software packages for simulation and gives the addresses for software and preprint archives and databases.

Papers on neural networks (usually from the statistical mechanics perspective) are published in physics journals, for example in the Physical Review A or the Journal of Physics A. A large number of journals devoted to neural networks appeared in the last few years: Neural Networks (Official Journal of International Neural Network Society), Neural Computation, Network: Computation in Neural Systems, IEEE Transactions on Neural Networks, International Journal of Neural Systems,

International Journal of Neurocomputing, Neural Processing Letters, Neural Computing and Applications, Neural Network News, Connection Science: Journal of Neural Computing, Artificial Intelligence and Cognitive Research, International Journal of Neural Networks, Sixth Generation Systems (formerly Neurocomputers).

Other journals related to cognitive modeling: Cognitive Science, Artificial Intelligence, Journal of Complexity, Cognition, Cognitive Psychology, Journal Of Mathematical Psychology, Complex Systems, Biological Cybernetics (Kybernetik), The Journal of Experimental and Theoretical Artificial Intelligence, The Behavioral and Brain Sciences, Bulletin of Mathematical Biology, Machine Learning, Intelligence - The Future of Computing, Journal of Mathematical Biology, Journal of Complex System, Computer Simulations in Brain Science.

Neural anonymous ftp archive site ftp.funet.fi directory /pub/sci/neural contains the public domain software and papers. A few good addresses for WWW browsing:
http://www.idiap.ch/html/idiap-networks.html
http://www.neuronet.ph.kcl.ac.uk
and the Neurosciences Internet Resource Guide
http://http2.sils.umich.edu/Public/nirg/nirg1.html

Genetic Algorithms are used to optimize structure of neural networks, simulating evolutionary and developmental processes. Genetic algorithms start with a population of encoded procedures mutating them stochastically and using selection processes to determine the most promising directions of search in the optimization procedure (mutants with high fitness). Selection process involves mutations, recombinations, crossovers and other operators. A newsgroup dedicated to the field of evolutionary computation is called comp.ai.genetic (for FAQ of tthis group see [10]).

Ultimately large and complex models of brain structures will have to be simulated using neural hardware. Several large-scale projects, some based on custom neural chips, are in the design phase (for a review see [41]). Brain-size neurocomputer (about 10^{10} neurons), build using current technology chips organized according to a "fractal architecture", would fill the room 32 by 10 by 10 meters (about the size of Mark I, one of the first computers), and should have about 25 TBytes of RAM [41]. Such a large size is due to the essentially two-dimensional structure of integrated circuits.

VI. SUMMARY

In the broad sense psychophysics is still being born. It should be one of the core sciences exploring the relations between the brain and the mind. Many branches of science contribute to the emerging identity of cognitive science as a unique science aimed at understanding the information processing capabilities of the brain, including mental phenomena. Neurosciences, cognitive psychology, linguistics, computer science (artificial intelligence) and even philosophy have contributed to cognitive science. Contribution of physics is indirect, via the experimental techniques in the brain research,

via biophysical models at the level of single cell, statistical methods applied to the recurrent neural networks [23] and various dynamical models of the brain processes [13,26]. Contributions of physics to cognitive science will not be recognized until psychophysics, the branch of physics devoted to understanding the relations of the brain and mental processes, will not establish itself within physics first. If physics is understood as an attempt to understand Nature than understanding of the brain is its greatest challenge and it is a job for computational physicists.

[1] E. Schrödinger, Ann. Phys. 63 (1920) 481
[2] D.J. Murray, Behavioral and Brain Sci. 16 (1993) 115-186
[3] P.S. Churchland, T.J. Sejnowski, The computational brain. (MIT, Bradford Book 1992)
[4] W. Pauli, Der Einfluss archetypischer Vorstellungen und die Bildungnaturwissenschaftlischer Theorien bei Kepler, in: Naturerklrung und Psyche (Rascher, Zurich 1952), pp. 109-194
[5] H.P. Stapp, Mind, matter and quantum mechanics (Springer Verlag, Heidelberg 1993)
[6] R. Penrose, The Emperor's new mind (Oxford Univ. Press 1989); In the Shadow of the Mind (Oxford Univ. Press 1994)
[7] D.C. Dennett, Consciousness explained (Little Brown, Boston 1991)
[8] A. Newell, Unified theories of cognition. (Harvard Univ. Press, Cambridge, MA 1990)
[9] E. Thelen, L.B. Smith, A Dynamic Systems Approach to the Development of Cognition and Action (MIT Press 1994)
[10] URL is http://wwwipd.ira.uka.de/˜prechelt/FAQ/ neural-net-faq.html or via ftp from rtfm.mit.edu, catalog pub/usenet/news.answers file neural-net-faq
[11] W. Duch, G.H.F. Diercksen, *Neural networks as tools to solve problems in physics and chemistry* Comp. Physics Communic. **82** (1994) 91-103
[12] N. Rashevsky, Mathematical Biophysics (Dover, NY 1960)
[13] J.A. Anderson, E. Rosenfeld (Eds). Neurocomputing: Foundations of Research (MIT Press, MA 1988); J.A. Anderson, A. Pellionisz, E. Rosenfeld (Eds). Neurocomputing 2: Directions for Research (MIT Press, MA. 1990)
[14] S. Grossberg, The Adaptive Brain (North Holland 1987)
[15] D. Hebb, The Organization of Behavior (J. Wiley, NY 1949)
[16] J. Murre, CALM, Categorization and Learning Modules (Erlbaum 1992)
[17] W. Duch, G.H.F. Diercksen, *Feature Space Mapping as a universal adaptive system*. Comp. Phys. Communic. (1995)
[18] T. Poggio and F. Girosi, Proc. of the IEEE 78 (1990) 1481; J. Platt, Neural Comput. 3 (1991) 213; V. Kadirkamanathan, M. Niranjan, Neural Comput. 5 (1993) 954

[19] L.D. Harmon and E.R. Lewis, Neural modeling. Physiological Reviews 46 (1968) 513-591

[20] J.D. Cowan, A statistical mechanics of nervous activity. Lectures on Math. in Life Sciences 2 (1970) 1-57, ed. by M. Gerstenhaber (Am. Math. Soc, Providence RI)

[21] W.J. Freeman, Mass Action in the Nervous system (Academic Press, NY 1975)

[22] J.J. Hopfield, Proc. Nat. Acad. Sci. 79 (1982) 2554; ibid 81 (1984) 3088

[23] D.J. Amit, Modeling brain function. The world of attractor neural networks. (Cambridge Univ. Press 1989); T.L.H. Watkin, A. Rau, M. Biehl, Rev. Modern Phys. 65 (1993) 499

[24] P.A. Annios, Mathematical models of memory traces and forgetfulness. Kybernetik 10 (1972) 165-167; 11 (1972) 5-14

[25] C. Skarda, W.J. Freeman, How brains make chaos to make sense of the world. The Behavioral and Brain Sci. 10 (1987) 161-195

[26] E.R. Caianiello, Outline of a theory of thought processes and thinking machines. Journal of Theor. Biology 2 (1961) 204-235; E.R. Caianiello, A theory of neural networks. In: Neural Computing Architectures, ed. I. Aleksander (MIT Press, MA 1989)

[27] T.H. Brown, P.F. Chapman, E.W. Kairiss, C.L. Keenan, Long-term synaptic potentiation. Science **242** (1988) 724–728

[28] D.S. Levine, Introduction to neural and cognitive modeling (L. Erlbaum, London 1991)

[29] E. Erwin, K. Obermayer, K. Schulten, Models of Orientation and Ocular Dominance Columns in the Visual Cortex: A Critical Comparison. Neural Computation 7 (1995) 425-468

[30] T. Kohonen, An Introduction to Neural Computing. Neural Networks 1 (1988) 3-16

[31] Pulvermueller F, Preissl H, Eulitz C, Pantev C, Lutzenberger W, Elbert T and Birbaumer N. (1994) PSYCOLOQUY 5(48) brain-rhythms.1.pulvermueller

[32] M. Griniasty, M. Tsodyks, D. Amit, Conversion of temporal correlations between stimuli to spatial correlations between attractors. Neural Comput. 5 (1993) 1-17

[33] A.K. Engel, P. König, A.K. Kreiter, T.B. Schillen, W. Singer. Temporal coding in the neocortex: new vistas on integration in the nervous system. Trends in Neurosc. 15 (1992) 218-226

[34] E.R. John, M. Schimokochi, F.P. Bartlett, Neural readout from memory during generalization. Science **164** (1969) 1534-1536

[35] R.E. Mayer, Thinking, problem solving, cognition. (WH Freeman 1992)

[36] W. Duch (1994) UMK-KMK-TR 1/94 report, *A solution to the fundamental problems of cognitive sciences*, available from ftp.phys.uni.torun.pl/pub/papers/kmk

[37] I. Aleksander, H. Morton, Neurons and symbols (Chapman and Hall 1993)

[38] B. MacLennan, Field computation in the brain, CS-92-174 (Univ. of Tennessee, Knoxville, TN 37996)

[39] M.P. Casey, Computation in Discrete-Time Dynamical Systems (UCSD 1995, available in neuroprose).

[40] G. Fauconniere, Mental Spaces (Cambridge Univ. Press 1994)

[41] J.N.H. Heemskerk, J.M.J. Murre, Brain-size neurocomputers. (1995, draft); J.N.H. Heemskerk, Overview of neural hardware (1995, draft), available from ftp.mrc-apu.cam.ac.uk/pub/nn);