Neuro-, Genetic-, and Quantum Inspired Evolving Intelligent Systems

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***Abstract* – This paper discusses opportunities and challenges for the creation of evolving artificial neural network (ANN) and more general – computational intelligence (CI) models inspired by principles at different levels of information processing in the brain – neuronal-, genetic-, and quantum, and mainly – the issues related to the integration of these principles into more powerful and accurate ANN models. A particular type of ANN, evolving connectionist systems (ECOS), is used to illustrate this approach. ECOS evolve their structure and functionality through continuous learning from data and facilitate data and knowledge integration and knowledge elucidation. ECOS gain inspiration from the evolving processes in the brain. Evolving fuzzy neural networks and evolving spiking neural networks are presented as examples. With more genetic information available now, it becomes possible to integrate the gene and the neuronal information into neuro-genetic models and to use them for a better understanding of complex brain processes. Further down in the information processing hierarchy, are the quantum processes. Quantum inspired ANN may help solve efficiently the hardest computational problems. It may be possible to integrated quantum principles into brain-gene inspired ANN models for a faster and more accurate modeling. All the topics above are illustrated with some contemporary solutions, but many more open questions and challenges are raised and directions for further research outlined.**

Keywords: Artificial neural networks, Computational Intelligence, Neuro-informatics, Bionformatics, Evolving connectionist systems, Gene regulatory networks, Computational neurogenetic modeling, Quantum information processing.

1. Introduction: Brain-, gene-, and quantum levels of information processing as inspirations for CI models

The brain is an evolving information processing system that evolves its structure and functionality in time through information processing at different levels – Fig.1.

At the quantum level, particles (e.g., atoms, electrons, ions, photons, etc.) are in a complex evolving state all the time (Hey 1999). The atoms are the material that everything is made of. They can change their characteristics due to the frequency of external signals (Feynman 1965, Brooks 1999).

At a molecular level, RNA and protein molecules evolve in a cell and interact in a continuous way, based on the stored information in the DNA and on external factors, and affect the functioning of a cell (neuron) under certain conditions (Crick 1970).

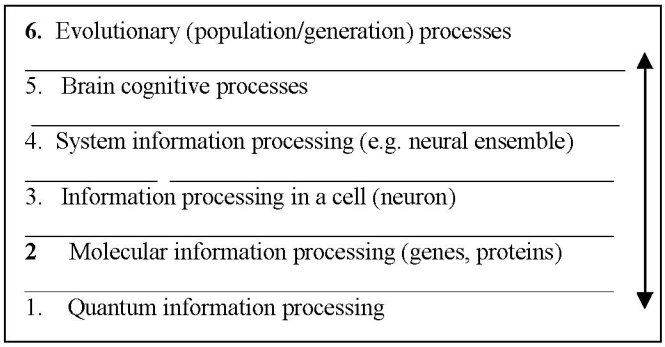

Fig. 1. Levels of information processing in the brain and the interaction between the levels.

At the level of a neuron, the internal information processes and the external stimuli cause the neuron to produce a signal that carries information to be transferred to other neurons.

At the level of neural ensembles, all neurons operate in a "concert", defining the function of the ensemble, for instance perception of sound.

At the level of the whole brain, cognitive processes take place, such as language and reasoning, and global information processes are manifested, such as consciousness.

At the level of a population of individuals, species evolve through evolution changing the genetic DNA code for a better adaptation.

The principles of each of the above processes have inspired the creation of different ANN models with the goals of:

- understanding the brain;
- creating powerful methods and systems of computational intelligence (CI) for solving complex problems in all areas of science and the humanity.

ANN models, that are brain-inspired (using some principles from the brain), or brain-like (more biologically plausible models, usually developed to model a brain function) have already been proposed (for references, see : Arbib 2003, Amari and Kasabov 1998). Examples are: models of single neurons and neural network ensembles (Rosenblatt 1962, Grossberg 1969 1982, (Amari 1967), Rumelhart et al,1986; Carpenter et al, 1991; Kohonen, 1997; Maas, 1996; Yamakawa et al, 1993;); cognitive ANN models (Arbib 2003, JG Taylor 1999; (Anderson); (Levine

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and Aparicio), etc.)

The information processes at each level from Fig.1 are very complex and difficult to understand, but much more difficult is to understand the interaction between the different levels. It may be that understanding the interaction through its modeling would help to understand better each level of information processing in the brain and perhaps the brain as a whole, a to create powerful tools to solve problems.

Some examples of ANN that combine principles from different levels in fig.1 are:

- Computational neuro-genetic models (Marnellos and Mjolsness 2003, Marcus 2004, Kasabov and Benuskova 2004, Benuskova 2006);
- Quantum inspired ANN (Ezhov and Ventura 2000, Perkowski 2005, Spector 2004, Brooks 1999, Pribram 1993);
- Evolutionary ANN models (D Fogel 1995, J Yao 1993).

Suggestions are made also that modeling higher cognitive functions and consciousness can be achieved only if the principles of quantum information processing are considered (Penrose 1989 1994).

There are many issues and open questions to be addressed when creating ANN and CI models that integrate principles from different levels. Here we will focus on the issues related to a class of ANN models called evolving connectionist systems (ECOS) (Kasabov 1998 2002). ECOS are ANN that develop their structure and functionality over time through incremental learning from incoming information and through interaction.

The paper discusses in section 2 two particular models inspired by the principles of evolving neuronal information processes – local learning ECOS and evolving spiking neural networks (SNN). In section 3, the issue of combining neuronal with genetic information processing is discussed and one particular computational neuro-genetic model (CNGM) is presented for illustration along with a list of open questions. Section 4 presents some ideas behind the quantum inspired ANN models and offers further open questions about the integration of principles from quantum-, -genetic- and neuronal information processing.

2. Some brain–inspired ECOS models

Many evolving ANN models have been suggested so far, where the structure and the functionality of the models evolve through incremental, continuous learning from incoming data, some times in an on-line mode, and through interaction with other models and the environment. Examples are: growing neural gas (Fritzek 1995), RAN (Platt 1991), cascade-correlation ANN (Fahlman and Lebiere 1990), on-line learning ANN (Heskes and Kapen 1993, Haykin 1994, Freeman and Saad 1997, Hinton 1989, Vapnik 1998, Blanzieri and Katenkamp 1996, Bishop 1995, Schaal and Atkenson 1998), FuzzyARTMAP (Carpenter et al, 1991), EFuNN (Kasabov, 1998, 2001), DENFIS (Kasabov and Song, 2002), evolving fuzzy systems (Angelov, 2002) and others Here two models are presented for illustration, mainly due to the author's personal involvement in their development, modifications and applications. General open questions are raised at the end of this section.

2.1 Local, knowledge–based learning: EFuNN, DENFIS and TWNF

Incremental, local learning from a stream of input data and specialization of an ensemble of neurons to perform a certain function as part of a more global goal is a principle of the human brain (Arbib 2003, W Freeman 2000).

Local learning ECOS are connectionist systems that evolve their nodes (neurons) and connections between them through incremental learning from data vectors where the nodes capture local information from the data in a supervised or unsupervised mode (Kasabov, 2002). One of the ECOS models, the evolving fuzzy neural network EFuNN (Kasabov, 2001), is shown in a simplified version in fig.2. It consists of five layers: input nodes, representing input variables; fuzzy input nodes, representing the degree to which input values belong to fuzzy membership functions that are used to define concepts such as Low value, or High value for a variable; rule nodes, representing cluster centers of samples in the problem space and their associated local output functions; fuzzy output nodes, representing membership degrees of the output values to predefined output membership functions; and output nodes that represent output variables. The fuzzy representation nodes are optional.

ECOS evolve incrementally rule nodes to represent cluster centers of the input data, where the first layer W1 of connection weights of these nodes represent their co-ordinates in the input space, and the second layer of connections W2 represents the local models (functions) allocated to each of the clusters.

Data samples are allocated to rule nodes based on their similarity, measured either in the input space - this is the case in some of the ECOS models, e.g. the dynamic neuro-fuzzy inference system DENFIS (Kasabov and Song, 2002) and the zero instruction set computers – ZISC, or in the input and the output space - this is the case in the evolving fuzzy neural networks EFuNN – fig.2. Samples that have a distance to an existing cluster center (rule node) N of less than a threshold Rmax (for the EfuNN models the output vectors of these samples have to be different from the output value associated with this cluster center in not more than an error tolerance E) are allocated in the same cluster Nc. Samples that do not fit into existing clusters form new clusters.

Cluster centers are continuously adapted to new data between samples and nodes can be measured in different ways. The most popular measurement is the normalized Euclidean distance as it is in the self-organised maps SOM (Kohonen 1997).

In case of missing values for some of the input variables, a partial normalized Euclidean distance can be used which means that only the existing values for the variables in a

current sample S (x,y) are used for the distance measure between this sample and an existing node N:

$$d(S,N) = \text{sqrt}\,(\Sigma_{i=1,..,n}\ (x_i - W1_{N(i)})^2)\ /n, \quad (1)$$

for all n input variables x_i that have a defined value in the sample S and an already established connection $W_{N(i)}$.

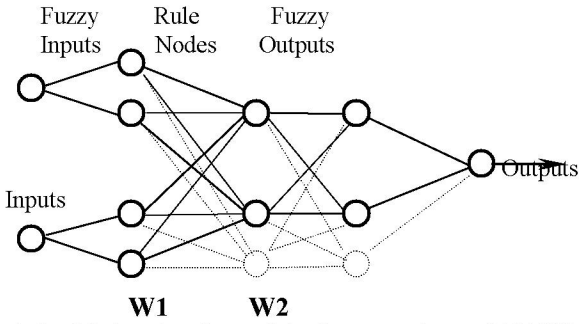

Fig.2. A simplified version of an evolving fuzzy neural network EFuNN (from Kasabov, 2001)

At any time of the EFuNN or DENFIS continuous and incremental learning, rules can be derived from the ANN structure that represent the local functions. Each rule associates a cluster area from the input variable space with a local output function applied to the data in this cluster, e.g.:

IF <data is in cluster Ncj , defined by a cluster center Nj, a cluster radius Rj and a number of examples Njex in this cluster> THEN < output function is Fc> (2)

In case of DENFIS, first order local fuzzy rule models are derived incrementally from data, for example:

IF <the value of x1 is in the area defined by Gaussian membership function with a center at 0.1 and a standard deviation of 0.05, AND the value of x2 is in the area defined by a Gaussian function with parameters (0.25,0.1) respectively> THEN <the output y is calculated by the formula: y=0.01+0.7x1+0.12x2> (3)

In case of EFuNN, local simple fuzzy rule models are derived, for example:

IF: IF x1 is (Medium 0.8) and x2 is (Low 0.6)
THEN y is (High 0.7), radius R=0.24; Nexamp= 6, (4)

where: Low, Medium and High are fuzzy membership functions defined for the range of each of the variables x1, x2, and y; the number and the type of the membership functions can either be deduced from the data through learning algorithms, or it can be predefined based on human knowledge (Zadeh 1965, Cloete and Zurada 2000, Yamakawa et al 1993); R is the radius of the cluster and Nexamp is the number of examples in the cluster.

Further development of the EFuNN and the DENFIS local ECOS models is the Transductive Weighted Neuro- Fuzzy Inference Engine (TWNFI) (Song and Kasabov, 2005). In this approach, for every new vector (sample S/example) a "personalized" model is developed from existing nearest samples, where each of the variables is normalized in a different sub-range of [0,1], so that they have a different influence on the Euclidean distance, therefore they are weighted in terms of their importance to the output calculated for any new sample individually. Samples are also weighted in the model based on their distance to the new sample, where in the Euclidean distance formula variables are also weighted. Each personalized model can be represented as a rule (or a set of rules) that represent the personalized profile for the new input vector. The TWNFI model is evolving as new data samples, added to a data set, can be used in any further personalized model development. That includes using different sets of variables, features.

2.2. Incremental feature selection for evolving connectionist systems

The brain has the ability to incrementally improve and optimize the set of features while learning continuously to recognize patterns. In many CI problems data samples arrive in chunks and sometimes – new class samples are presented – see for illustration fig.3. Inspired by the brain ability to select features incrementally, several methods have been proposed.

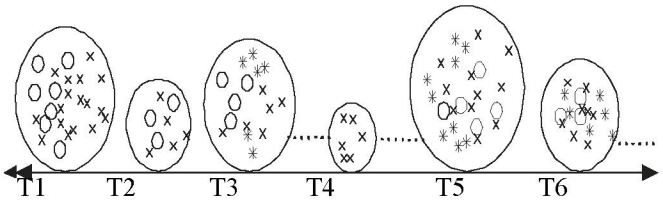

Fig.3. Incremental presentation of chunks of data over time periods T1,T2,…, having samples of initially 2 classes (time T1), but introducing at a time T3 a third class samples (from Ozawa, et al, 2005).

In (Ozawa et al 2005 2006) a method for incremental PCA learning from a stream of data is presented. In (Pang et al, 2005) a method for incremental LDA feature selection is proposed. While the structure of an ECOS is evolving incrementally, the set of the input variables (features) in the model can also be evolving, changing over time.

2.3. Evolving spiking neural networks (SNN)

Spiking models of a neuron and of neural networks – spiking neural networks (SNN), have been inspired and developed to mimic more biologically the spiking activity of neurons in the brain when processing information (Maas 1996).

One model - the spike response model (SRM) of a neuron (Maass and Bishop 1999, Gerstner and Kistler 2002) is described below and extended to an evolving SNN. It is also used in section 3 to create a computational neuro-genetic model (CNGM).

A neuron i receives input spikes from pre-synaptic neurons $i \in \Gamma i$, where Γi is a pool of all neurons pre-synaptic to neuron i. The state of the neuron i is described by the state variable ui(t) that can be interpreted as a total postsynaptic potential (PSP) at the membrane of soma. When ui(t) reaches the firing threshold $\vartheta i(t)$, neuron i fires, i.e. emits a spike – fig.4, fig.5. The moment of $\vartheta i(t)$ crossing defines a firing time ti of an output spike. The value of the state variable ui(t) is the sum of all postsynaptic potentials, i.e.

$$u_i(t) = \sum_{j \in \Gamma_i} \sum_{t_j \in F_j} J_{ij} \varepsilon_{ij}(t - t_j - \Delta_{ij}^{ax}) \quad (5)$$

The weight of synaptic connection from neuron j to neuron i is denoted by Jij. It takes positive (negative) values for excitatory (inhibitory) connections, respectively. Depending on the sign of Jij, a pre-synaptic spike generated at time tj increases (or decreases) ui(t) by an amount $\varepsilon_{ij}(t - t_j - \Delta_{ij}^{ax})$, where Δ_{ij}^{ax} is an axonal delay between neurons i and j which increases with Euclidean distance between neurons.

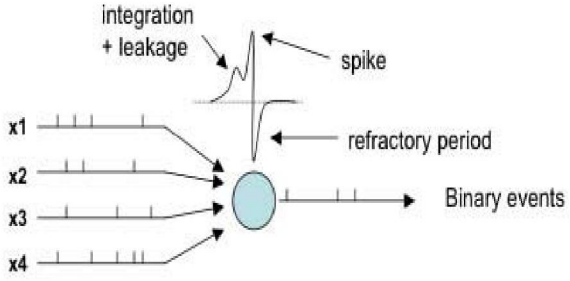

Fig. 4. A general representation of a spiking neuron model (from Kasabov, Benuskova, Wysoski, 2004).

The positive kernel $\varepsilon_{ij}(t - t_j - \Delta_{ij}^{ax}) = \varepsilon_{ij}(s)$ expresses an individual postsynaptic potential (PSP) evoked by a presynaptic neuron j on neuron i.

A double exponential formula can be used, where $\tau_{decay/\,rise}^{synapse}$ are time constants of the rise and fall of an individual PSP, A is the PSP's amplitude, and synapse = fast_excitation, fast_inhibition, slow_excitation, and

$$\varepsilon_{ij}^{synapse}(s) = A^{synapse}\left(\exp\left(-\frac{s}{\tau_{decay}^{synapse}}\right) - \exp\left(-\frac{s}{\tau_{rise}^{synapse}}\right)\right) \quad (6)$$

slow_inhibition, respectively. These types of PSPs are based on neurobiological data (Destexhe 1998, Semyanov 2002).

Immediately after firing an output spike at time ti, the neuron's firing threshold ϑi(t), increases m times and then returns to its initial value ϑ0 in an exponential fashion:

$$\vartheta_i(t - t_i) = m \times \vartheta_0 \exp\left(-\frac{t - t_i}{\tau_{decay}^{\tau}}\right) \quad (7)$$

where $\vartheta_{decay}^{\vartheta}$ is the time constant of the threshold decay. In such a way, absolute and relative refractory periods are modeled – fig.5.

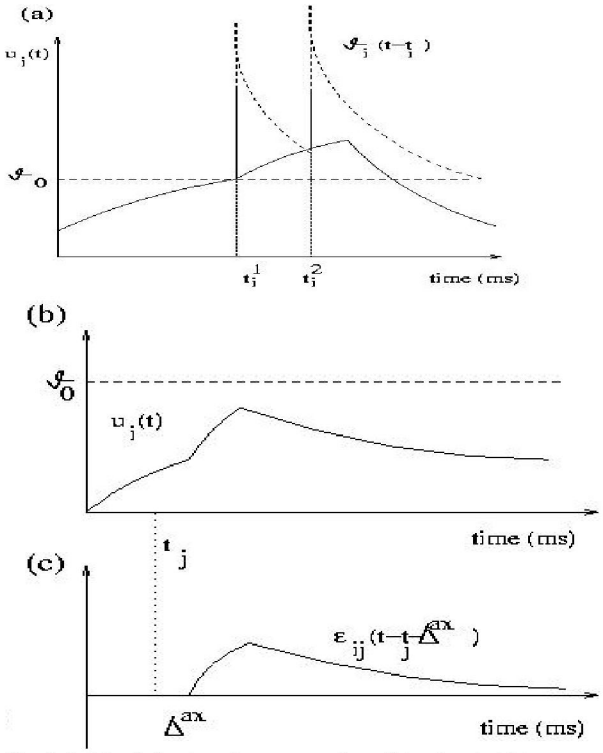

Fig. 5. Spiking behavior of a neuron – the spiking threshold increases after the first spike and then goes back to a normal state (from Kasabov, Benuskova, Wysoski, 2005)

External inputs from the input layer are added at each time step, thus incorporating the background noise and/or the background oscillations. Each external input has its own weight $J_{ik}^{ext\_input}$ and $\varepsilon_k(t)$, such that:

$$u_i^{ext\_inpu}(t) = J_{ik}^{ext\_input} \varepsilon_{ik}(t) \quad (8)$$

It is optional to add some degree of Gaussian noise to the right hand side of the equation above to obtain a stochastic neuron model instead of a deterministic one.

Spiking neurons within a SNN can be either excitatory or inhibitory. Lateral connections between neurons in a SNN may have weights that decrease in value with distance from neuron i for instance according to a Gaussian formula while the connections between neurons themselves can be established at random.

SNN can be used to build biologically plausible models of brain sections as illustrated in (Destexhe 1998, Kasabov and Benuskova, 2004).

In evolving SNN new neurons and connections can be created incrementally to accommodate new data samples over time. For example, in (Wysoski et al 2006) a new sub-module of several spiking neurons and connections is evolved when a new class of objects (e.g. a new face, in case of face recognition problem) is presented to the system for learning at any time of this process. In addition to the on-line creation of new class structures in a SNN, such new structures can be created when a new sample of a previously

introduced class does not activate any of the existing neurons (structures), similar to the ECOS described in the previous section. This work extends the work in (Delorme et al 1999).

Developing new methods for learning in evolving SNN is a challenging direction for future research with a potential for applications in multimodal information processing (e.g. speech, image, odor, gestures).

2.4. Some open questions

Further development of brain-like or brain-inspired ANN requires some questions to be addressed:

- How much should an ANN mimic the brain in order to be an efficient CI model?
- How is a balance between structure definition and learning achieved in ANN?
- How can ANN evolve and optimize their parameters and input features over time in an efficient way?
- How incremental learning in ANN can be achieved without a presentation of an input signal ("sleep" learning)?
- Can ANN have "dreams" and how that can affect their evolving learning and structure?

3. BRAIN-GENE INSPIRED COMPUTATIONAL NEURO-GENETIC MODELS (CNGM)

3.1. General notions

With the advancement of molecular and brain research technologies more and more data and information is being made available about the genetic basis of some neuronal functions (see for example: the brain-gene map of mouse at http://alleninstitute.org; the brain-gene ontology BGO at http://www.kedri.info).

This information can be utilized to create biologically plausible ANN models of brain functions and diseases that include models of gene interaction. This area integrates knowledge from computer and information science, brain science, molecular genetics and it is called here computational neurogenetic modeling (CNGM) (Kasabov and Benuskova 2004).

Several CNGM models have been developed so far varying from modeling a single gene in a biologically realistic ANN model, to modeling a set of genes forming an interaction gene regulatory network (GRN) (Marnellos and Mjolsness 2003, Kasabov and Benuskova 2004, Marcus 2004, Benuskova et al 2006). In this section we give an example of a CNGM that combines SNN and GRN into one model.

3.2. Am abstract computational neuro-genetic model (CNGM) that integrates GRN within a SNN model

The main idea behind the model proposed in (Kasabov and Benuskova 2004) is that interaction of genes in neurons affect the dynamics of the whole ANN through neuronal parameters, which are no longer constant, but change as a function of gene/protein expression. Through optimization of the GRN, the initial gene/protein expression values, and the ANN parameters, particular target states of the ANN can be achieved, so that the ANN can be tuned to model real brain data in particular.

This idea is illustrated here by means of a simple neurogenetic model of a SNN. The behavior of the SNN is evaluated by means of the local field potential (LFP), thus making it possible to attempt modeling the role of genes in different brain states, where EEG data is available to test the model. A standard FFT signal processing technique is used to evaluate the SNN output and to compare it with real human EEG data. Broader theoretical and biological background of CNGM construction is given in (Kasabov and Benuskova, 2004). A simple linear version of an internal GRN with preliminary results on epilepsy modeling can be found in (Kasabov and Beniskova, 2004). In (Benuskova et al 2006) a more realistic nonlinear model of GRN is proposed with a list of real proteins/genes that are involved in CNGM. The model performance is compared to real human EEG data using the same signal processing technique, where an optimization procedure is proposed to obtain a CNGM with parameters leading to modeling of the real EEG signal.

In general, we consider two sets of genes – a set G_{gen} that relates to general cell functions, and a set G_{spec} that defines specific neuronal information-processing functions (receptors, ion channels, etc.). The two sets form together a set $G=\{G_1, G_2, \ldots, G_n\}$. We assume that the expression level of each gene is a nonlinear function of expression levels of all the genes in G, inspired by discrete models:

$$g_j(t+\Delta t') = \sigma\left(\sum_{k=1}^{n} w_{jk} g_k(t)\right) \quad (9)$$

It is assumed here that: (1) one protein is coded by one gene; (2) relationship between the protein level and the gene expression level is nonlinear; (3) protein levels lie between the minimal and maximal values. Thus, the protein level is expressed by the following equation:

$$p_j(t+\Delta t) = (p_j^{\max} - p_j^{\min})\sigma\left(\sum_{k=1}^{n} w_{jk} g_k(t)\right) + p_j^{\min} \quad (10)$$

The delay constant introduced in the formula corresponds to the delay caused by the gene transcription, mRNA translation into proteins and posttranslational protein modifications, and also the delay caused by gene transcription regulation by transcription factors.

Some proteins and genes are known to be affecting the spiking activity of a neuron represented in a SNN model by neuronal parameters. Some neuronal parameters and their correspondence to particular proteins are summarized in Table 1.

Relevant protein expression levels are directly related to neuronal parameter values P_j such that:

$$P_j(t) = P_j(0)\, p_j(t) \qquad (11)$$

where Pj(0) is the initial value of the neuronal parameter at time t = 0.

Besides the genes, coding for the proteins mentioned above and directly affecting the spiking dynamics of a neuron, a GRN model can include other genes relevant to a problem in hand, e.g. modeling a brain function or a brain disease. In (Benuskova et al 2006) these genes/proteins are: c-jun, mGLuR3, Jerky, BDNF, FGF-2, IGF-I, GALR1, NOS, S100beta.

An example of a CNGM is given in fig.6 for the purpose of modeling inputs from the thalamus to the cortex. It uses the Spike Response Model (Gerstner and Kistler 2002), with excitation and inhibition having both fast and slow components, both expressed as double exponentials with amplitudes and the rise and decay time constants.

The goal of the CNGM is to achieve a desired SNN output through optimization of the model parameters. The LFP of the SNN, defined as LFP = $(1/N)\Sigma\, u_i(t)$, by means of FFT is evaluated in order to compare the SNN output with the EEG signal analyzed in the same way. It has been shown that brain LFPs in principle have the same spectral characteristics as EEG (Kirk and Mackay 2003).

In order to find an optimal GRN within the SNN model, so that the frequency characteristics of the LFP of the SNN model are similar to the brain EEG characteristics, the following evolutionary computation procedure is used:

1. Generate a population of CNGMs, each having randomly generated values of coefficients for the GRN matrix W, initial gene expression values g(0), initial values of SNN parameters P(0), and different connectivity;
2. Run each SNN over a period of time T and record the LFP
3. Calculate the spectral characteristics of the LFP using FFT;

TABLE I
NEURONAL PARAMETERS AND THEIR RELATED PROTEINS

Neuronal parameter AMPLITUDE AND TIME CONSTANTS OF	Protein*
Fast excitation PSP	AMPAR
Slow excitation PSP	NMDAR
Fast inhibition PSP	GABRA
Slow inhibition PSP	GABRB
Firing threshold	SCN, KCN, CLC

*Abbreviations: PSP = postsynaptic potential, AMPAR = (amino-methylisoxazole- propionic acid) AMPA receptor, NMDAR = (N-methyl-D-aspartate acid) NMDA receptor, GABRA = (gamma-aminobutyric acid) $GABA_A$ receptor, GABRB = $GABA_B$ receptor, SCN = Sodium voltage-gated channel, KCN = kalium (potassium) voltage-gated channel, CLC = chloride channel.

4. Compare the spectral characteristics of SNN LFP to the characteristics of the target EEG signal. Evaluate the closeness of the LFP signal for each SNN to the target EEG signal characteristics. Proceed further according to the standard GA algorithm to find a SNN model that matches the EEG spectral characteristics better than previous solutions;
5. Repeat steps 1 to 4 until the desired GRN and SNN model behavior is obtained;
6. Analyze the GRN and the SNN parameters for significant gene patterns that cause the SNN model to manifest similar spectral characteristics as the real data.

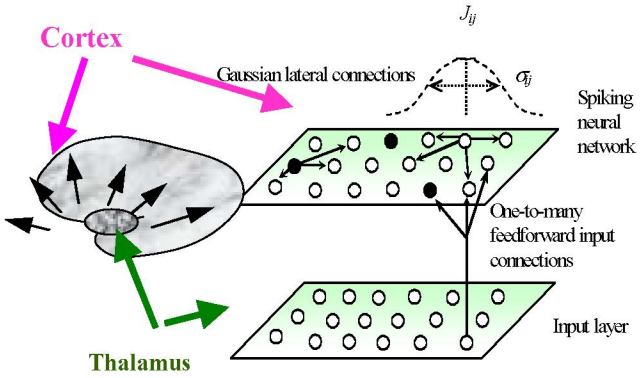

Figure 6. An example of a SNN model used in a CNGM. About 10-20% of N = 120 neurons are inhibitory neurons that are randomly positioned on the grid (filled circles). External input is random with a defined average frequency (e.g. between 10-20 Hz) (from Benuskova et al 2006).

In (Kasabov et al 2005) some preliminary results of analysis performed on real human interictal EEG data are presented. The model performance and the real EEG data are compared for the following relevant to the problem sub-bands: delta (0.5-3.5 Hz), theta (3.5-7.5 Hz), alpha (7.5-12.5 Hz), beta 1 (12.5-18 Hz), beta 2 (18-30 Hz), gamma (above 30 Hz). This particular SNN had an evolved GRN with only 5 genes out of 16 (s100beta, GABRB, GABRA, mGLuR3, c-jun) and all other genes having constant expression values. A GRN is obtained that has a meaningful interpretation and can be used to model what will happen if a gene/protein is suppressed by administering a drug, for example.

In evolving CNGM new genes can be added to the GRN model at a certain time, in addition to the new spiking neurons and connections created incrementally, as in the evolving SNN. Developing new evolving CNGM to model brain functions and brain diseases, such as epilepsy, Alzheimer, Parkinson disease, Schizophrenia, mental retardation and others is a challenging problem for a future research.

We should again emphasize on the fact that the above described model is an abstract one and not necessarily modeling real genes and their physical and chemical connections and functions, but rather – their indirect relationship and interaction.

There are some technical questions that emerged from the first CNGM experiments, such as:

- How many different GRNs would lead to similar LFPs of the same SNN and what do they have in common?
- What neuronal parameters to include in the SNN model and how to link them to activities of genes/proteins?

- What genes/proteins to include in the model and how to represent the gene interaction over time within each neuron?
- How to integrate in time the output activity of the SNN and the genes, as it is known that neurons spike in millisecond intervals and the process of gene transcription and translation into proteins takes minutes?
- How to create and validate a CNG model in a situation of insufficient data?
- How to measure brain activity and the CNGM activity in order to validate the model?
- What useful information (knowledge) can be derived from a CNG model?
- How to adapt incrementally a CNGM model in a situation of new incoming data about brain functions and genes related to them?

3.3. Open questions

Integrating principles from gene- and neuronal information processing in a single ANN model raises many general questions that need to be addressed in the future, for example:

- Is it possible to create a truly adequate CNGM of the whole brain? Would gene-brain maps help in this respect (see http://alleninstitute.org)?
- How can dynamic CNGM be used to trace over time and predict the progression of a brain diseases, such as epilepsy and Parkinson's ?
- How to use CNGM to model gene mutation effects?
- How to use CNGM to predict drug effects?
- How CNGM can help understand better brain functions, such as memory and learning?
- What problems of CI can be efficiently solved with the use of a brain-gene inspired ANN?

4. QUANTUM INSPIRED EVOLVING CONNECTIONIST MODELS

4.1. Why quantum inspired models and systems?

Quantum computation is based upon physical principles from the theory of quantum mechanics. (see R. P. Feynman et al, 1965).

One of the basic principles is the linear *superposition* of states. At a macroscopic or classical level a system exists only in a single basis state as energy, momentum, position, spin and so on. However, at microscopic or quantum level a quantum particle (e.g., atom, electron, positron, ion), or a quantum system is in a superposition of all possible basis states. At the microscopic level any particle can assume different positions at the same time, can have different values of energy, can have many values of the spins and so on. This superposition principle is counterintuitive.

If a quantum system interacts in any way with its environment, the superposition is destroyed and the system collapses into one single real state as in the classical physics (Heisenberg). This process is governed by a probability amplitude. The square of the intensity of the probability amplitude is the quantum probability to observe the state.

Another quantum mechanics principle is the *entanglement* - two or more particles, regardless of their location, are in the same state with the same probability function. The two particles can be viewed as "correlated", undistinguishable, "synchronized", coherent. An example is a laser beam consisting of millions of photons having same characteristics and states.

Quantum systems are described by a probability density ψ that exists in a Hilbert space. The Hilbert space has a set of states $|\varphi i\rangle$ forming a basis. A system can exist in a certain quantum state $|\psi\rangle$ which is defined as:

$$\psi\rangle = \sum ci|\varphi i\rangle, \quad (12)$$

where the coefficients ci may be complex. $|\psi\rangle$ is said to be in a superposition of the basis states $|\varphi i\rangle$. For example the quantum inspired analogue of a single bit in classical computers can be represented as a qu-bit in a quantum computer:

$$|x\rangle = a|0\rangle + b|1\rangle \quad (13)$$

where $|0\rangle$ and $|1\rangle$ represent the states 0 and 1. The qu-bit is not a single value entity, but is a function of parameters which values are complex numbers. After the loss of coherence the qu-bit will collapse into one of the states $|0\rangle$ or $|1\rangle$ with the probability a^2 for the state $|0\rangle$ and the probability b^2 for the state $|1\rangle$, where: $|a|^2 + |b|^2 = 1$.

So, in quantum mechanics and in any scientific domain, where we use the superposition, the introduction of the qu-bit to measure information states change radically any interpretation of the information processes and also of any computation.

The state of a qu-bit can be changed by an operation called a *quantum gate*. A quantum gate is a reversible gate and can be represented as a unitary operator U acting on the qu-bit basis states. The defining property of an unitary matrix is that its conjugate transpose is equal to its inverse. There are several quantum gates already introduced, such as the NOT gate, controlled NOT gate, rotation gate, Hadamard gate, etc. (Perkowski 2005, Collin et al 1998).

Quantum mechanical computers and quantum algorithms try to exploit the massive quantum parallelism which is expressed in the principle of superposition. The principle of superposition can be applied to many existing methods of CI, where instead of a single state (e.g. a parameter value, or a finite automata state, or a connection weight, etc.) a superposition of states will be used, described by a wave probability function, so that all these states will be computed in parallel increasing the speed of computation by many orders of magnitude.

Quantum mechanical computers have been proposed in the early 1980s and a description was formalized in the late 1980s (P. Benioff 1980). This kind of computers proved to be superior to classical computers in various specialized problems. Many efforts were undertaken to extend the principal ideas of quantum mechanics to other fields of interest. There are well known quantum algorithms such as Shor's quantum factoring algorithm (P. W. Shor 1997) and Grover's database search algorithm (L. K. Grover 1996).

Hogg extended the work of Grover in order to demonstrate the application of quantum algorithms in the context of combinatorial search (T. Hogg and D. Portnov, 2000).

The advantage of quantum computing is that, while a system is uncollapsed, it can carry out more computing than a collapsed system, because, in a sense, it is computing in many universes at once. The above quantum principles have inspired research in both computational methods and brain study.

It is widely accepted now that NP-hard problems (e.g. time complexity grows exponentially with the size of the problem) can be solved by a quantum computer. Penrose (1994) argues that solving the quantum measurement problem is pre-requisite for understanding the mind as consciousness emerges as a macroscopic quantum state due to a coherence of quantum-level events within neurons.

4.2. Quantum inspired evolutionary and connectionist models

Quantum inspired methods of evolutionary computation (QIEC) have been already discussed in (K.-H. Han and J.-H. Kim 2002, J.-S. Jang et al 2003), that include: genetic programming (L. Spector 2004), particle swarm optimizers (J. Liu et al, 2005), finite automata and Turing machines (P. Benioff, 1980). In QIEC, the population of Q-bit individuals at time t can be represented as:

$$Q(t) = \{q_1^t, q_2^t, \ldots, q_n^t\} \quad (14)$$

where n is the size of the population.

Evolutionary computing with Q-bit representation has a better characteristic of population diversity than other representations, since it can represent linear superposition of states probabilistically. The Q-bit representation leads to a quantum parallelism in the system as it is able to evaluate the function on a superposition of possible inputs. The output obtained is also in the form of superposition which needs to be collapsed to get the actual solution.

Recent research activities focus on using quantum principles for ANN (Venrura 1999, Ezhov and Ventura 2000; Resconi et al 1999 2000, Narayanan and Meneer 2000; Venayagamoorthy et al, 2006). Considering quantum ANN seems to be important for at least two reasons. There is evidence for the essential role that quantum processes may play in realizing information processing in the living brain. Roger Penrose argued that a new physics binding quantum phenomena with general relativity can explain such mental abilities as understanding, awareness and consciousness (R. Penrose, 1994). The second motivation is the possibility that the field of classical ANN could be generalized to the promising new field of quantum computation (M. Brooks 1999). Both considerations suggest a new understanding of mind and brain function as well as new unprecedented abilities in information processing. Ezhov and Ventura are considering the quantum neural networks as the next natural step in the evolution of neurocomputing systems (A. Ezhov and D. Ventura, 2000). Several quantum inspired ANN models have been proposed and illustrated on small examples. In (Venayagamoorthy et al, 2006) a QIEA is used to train a MLP ANN.

Naraynan and Meneer simulated classical and various types of quantum inspired ANN and compared their performance (A.Narayanan and T. Meneer, 2000). Their work suggests that there are indeed certain types of problems for which quantum neural networks will prove much superior to classical ones.

Other relevant work includes quantum decision making (M. T. D. Cronin et al 2003), quantum learning models (N. Kouda 2005), quantum networks for signal recognition (X.-Y. Tsai et al 2005) and quantum associative memory (C. A. Trugenberger 2002, D. Ventura and T. Martinez 2000). There are also recent approaches to quantum competitive learning where the quantum system's potential for excellent performance is demonstrated on real-world data sets (D. Ventura, 1999; G. Xie and Z. Zhuang, 2003).

The quantum inspired neural network (QUINN) proposed by Narayanan and Meneer (2000) interprets each input pattern Sp (p=1,2,…k) as a particle, being learned in a separate NNp model in a separate universe Up, the superposition of all ANN constituting the ANN model. The structure of all ANN is the same, so that a connection weight between neuron Ni and neuron Nj in the total model is a superposition of all connection weights Wij (k) of all k ANNs. When an input pattern S is presented, the ANN model "collapses" into a particular NN-S that recognises this pattern. Each pattern needs to be presented only once in order a NN model to be created for this pattern and become part of the superposition of all NN models.

In *evolving* quantum inspired ANN, presenting a new pattern S k+1 (a new particle) would cause the creation of a new ANN model that becomes part of the superposition of connection weights and states of the whole system.

Quantum inspired SNN would have a smaller number of neurons and a much larger number of states due to the superposition principle. A challenge would be to represent the spikes as superposition of trains of signals across many QI-SNN.

4.3. A quantum inspired CNGM – a preliminary conceptual model

A QI-CNGM would open new possibilities for modelling gene-neuron interactions. In section 3 a CNGM was presented that combines principles of information processing in gene/protein molecules with neuronal spiking activity, and then – to the information processing of a neuronal ensemble that is measured as local field potentials (LFP). How the quantum information processes in the atoms and particles (ions, electrons, etc), that make the large gene/protein molecules, relate to the spiking activity of a neuron and to the activity of a neuronal ensemble, is not known yet and it is a challenging question for the future.

What is known at present, is that the spiking activity of a neuron relates to the transmission of thousands of ions and neurotransmitter molecules across the synaptic clefts, and to

the emission of spikes. Spikes, as carriers of information, are electrical signals made of particles that are emitted in one neuron and transmitted along the nerves to the synapses of many other neurons. These particles are characterized by their quantum properties. So, quantum properties may influence, under certain conditions, the spiking activity of neurons and of the whole brain, as brains obey the laws of quantum mechanics (as everything else does).

Similarly to a chemical effect of a drug to the protein and gene expression levels in the brain, that may affect the spiking activity and the functioning of the whole brain (modelling of these effects is subject of the computational neurogenetic modelling CNGM), external factors like radiation, high frequency signals etc. may influence the quantum properties of the particles in the brain through gate operators and their spiking activity as well. According to Penrose (1989), microtubules in the neurons are associated with quantum gates.

So, the question is: Is it possible to create *CNGM that incorporate some quantum principles, QI-CNGM?*

We can represent the above problem as a set of preliminary hypothetical functions as follows. A future state Q` of a particle or a group of particles (e.g. ions, electrons, etc.) depends on the current state Q and on the frequency spectrum Eq of an external signal, according to the Max Planck constant:

$$Q` = Fq\ (Q, Eq)), \qquad (15)$$

A future state of a molecule M` or a group of molecules (e.g. genes, proteins) depends on its current state M, on the quantum state Q of the particles that make this molecule, and on an external signal Em:

$$M` = Fm\ (M, Q, Em), \qquad (16)$$

A future state N` of a spiking neuron, or an ensemble of neurons will depend on its current state N, on the state of the molecules M, on the state of the particles Q and on external signals En

$$N` = Fn\ (N, M, Q, En), \qquad (17)$$

A future cognitive state C` of the brain will depend on its current state C and also on the neuronal N, on the molecular-M, and on the quantum Q states of the brain:

$$C` = Fc\ (C, N, M, Q, Ec), \qquad (18)$$

Some support for the above hypothetical model of integrated function representation comes from the following assumptions (Penrose 1989 1994, Arbib 2003, JG Taylor 1999, Freeman 2000):

- A large amount of atoms are characterised by the same quantum properties, possibly related to the same gene/protein expression profile of a large amount of neurons characterised by spiking activity;
- A large neuronal ensemble can be represented by a single LFP;
- A cognitive process can be represented perhaps as a complex function Fc that depends on all previous levels.

4.4. Some open questions

Many open questions need to be addressed before the quantum inspired models and systems are established as part of the area of CI and especially – to model bioinformatics and neuro-informatics data. Some of them are listed below:

- How quantum processes affect the functioning of a living system in general?
- How quantum processes affect cognitive and mental functions?
- Is it true that the brain is a quantum machine – working in a probabilistic space with many states (e.g. thoughts) being in a superposition all the time and only when we formulate our thought through speech or writing, then the brain "collapses" in a single state?
- Is fast pattern recognition in the brain, involving far away segments, a result of both parallel spike transmissions and particle entanglement?
- Is communication between people and between living organisms in general, a result of entanglement processes?
- How does the energy in the atoms relate to the energy of the proteins, the cells and the whole brain?
- Would it be beneficial to develop different quantum inspired (QI) computational intelligence techniques, such as: QI-SVM, QI-GA, QI-decision trees, QI-logistic regression, QI-cellular automata, QI-ALife?
- How do we implement the QI computational intelligence algorithms in order to benefit from their high speed and accuracy? Should we wait for the quantum computers to be realised many years from now, or we can implement them efficiently on specialised computing devices based on classical principles of physics?

5. Conclusions and directions for further research

This paper presents some CI methods and in particular - evolving ANN models, inspired by principles from different levels of information processing in the brain – including higher cognitive level, gene/protein level, and quantum level, and argues that ANN models that integrate principles from different levels of information processing would be beneficial for a better understanding of brain functions and for the creation of more powerful methods and systems of computational intelligence in general.

Integrating principles from quantum-, molecular-, and brain information processing is important because:

- This would lead to a better understanding of both molecular and quantum information processing;
- Modelling molecular processes is needed for progress in many areas of biology, chemistry and physics;
- At the nano-level of microelectronic devices, quantum processes may have a significant impact;
- Using these processes is a strong inspiration for new computer devices – million times faster and more accurate

Further directions in this research are:

- Building large ontology systems that integrate facts, information, and CI models of the three levels of information processing in the brain and their interaction, such as brain-gene-quantum ontology systems;
- Building novel brain-, gene-, and quantum inspired ANN and CI models, such as: new ECOS, evolving SNN, evolving CNGM, QI-CNGM, QI-SVM, etc.
- Studying the characteristics of the above models and interpreting the results
- Applying the new methods to solving complex problems in neuro-informatics, such as modeling learning and memory, understanding brain diseases, etc.
- Applying the new methods to solve complex problems in bioinformatics, such as selecting dynamically genes and proteins related to cancer, modeling cellular processes, modeling gene regulatory networks and metabolic pathways
- Applying the new methods for multimodal information processing, biometric tasks, robotics, and other practical tasks of computational intelligence.

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