Cognition: Characteristic Waveform Correlates*

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Abstract:
The integration between psychological concepts and neurophysiological data pose many epistemic difficulties which create almost unsolvable problems.
We used the strategy of reconsidering experimental data and theoretical concepts within the frame of reference of some concepts from Quantum Physics and Chemistry.
The model of a particle in a box against a potential barrier proved to be adequate to describe and interpret behavioural data from a neurophysiological viewpoint.
Concerning cognitive processes we used the model of atom orbitals and of isolobal fragments to build a model of information processing in the frequency domain.
After examining some problems related to anticipation, hypothesis construction and transformation we tested experimentally some of these ideas.
Analysis of EEG records using Lee method of cross-correlation with Dirac delta waves repeated periodically yields distinctive spatial distributions of patterns of periodic waveforms for cognitive-affective states- joy, sadness, anxiety, anger and mistrust.
It was possible, using exclusively electrophysiological indicators in the frequency domain, to classify adequately a group of 35 subjects that experienced these five cognitive-affective states.
Keywords: logical transformation groups; frequency domain; cognition; quantum theory; neural networks

1 Introduction

The reinterpretation of Clark Hull's relationship concerning the probability of acquired responses during learning led to an equation similar to the Hamiltonian of a mechanical system. In Clark Hull's expression (1) D stands for Drive sHr stands for the strength of habit and P(r) for the probability of response.

$$P(R) = D\ {}_{S}H_{R} \qquad (1)$$

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At the end of the acquisition process P(r) has value 1 approximately but as Drive has dropped to zero this relationship does not describe the learning events conveniently. Introducing a new term V(H(s,r)) to take care of the static value of sHr and substituting sHr by its rate of variation dh(s,r)/dt we have

$$P(r) = D\frac{dh(s,r)}{dt} + V(h(s,r)) \tag{2}$$

Noting that we can define a momentum of learning p=n dh(s,r)/dt in which n stands for the number of neural operators which participate in the learning process we can now write an expression for the commitment in learning (a concept analogue to an amount of energy). We have then

$$E = \frac{1}{2n}p^2 + V(h(s,r)) \tag{3}$$

As learning is performed by microscopic operators- either neurons or else subcellular components we can predict that for this microscopic level of description the following Schrödinger's time equation can adequately describe the learning process at the cellular level.

$$E = -i\hbar\frac{d^2h(s,r)}{dt^2} + V(h(s,r)) \tag{4}$$

If we reconsider information transmission along chains of neurons with long axons we verify that in axons information is carried by discrete nerve pulses and in dendrites and cell body these discrete pulses disappear to be substituted by oscillatory phenomena that correspond to continuous potential variations in the cell membrane.

These continuous variations in the cell membrane can be converted into discrete pulses at the axon Hillock or else even in dendrites or different places of the cell body as Shepherd has observed in Mitral cells of the Olfactive Bulb.

Relatively to the conversion of discrete signals into continuous signals in a restrict synaptic area we can follow the proposal of Max Born and define the square of continuous potential $\psi(x,t)$ as the density of discrete signals in that restrict area.

In a flow of action potentials of uniform density and that is accompanied by the expression of a continuous phenomenon of frequency ω we have

$$\psi(x,t) = a\exp i\left(\frac{2\pi}{\lambda}x - \omega t\right) \tag{5}$$

The density of those discrete components is measured by $|\psi(x,t)|^2$, assuming a uniform sequence or bundle of potentials, that is, with the same energy E given by

$$E = \hbar\,\omega = h\,\nu \tag{6}$$

Considering each action potential as an analogue of a wave packet, what is justified in the case of synapses in which the transmission and conversion of discrete potentials (action potentials) into continuous potentials (excitatory pos-synaptic potentials) it make sense to interpret their frequencies as measures of their energies.

The wave function $\psi(x,t)$ can be written as

$$\psi(x,t) = a\exp\frac{i}{\hbar}(p\,x - E\,t) \tag{7}$$

where p and E are the momentum and energy of a sequence of action potentials. Obtaining the partial derivatives of $\psi(x,t)$ in order to x and to t and since the energy E can be expressed as

$$E = \frac{1}{2m}p^2 \tag{8}$$

we have

$$i\hbar\frac{\partial\psi}{\partial t} = -\frac{\hbar^2}{2m}\frac{\partial^2\psi}{\partial x^2} \tag{9}$$

Considering now three coordinates x, y, z we have

$$i\hbar\frac{\partial\psi}{\partial t} = -\frac{\hbar^2}{2m}\nabla^2\psi \tag{10}$$

As in general along a membrane which is traversed by the waves generated from the synaptic junction there exist variations of potential that express the excitability of the membrane at a local level which varies with the position, (10) assumes the form

$$i\hbar\frac{\partial\psi}{\partial t} = -\frac{\hbar^2}{2m}\nabla^2\psi + \mathrm{V}(\mathrm{x},\mathrm{y},\mathrm{z})\,\psi \tag{11}$$

This equation is the time dependent Schrödinger's equation.
$|\psi(x,y,z,t_0)|^2$ represents, for a given instant $t=t_0$, the density function of discrete waves in a certain volume V.

In other words

$$\int_V |\psi(x,y,z,t_0)|^2 dV = N(t_0) \tag{12}$$

For the particular case of $N(t_0)=1$, $|\psi(x,y,z,t_0)|^2$ represents the probability distribution of finding a certain discrete wave in the point (x,y,z) that belongs to the volume V. So in this case (12) assumes the form

$$\int_V |\psi(x,y,z,t_0|^2 dV = 1 \tag{13}$$

For a system in a given state with defined energy the wave function ψ can be written as

$$\psi(x,y,z,t) = \Psi(x,y,z)e^{-iEt\ \hbar} \tag{14}$$

Since we have that

$$i\hbar\frac{\partial\psi}{\partial t} = E\psi \tag{15}$$

the Schrödinger's equation assumes the form

$$H\Psi \equiv \left(-\frac{\hbar^2}{2m}\nabla^2\right)\Psi = E\Psi \tag{16}$$

This equation is the time independent Schrödinger's equation where h should be substituted by l.

2 Quantum Theoretical Models for Learning and Cognition, Anticipation and Hypothesis Formation and its Transformation

2.1 An example of a learning process

In a situation of decision making implying instrumental learning subjects should try to avoid disagreeable stimuli which would follow flashes of light. The observable states were pressing keys on a table in front of the subjects. Subjects were supposed to make decisions according to hypotheses with distinct degrees of difficulty in their formulation and transforming their last preceding decision. The following matrix represents the probabilities for state transitions.

Table 1- Probability distribution for transformations of decision functions empirically obtained in a group of normal subjects.

	$\bar{D}\bar{E}R$	$\bar{D}ER$	DR	$D\bar{R}$
$\bar{D}\bar{E}R$	.1555	.0338	.0190	.0039
$\bar{D}ER$	.0568	.0930	.0448	.0095
DR	.0205	.0538	.2550	.0560
$D\bar{R}$	.0211	.0317	.1169	.0399

Considering only the probability of observables we obtain the following Bernoulli distribution.

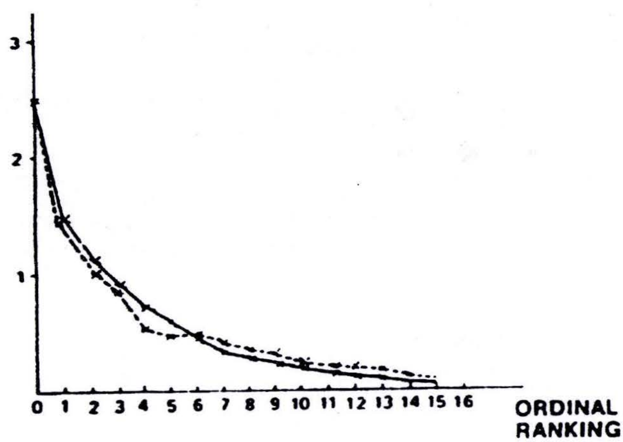


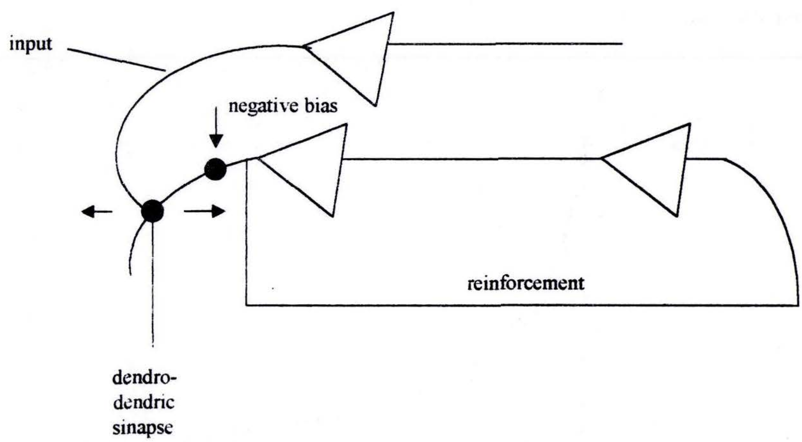
Figure 1- In ordinates is represented l.n of the expression $p_n = e^{-l\,n}$.

It was observed that subjects spent more time without taking any active decision or else making inefficient or partially efficient decisions than making efficient decisions. This situation may be represented using a model of a particle in a box against a potential barrier with $E_0<V$, in which E_0 stands for the energy of the particle and V for the potential barrier. The Quantum Mechanics model for this situation provides the following expression for the Schrödinger's equation for the potential barrier

$$\left(-\frac{\hbar^2}{2m}\frac{\partial^2}{\partial x^2}+V(x)\right)\psi_E(x)=E_0\psi_E(x) \tag{17}$$

Admitting that decision making is due to the intervention of a neural network, the conditions represented in the model of the particle against a potential barrier can be translated as a situation in which a synaptic input is established between an axon and a first dendritic tree. Excitation propagates then from that first dendritic tree to a second one through excitatory dendrodendritic synapses which require a very low potential to be activated. Excitation so produced is propagated along the second dendritic tree crossing a barrier formed by an inhibitory potential. The excitation that goes beyond that point propagates to the axon Hillock and then further along the axon as a discrete signal which attains a third neuron. Feedback reinforcement modulates this input and the output is backpropagated to the second neuron where the dendritic potential which is generated modulates the inhibitory potential barrier.

Figure of neural model of potential barrier:



$$\psi_E(x) = \frac{2k_0}{k_0 + iK} e^{-Kx}, \mathrm{K}^2 = \frac{2\mathrm{m}}{\hbar^2}(\mathrm{V} - \mathrm{E}_0) \tag{18}$$

Considering that E_0=l ν we are in conditions to build a theoretical prediction about the frequencies ν_i determined by the discrete values of energy of the neurones involved in the process of making decisions during learning.

As it could be predicted higher probability values are related to higher frequencies. It is nevertheless interesting that most accurate decisions are the least probable ones and correspond to lower frequencies of oscillation. As a matter of fact during cognition periodic oscillations in the brain have frequencies mainly in the range 1-10Hz. All these considerations imply that the acquisition state during a learning process should be considered as approximately stationary until the moment in which the acquisition is concluded. In that instant occurs a global transformation of the state of the system.

The next step aims to clarify if cognitive states are characteristically correlated with specific frequencies of oscillation in dendritic trees.

2.2 An example of cognitive process

From the variety of cognitive processes we aim to first discuss those types of processing that occur during the monitoring and evaluation of semantic or episodic memory evocations, image producing and decision making.

In our model we leave aside for the moment those problems that are connected with the nature of self-reflexive consciousness.

The main characteristics of the model are the formation of classes of equivalence of representations and on the other hand the consideration of microstructures of dendritic and neuronal processing in which from differences between micro physiological events emerge distinct macroscopic qualities.

We advance the hypothesis that to each neuron is attached a characteristic set of dendrodendritic closed loops.

2.3 Neuronal implementation- the dendro-dendritic network model

If we consider neural architectures, dendro-dendritic networks possess the remarkable characteristic of allowing both forward and backward propagation. The complex geometry of these networks permits back propagation of action potentials generated at the axon hillock. Ultimately when such potentials attain fine dendritic ramifications they can eventually fade out. When this is not the case such potentials can circulate along dendro-dendritic closed loops which implement local computations.

Although dendro-dendritic networks are extremely dense anatomical structures with interspersed almost reticulate structures linked by multiple synapses, they may be thought of as an ensemble of computational compartments. Let us consider the case in which information arrives to the dendritic neuropile through axo-dendritic and dendro-dendritic synapses.

If we attribute to each neuronal cell body a set of characteristic dendro-dendritic closed loops we may consider each such set as an ensemble of oscillators with characteristic frequencies. We assume that complex information processing is performed by each neuron due to its closed loops. Similar functions are served by identical sets of closed loops and distinct functions are implemented by different sets of closed loops, A, B,..., Z.

If the same information arises to an ensemble of distinct sets of closed loops each one performing the analysis and processing of the incoming information from a distinct viewpoint, we may assert that an input vector {Y} (coming from the output of a predecessor structure) activates distinct sets A, B, ..., Z of dendro-dendritic closed loop operators.

From the viewpoint of our analysis it may be considered that 'compounds' Ay, By, ..., Zy have been formed and the corresponding information will be transmitted by neuronal cell bodies at a distance to decision making neurons responsible for the generation of coordinated patterns of action. A, B, ..., Z, are closed loop operators and oscillators $y \in \{Y\}$ are a subset of ordered components of $\{Y\}$ with dimension $\dim.(y) \leq \dim(\{Y\})$.

2.4 Towards an Homeomorphism of Isolobal Analogy

One of the main theories, which explain chemical reactions, is the molecular orbital theory. In organic molecules it is possible to substitute carbon atoms by metallic heteroelements if we use metal ligands and we create fragments with the adequate symmetry, level of energy and adequate valence structure in the bounding surface of the new component fragments.

The valence frontiers of both the organic fraction and the metallic complex do not need more than an approximate match. Hoffmann used a transformed Mendeleiff table to characterise the orbital structure of each element.

These two fragments are called *isolobal* if the number, symmetry properties, approximate energy and shape of the frontier orbital and the number of electrons in them are similar (Hoffmann, 1982).

With the support of this data and using considerations issued from group theory and Quantum Mechanics Perturbation Theory he was able to make exact predictions about sets of equivalent component fragments that matched and reacted with complex organic molecules.

Here we find a paradigm for classes of equivalence of organometallic compounds.

Returning to the proposed homeomorphism between dendro-dendritic closed loops on one hand and orbitals on the other, we can define interactional surfaces that are composed by dendritic computational compartments that are attached to a complex set of neural bodies.

The valence sites are identified as computational compartments of dendro-dendritic closed loops which include input and output synapses. These synapses contribute to an interaction surface through which this computational assembly can be linked to distinct assemblies. This metaphor is convenient to represent some characteristics of cognitive processes.

Namely we are thinking about the knowledge that cognitive operators concerning lower level sensory and motor processes and memory representations.

The inquiry about what is occurring at a sensory and motor level in a transaction with the environment may be compared to the successive linkage of a matrix of organic complex molecule to distinct equivalent isolobal metallic fragments.

A first characteristic of this class of equivalence is that it may represent a concept in extenso. On the other hand as this organometallic complexes are very unstable they may contribute to represent a sequence of inquiry operations in which distinct attributes of a concept are successively scanned.

All of them remain available to a further inquiry but only those which form stable complexes give rise to a conscious experience.

The correlate for the conscious character of cognition may be found in the way microscopic interactions generate the emergence of macroscopic qualities. Comparative neuroanatomy and neurophysiology help to specify as a further requirement that consciousness must be related to secondary and tertiary multisensory and idiomotor areas of the Brain in Primates and Man.

Ultimately the Quantum valence bounding surfaces may be considered putatively as a possible correlate for the type of binding of distinct sources of information which are involved in complex cognitions.

The resemblance between two neuron assemblies together with their characteristic dendro-dendritic closed loops that can participate in neural connections allows them to generate a complex and self-organised structure. In our proposal it can be defined as an isocompartment analogy, which can hold a distributed micro-resemblance defining an isosynaptic structural analogy. We will call two neurones or neural structures *isocompartment* if the number, symmetry properties, approximate energy and shape of the ensemble of the computational compartments corresponding to dendro-dendritic circuits on the neuron and the geometrical properties and number of synapses in them are similar. The isocompartment analogy provides the connection capabilities and the self-organisation of the neural structures needed to represent high level symbolic operations. Finally, this analogy also provides a hypothetical framework to understand abstract cross-modal representations.

2.5 The relationship of signification in visual cognitive processes

Dendritic computation in the Brain provides very powerful means for information processing which are involved in cognitive operations. If we consider visual cognition the observations we made in preceding sections need to be completed by additional features which are required if we try to represent symbolic processing for example in perceptive phenomena that attain the cognitive level. The basic stages of perceptive processes have been discovered in visual perception in very ingenious experiments first by Lettvin, Maturana, Pitts and McCulloch (1959), Hubel and Wiesel (1965), Blakemore (1974) to mention only the initial works in which the concept of feature detectors was introduced. Results concerning the study of simple cells by Hubel and Wiesel imply a referential level of processing in which elementar mappings in the Brain are directly related to elementary characteristics of stimuli. At this first level neuronal structures and their dendro-dendritic networks are responsible for a referential attribution. This reference to external objects represented by analagous mappings is in itself already very complex as it can be immediately verified if we consider the phenomenon of sensory projection on peripheral receptors or the phenomena of phantom limb.

At this level an analogical relationship between the spatial distribution of the stimuli and spatial configuration of dendro-dendritic and cell body mappings in the Brain is a first mode of iconic and diagrammatic representation of visual information. These simple components of sensory information are combined by dendro-dendritic networks that implement the specification of functions defined over sets of components of the iconic and diagrammatic level of representation. The complex and hipercomplex types of response (detection of segments of straight line with variable lengths and detectors of angles independently of rotation keeping constant vertex) suggest that the relationships necessary to represent data at a higher symbolic level are already present but the representation is still referentially linked to the characteristics of stimuli in an analogous manner. The encoding is still genetically determined, although it suffers the influence of the interaction with the environment along some initial stages of the development process (Blakemore, 1972). The next step introduces the type of encoding which is characteristic for cognition, namely the referential mappings are substituted by abstract relationships defined over them. The relationship is already not analogical but rather belongs to a second level of symbolisation. At this second level the relationship is one of significant-significate in which the significate is derived by specific rules associated to the significant. These rules are formed under the influence of experience and learning and give to knowledge structures an abstract character adequate for cognitive processes. Data concerning possible schemes of motor interaction and predictions about the outcome of transactions with the environment, are integrated in multi-modal sensory and motor secondary and tertiary representations. At this stage the isolobal inquiry matrices scan data selecting those which may contribute to successive stages of cognition. The final choice of attributes is attained and they acquire a stable configuration which gives rise to the cognitive experience. Attributes not essential for immediate cognition are organised as a field which remains available to further scanning whenever knowledge actualisation requires it.

The isolobal matrices are responsible for the implementation of the signification relationship which leads to the characterisation of the concept through its attributes and to the subjective experience which acquires a transient conscious dimension.

Complex forms imply the constitution of predicates and relationships in a visual language largely independent of the linguistic system of reference. A visual pattern can then be represented by a set of complex descriptors **P(X)** and a relationship **R** defined over them. The implementation of recognition of a pattern by a dendritic network might correspond to an input formed by the assembling of descriptors **P(X)** defined over an ensemble of elementary symbols either visual or belonging to other modalities as well as motor data and motor predictions and components of past sensory meanings assembled by isolobal matrices. The final stable result may be mathematically specified by **R** that correspond to a matrix which would produce a new vector of identified pattern components. Characterisation and identification may be represented formally by the comparison between a final vector of attributes and a reference vector. Identification would correspond to the fulfilment of a distance criterion and subjective experience would be due to the formation of a stable complex which would link the inquiry relationships to members of the class of isolobal intermediate level attribute representation. A criterion vector **Ref** would be compared with **C** and the pattern recognition would correspond to the verification that distance between **C** and **Ref** was smaller than a criterion α. This corresponds to

$$[R]\,[X]=[C] \qquad\qquad \mathrm{dist}([C],[Ref]) < \alpha$$

2.6 Anticipation and hypothesis transformation

The isolobal model was used as a paradigm for the representation of classes of equivalence which define ideas or concepts in extenso.

It was hypothesised that memory processes as well as perceptive, imagination and decision making processes would attain cognitive level due to the intervention of a characteristic relationship for each of them that operationally define those representations or decisions that belonged to a given class of equivalence which defined the concept in extenso.

It was also hypothesised a dynamic process of choice in which the relationship that was applied on more elementary data was successively iterated in a temporal sequence. Cognition about the inclusion of particular attributes of a given object that belonged to the class would be unstable. It would only last the time of application of the selective relationship- that is while the isolobal compound would remain stable, in terms of our metaphor.

Advancing a step more in our hypothesis we can consider those relationships that are anticipated or predicted before data of reality confirm or refute them. Furthermore we examine a group of transformations that change relationships in a systematic manner to find those concepts that fit better data of reality.

Following Piaget suggestion we can suppose that given the values of two logical variables some logical function f(x,y) holds true over them and this anticipation must be confirmed by observable data.

Defining an hypothetical logical function f(x,y) as a union of one or more minterms we may test its referential validity and explore all alternative functions.

Piaget observed that when children attain the level of formal operations in their intellectual development they cease to use intuitive combinatorial methods and start using a group of transformations of logical functions after they attain 9-11 years of age. He called this group INRC. I stands for identity; N for complementation of minterms; R for complementation of all individual variables present in minterms; C for the successive application of R and N.

As not all functions can be obtained by these transformations we add two further transformations: P1 that posits a single minterm and annihilates all further minterms and P2 which posits a given minterms and leaves unchanged all the other minterms.

The following neural networks implement these transformations. It is immaterial to represent these transformations using neural networks or else chemical models that use enzymes to implement minterms. Those transformation networks are supposed to be substituted and activated intentionally using a control network.

N function

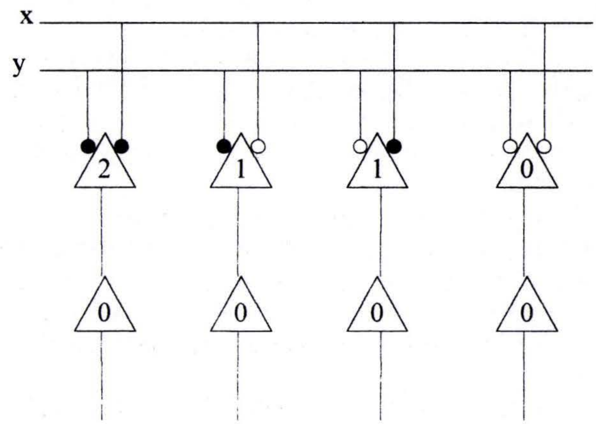


Figure 2- Implementation of Piaget's N function with a neural network.

R function

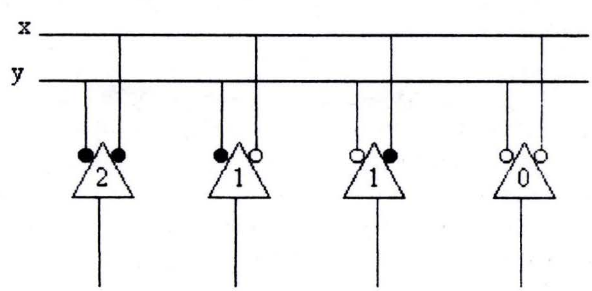


Figure 3- Implementation of Piaget's R function with a neural network.

RN function

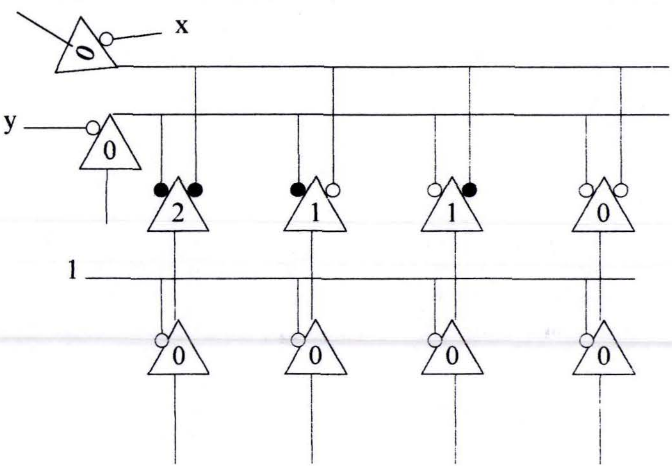


Figure 4 – Implementation of Piaget's RN function with a neural network

Pointer 1 Function

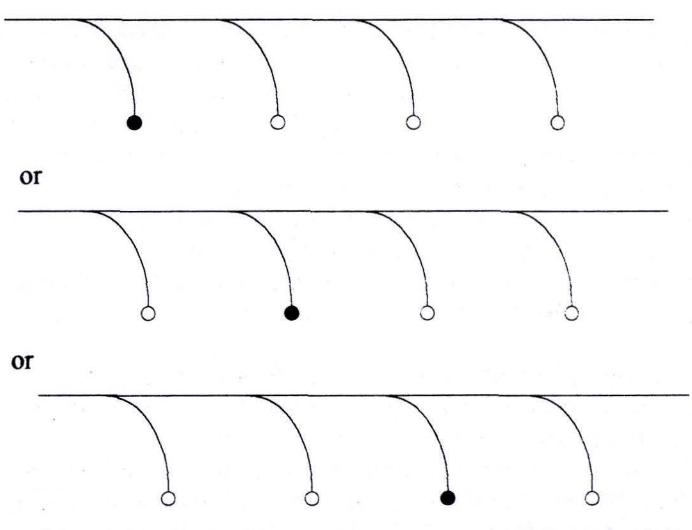


Figure 5- Implementation of Pointer1 function with a neural network.

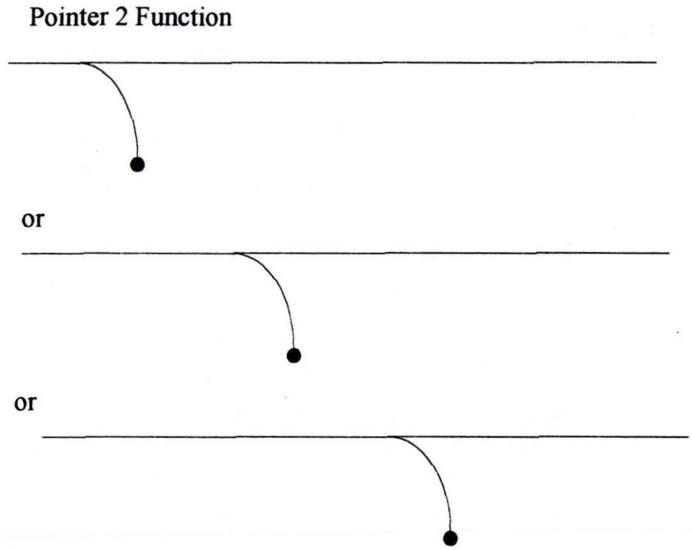


Figure 6- Implementation of Pointer2 function with a neural network.

3 Experimental Results on Cognition

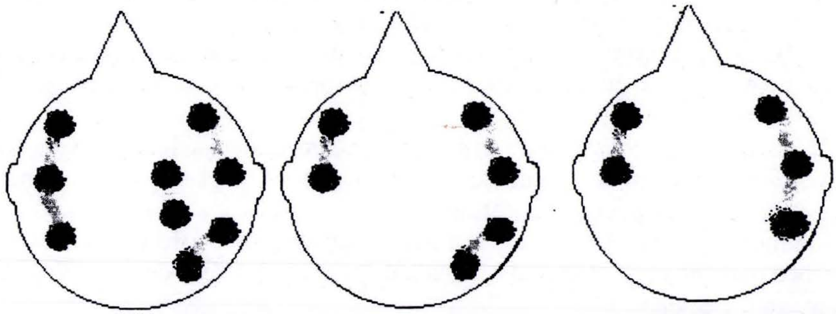
To obtain electrophysiological correlates of cognition we asked thirty five normal volunteers to imagine situations of joy, sadness, anger, anxiety, and mistrust. Subjects were kept in relative darkness and did not receive any sensory stimulus related to the task. When they were in the cognitive state they were required to press a button that triggered the recording of the electroencephalographic activity of the brain concerning the last second prior to the trigger and two seconds thereafter.

Records were made using differential amplification in 8 channels with electrodes placed on the scalp according to the 10-20 international system.

EEG waveforms were submitted to cross correlation with a sequence of Dirac delta waves repeated with the frequency of the waveforms we wanted to extract from noise.

Periodic waveforms so obtained for each frequency respectively were then synchronised using as a reference their passage through their peak and an averaging procedure was performed over 30 samples for each frequency.

Finally FFT and power spectrum were calculated for each subject and cognitive state and group comparisons of power spectrum amplitude indicators were made using multivariate stepwise discriminant analysis. The following figure summarises those places of recording in the brain in which significant differences were found concerning pairwise comparisons between groups with distinct cognitive states.



Joy - Anxiety Joy - Sadness Sadness - Anger

Figure 7: Macroscopic localisation of the leads in which the periodic wave forms extracted from EEG records obtained during the cognitive-affective states were significantly different in the comparisons between conditions indicated (35 subjects).

Results show a predominant involvement of Fronto-Temporal regions in both Hemispheres of the Brain but significant differences were also observed in the Temporal, Parietal and Occipital lobes of the Brain.

Concerning those frequencies which contributed more to correct classification of subjects there were also observed characteristic patterns of clustering in each pairwise comparison. The following table gives some examples of such patterns.

Table 2: An example of a comparison in which a complex pattern of periodic waveforms with a characteristic macroscopic distribution contributed to the distinction, in this case between joy and anxiety. FAT stands for Frontal - Anterior Temporal Lead, ATPT for Anterior Temporal - Posterior Temporal lead, PTOC for Posterior Temporal - Occipital Lead an APPP Anterior Parietal, Posterior Parietal Leads. R denotes right and L left. In each cerebral region the fundamental frequencies and respective harmonic components which contributed to the distinction are indicated by F (fundamental frequency and C, harmonic component).

Joy - Anxiety

RF-AT	RATPT	RPTO	APPP	LF-AT	LAT-PT	LPTO	LAPP
F2 C16		F20	F5 C10	F1 C8	F3 C12		
F1 C7		F11	F3 C12	F1 C5	F2 C12		
F5 C10		F15	F7 C7	F2 C2	F1 C5		
F1 C2		F9 C18	F1 C5	F2 C4	F9 C18		
F11		F5	F1 C8	F3 C18	F6 C18		
F13		F6 C18	F1 C14	F1 C16	F1 C2		
F20		F4 C12	F2 C20	F9 C9	F2 C16		
		F4 C20	F6 C6	F1 C15	F7 C16		
		F1 C15	F3 C6	F16	F1 C17		
		F1 C6	F3 C18	F5 C10	F1 C16		
		F2 C16		F4 C16	F2 C10		
		F2 C12			F11		

It should be noted the predominance of indicator components of the power spectrum of the lower frequency range as our learning studies might predict.

As far as relationships between a fundamental frequency and its harmonics is concerned as we performed averaging with synchronisation with the passage of the periodic waveforms through their peak the presence of harmonics with relevant amplitude means that harmonics and the fundamental oscillation were phase synchronised- otherwise there would be a scattering of their phase relations and they would be reduced by the averaging procedure.

Summarising these results we can assert that cognitive-affective states can be distinguished and subjects adequately classified using exclusively electrophysiological phenomena of the Brain.

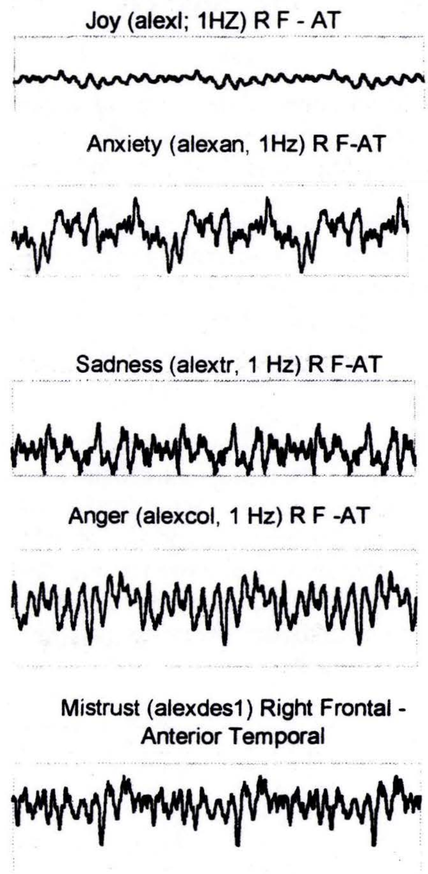


Figure 8. An example of periodic waveforms of frequency 1 Hz (it is represented 3 seconds) obtained in each cognitive-affective state, same subject, Right Frontal - Anterior Temporal leads. The waveforms were obtained by cross-correlation between EEG records and a Delta wave of Dirac followed by averaging.

On the other hand there are characteristic locations in which those differences are more distinctly observed and there are characteristic patterns of power spectrum components relevant for each distinction.

It is very probable that phase synchronisation plays a relevant role in the patterning of electrophysiological phenomena related to cognition along all the power spectrum. It is likely that some dendrodendritic clustering set of operators is responsible for this phase synchronisation and frequency binding and this process is a strong putative candidate as a support for the conscious quality of cognition.

We admit a parallel flow of information with multiple loci of predominant computations for each type of cognitive experience.

The exclusive consideration of phenomena that occur in the Cortex of the Brain is due to the limitations of the electrophysiological methods we did use. In any event it is the Cortex of the Brain the most likely candidate for the localisation of cognitive processes if we consider them at the representational and semantic levels.

4 Conclusions

1. Our attempt to represent learning processes using an analogical model based in Quantum Mechanics allowed an adequate and detailed representation of both psychological and neurophysiological processes involved in the acquisition phase of a learned adaptive process in Human subjects.
2. A putative model based in an analogue representation of phenomena of Quantum chemistry provided what proved to be an adequate framework for the theoretical understanding of electrophysiological correlates of cognitive processes.
3. It was shown that not only actual data with immediate reference to reality but also anticipation and hypothesis testing and transformation can be represented by neural networks.
4. Experimental data in the electrophysiological study of cognition point with high likelihood to the relevance of dendrodendritic processes in the frequency domain. Spatial and frequency patterns of clustering together with phase synchronisation of distinct frequency components of Brain waveforms appear as strong candidates for the self-reflexive conscious characteristics of cognition.

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