

Venn-like models of neo-cortex patches

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Abstract— This work presents a new architecture of artificial neural networks – Venn Networks, which produce localized activations in a 2D map while executing simple cognitive tasks. These activations resemble the ones observed in patches of the cerebral cortex when inspected by functional imaging methods such as fMRI. Venn-networks allow simultaneous incorporation of four distinct and independent concepts, all present in biological neural network. These concepts are (a) cyto-architectonic regions, (b) localization of functional activations, (c) complex pattern of intra-/interregional connectivity, and (d) definable damages to the neurons and axons. The dynamics of Venn-networks is highly influenced by these concepts. The proposed architecture incorporates both unsupervised and supervised learning paradigms; it also implements open and closed loops that can be assembled with *afferent*, *efferent* and *U-fiber* type of connections. Venn-networks were devised to integrate in one single model the topographical representation of neural activations and also functional results evoked by these activations. Following the description of the architecture and its components, we present some simulation results that implement above-mentioned concepts (a), (b) and (c). In those simulations, virtual fingers are controlled by Venn-networks similarly to the sensorimotor feedback that controls fine movements of fingers in the CNS. The trained Venn-networks emulate the finger movements of a piano player performing *The Sonata Facile* of Mozart.

I. INTRODUCTION

THE CNS is vastly complex and its understanding represents an enormous challenge to scientists. Even so, physiologists know fairly well the microscopic biology of the nervous system. So do other neuroscientists, comprehending how macroscopic functional activations of neural populations result from stimuli presentation or task realization [7]. However, the mechanisms that link these two organization levels of the nervous system still need to be investigated

In this work we present a computational model of brain

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inspired neural networks – the Venn-network – that is able to execute simple cognitive tasks while at the same time exhibiting activations that resemble images produced by functional methods. These two observable aspects of the functioning of the brain, namely, (1) elicited cognitive tasks and (2) topographical map formation of the activity within a simulated patch of the cortex, are caused by the same collective phenomena, *i.e.* interactions of large neural populations. This implies that they are highly non-linear and interrelated, hence very hard to formalize mathematically. From this arises the necessity of a single computational model that is able to perform simulations in which all those aspects are incorporated .

A. Cerebral Cortex – the inspiration for Venn-networks

The cortex can be classified using many criteria such as: architectonics - observing the distinct structures (either cyto- / myeloarchitectonics or histochemical / non-histochemical); connectivity – focusing on patterns of input/output for groups of neurons; topographical mappings (either anatomical or of physiological areas); behavioral studies – observation of diseases, impairments etc; or any combination of above [4].

Macroscopically, the cortex can be divided, using a functional activity criterion, into areas that do not match with the cerebral lobes, e.g. visual, auditory and motor cortices [1]. As opposed to the above regional differences, *microscopically* the cerebral cortex has a quite regular organization where cylindrical columns of cells seem to be involved with same tasks. It is generally true that the bottom layer of these cortical columns acts as *outbox* for neurocommunication, whereas the middle layers acts like an *inbox*, and the superficial layer, as inter-columnar links [3].

Despite the huge number of cells and columns existing in the cortex, advances in medical imaging techniques (e.g. functional Magnetic Resonance Imaging, Magneto-encephalography, etc) contribute to a rather fast and precise understanding of where function is located within the nervous system. In other words, the recent advances reveal where and what neural populations are active whilst a correlated behavior is observed, or a stimulus is presented.

Although function localization is primarily driven by the hard wiring of axonal connections (*i.e.* nervous pathways) [7], there are also other facts that greatly contribute to it, namely competition and lateral inhibition. The first is due to the massively parallel manner in which the brain operates. The second is due to the inhibitory processes that are observed whenever an active neuron uses its axon collaterals to inhibit other neighbors.

B. Venn diagrams – the mathematical paradigm

Venn-networks were named after John Venn, as his ideas on Venn-diagrams [10] are suitable as a metaphor to understanding, visualizing and computing the independent and intersecting concepts tackled by Venn-networks: (a) cyto-architectonic regions, (b) localization of functional activations, (c) complex pattern of intra-/interregional connectivity, and (d) definable damages to the neurons and axons.

C. Artificial neural networks – the computational approach

Connectionist systems, as any other AI approach, are able to learn from experience. The learning algorithms and distributed manner by which the acquired knowledge is stored in the ANN confers to systems that use this technique features such as non-linearity, adaptability, robustness, and generalization ability (*i.e.* flexibility). This group of characteristics is necessary to tackle complex tasks. Hence, artificial neural network methods represent nowadays one of the most important sets of techniques for modeling and solving real world problems [6]. Moreover, as highlighted by *De Wilde* [11], another interesting feature of ANNs is their ability to relate (non-trivially) *microscopic* to *macroscopic* phenomena. Ultimately, this was the key argument to use ANNs as the computational approach adopted in Venn-networks.

D. Models of neural processing

By any means, modeling neural processing is a trivial task, especially if the modeled neural function implies plurality and diversity of intercommunicating regions. The literature of the field has plenty of map-based models for neural processing [34], *e.g.* early ones as *von der Malsberg's* [13]. Others incorporate the notion of hierarchical communicating regions [33] and recently, topographical cortical maps [32]. All of them (including Venn-network) have highlights and shortcomings. However, Venn-network [21] is a special one as it incorporates, in the same model, delays, topographical neural activation representation as well as effectors control.

II. THE VENN-NETWORK ARCHITECTURE

A. Model description - Overview

Venn-networks (short for Venn-like neural networks), the architecture proposed by Buarque[21], create a non-linear association between input and output spaces by utilizing a 2-dimensional (2D) map composed of processing elements (P). Similar to cortical columns, each processing unit of the 2D map represents the average activity observed in the micro-region patch of the cortex being modeled. As was specified in Venn-networks, P_n can receive simultaneous connections among the different types of fibers existing in the model (as happens in the cortex).

The proposed model allows definition of an arbitrary number of cyto-architectonical regions that includes many

processing elements, and arbitrary sets of inbound, outbound and interconnecting fibers. Regions are the main loci of neural signal processing. Adherent to regions, fibers (of various kinds) carry these signals all around the network. Every fiber has associated to it a number of features such as *synaptic weights, delay and cardinality*. This confers to each bunch of them very distinct behaviors. In Venn-networks, the fiber's names are given according to their functionality, namely, (a) *afferent* for the ones specialized for incoming signal; (b) *efferent* for the ones specialized for outgoing signal; connections; and (c) *u-fibers* for the ones specialized in interconnecting regions. Figure 1 contains a schematic view of the architecture. In the figure, the reader can observe all elements that make this kind of neural network so unique: different types of columns, different types of fibers, and different types and dimensions of regions.

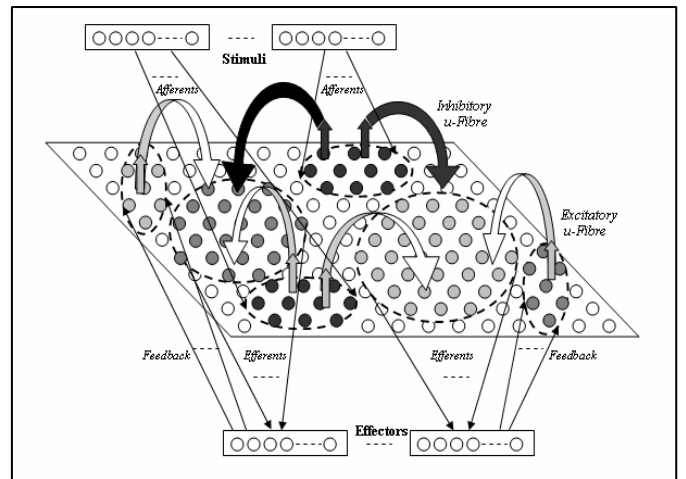


Fig. 1. Schematic view of Venn-network architecture; *afferents, efferents* (including *feedback*) and *u-fibers* (both *inhibitory* and *excitatory*) can be seen as well as regions, and external components: *stimuli* sources and *effectors*. Note that arrows indicate bunches of fibers that connect origin and target regions in a massively parallel manner.

B. Model dynamics – neural activation

As opposed to many connectionist systems, but consistent with biological evidence of delays in nervous fibers [12], we decided that this feature should not to be abstracted. This means that transmission time of axons is not considered to be negligible, as in other connectionist systems. Thus, in addition to the features previously mentioned, Venn-networks bundles of fibers have also specific associated delays. This other feature allows interesting properties to be investigated – especially in pathological scenarios. This means that, myelinated, un-myelinated, and demyelinated fibers can all be used in Venn-networks by only adding their overall transmission delays. Note that the model still copes with cases where fibers delays cannot be estimated (by simply assuming no fiber-delay).

In Venn networks one processing unit (P) abstracts the behavior of populations of biological neurons within the same location, *i.e.* the cortical column. Thus, respecting region boundaries and unit features, activation of P_n – shown in Equation 1 – is an independent activation function

summation (f is the *logistic* function) upon all N incoming signals – both excitatory (**Exc**) and inhibitory (**Inh**) – directed towards the P_n , where **Exc** and **Inh** are weighted (synaptic) signals from other P_n ; θ is a threshold value. Time is indicated in all equations by t_i .

$$P_n(t_{i+1}) = f\left(\sum_{k=1}^N P_n^{Exec}(t_i) - \sum_{k=1}^N P_n^{Inh}(t_i)\right) - \Theta$$

Eq. 1. Activation of a processing unit n (*i.e.* column) as a summation of all *excitatory* and *inhibitory* signals arriving in the unit; the selection of the unit is random.

Even though processing of “columns” (*i.e.* P_n), is randomly selected for the calculation purposes explained in Equation 1, an abstract closed processing cycle for Venn-networks can be assumed. This continuous cycle follows an intuitive (biologically inspired) sequence of five steps in which:

- (1st) *afferent* signals arrive to the computed map from areas external to the model;
- (2nd) the cortical map “reacts” to that stimulation;
- (3rd) *efferent* signals are issued to effectors;
- (4th) signals from *effectors* are fed back to the map; and finally
- (5th) the cortical map “reacts” again to the fed back stimulation.

C. Model dynamics – learning and signal propagation

1) Processing cycle step 1: afferent fiber processing

The first step of neural computation in Venn-networks starts abstractly with afferent signals arriving from areas external to the model, e.g. frontal lobe, eyes, ears etc. If the network is engaged in learning tasks, a self-organizing process follows such as suggested by *von der Malsberg* [13] and *Barlow*.¹ This happens to all processing units within participating regions of the map provided they are the destination of those incoming signals. This self-organizing process is mainly responsible for the map formation within regions. In addition, respecting regional boundaries, it occurs in three sequential and distinct activities, namely, (i) competition, (ii) collaboration, and (iii) weight adaptation of afferent fibers.

The competition of the self-organizing process is inspired by the well-known biological process of *lateral inhibition* [7]. This activity happens in all regions receiving stimulation. Each stimulated region has the most excited of their cell group elected as the competition winner for that

¹ There are four principles that subsume ‘self-organization’ as it happens in biological and artificial neural networks [13]: (1) Modification of synaptic weights tends to self-amplify [18]; (2) Limited resources induce competition among synapses, with growth of the fittest and reduction of others; (3) Following competition, modification in synaptic weights tends to cooperate with the production of desired outcomes; (4) Redundancy in input patterns is the reason why networks manage to learn in a self-organized manner [15] [16].

particular stimulation. In Venn-networks, the winning unit has a central role in further activities of afferent fiber processing. Equation 2 contains the formalization of the competition process carried out for every region comprising Venn-network maps.

$$P_{win}^{R_m}(t_{i+1}) = P_{\arg \text{Max}(P_n(t_i))} \forall P_n \because P_n \in R_m$$

Eq. 2. Competition among processing units of one region – *max* activation is the winner of the competition among units; *arg* gives the unit’s location instead of activation (here, the unit of maximal activation within the processing region m).

Collaboration among processing units is what happens after the selection of the winning processing unit for each region. That is, all processing units are within the boundaries of every region. Collaboration is also neural-inspired; refer to ‘Hebbian’ learning [14]. It is assumed that collaboration between cells is directly proportional to how topographically close they are in respect to the previously selected winner. Closeness to winner is a concept that can be implemented computationally in various ways. In the Venn-network implementation we offer two possibilities: one ‘linear’, and the other ‘Gaussian’, as described in Equation 3. In Venn-networks clear regional boundaries are considered as another mandatory condition for collaboration because connectivity among different regions (regardless of neighborhood) will be different.

$$D_n^i = \frac{\left(\sqrt{\begin{matrix} (w) & (h) \\ D_n^2 & + & D_n^2 \end{matrix}}\right)}{CR_n(t_i)}, D_n^e = \exp\left(\frac{\left(\begin{matrix} (w) & (h) \\ D_n^2 & + & D_n^2 \end{matrix}\right)^2}{CR_n(t_i)}\right)$$

Eq. 3. Two ways of calculating column distances to the winner: (D^i) linear and (D^e) Gaussian legends w and h are width and height components of distance.

In addition to the distance from the competition winner, the collaboration process in a Venn-network also obeys a proportionality defined by a neighborhood parameter, *i.e.* cooperation radius (CR). This additional parameter serves to help on the global map formation described by *Kohonen* [18] (here the map formation is of *regional* circumscription). This parameter shrinks monotonically during the learning process as the map is being formed. Neighborhoods here are square and, because the map is not toroidal, there is some border effect (*i.e.* possible irregular formation). Equation 4 shows the formalization of the collaboration process C as proportional to the distance D between a given processing unit P_n and the winning unit P_{win} of each region R_m .

$$C_m \otimes P_n(t_{i+1}) \approx D_{[P_n, P_{win}^{R_m}]}(t_i) \forall P_n \because P_n \in R_m$$

Eq. 4. Collaboration among each processing unit of one region is proportional of distance to winner (of that region in a given time t)

Following the computation of collaboration between processing units, the final activity of afferent fiber processing in Venn-networks is synaptic updating (if the network is in learning mode). This activity is the one in which the network effectively processes² the stimulus representation. Equation 5 shows how weights of afferent fibers are strengthened based on learning rate n_a and collaboration factors C . There is also a linear reduction of learning rate by the parameter nn_a (i.e. decrement of learning rate).

$$F_r^{S_s, R_m}(t_{i+1}) = F_r^{S_s, R_m}(t_i) \cdot \left[1 + \left(\frac{n_a}{nn_a(t_i)} \cdot C_m \otimes P_n(t_i) \right) \right]$$

Eq. 5. Weight update rule for afferent fibers connecting S_s , stimulus sources and R_m , target region.

2) Processing cycle step 2: u-fiber (type 1) processing

Immediately after afferent fibers computation i.e. after these have conveyed their “messages” to the processing units on the map, the second step of the (abstract) processing cycle of Venn-networks is the computation of type 1 u-fibers³. Equation 6 shows how u-fiber (type I) signals are computed.

$$F_r^{R_{m1}, R_{m2}}(t_{i+1}) = fa \cdot P_n(t_i)$$

$$\begin{cases} \text{if } |F_r^{R_{m1}, R_{m2}}| \in \text{Excitatory} \Rightarrow fa = +1, \\ \text{otherwise, } fa = -1. \end{cases}$$

Eq. 6. u-Fiber processing rule (dependant on fiber activity fa , i.e. excitatory or inhibitory). This implies that u-fibers have a powerful ability to excite or inhibit target regions that they are connected to.

These fibers perform interregional connections that can either be of ‘excitatory’ or ‘inhibitory’ nature (i.e. activity type of u-fiber). They can connect adjacent regions as well as form long-range connections like commissural fibers in the human nervous system [1].

3) Processing cycle step 3: efferent fibers processing

Subsequent to u-fiber computation, efferent fibers are handled next in the Venn-networks processing cycle. This step is another important part in the overall functioning of Venn-networks and is the one in which the network effectively processes⁴ suitable output behavior. If the network is in the learning mode, equation 7 shows how weights of efferent fibers are strengthened based upon gradient descent of output-evoked errors [31], which is

² *Process* encompasses two distinct actions depending on what the network is performing. It can be either *learning* new input representations of the problem or solely reproducing already known ones.

³ Type 1 u-fibers refers to fibers that are originated from regions targeted by afferent fibers

controlled by the learning rate n_e . Here, there is again a linear reduction of learning rate by the parameter nn_e .

$$F_r^{R_m, E_t}(t_{i+1}) = F_r^{R_m, E_t}(t_i) - \left(\frac{n_e}{nn_e(t_i)} \cdot Error_n(t_i) \cdot P_n(t_i) \right)$$

Eq. 7. Weight update rule for efferent fibers. Note that each fiber here connects one P_n to an efferent target.

4) Processing cycle step 4: efferent-feedback fibers processing

Efferent-feedback fibers are computed when signals are propagated back to the map from effectors. This step happens in a similar way to self-organizing (i.e. step1 of the processing cycle of Venn-networks). Likewise, this self-organizing process is responsible for more map formation within regions and also happens in three sequential and distinct activities, namely, (i) competition, (ii) collaboration, and (iii) weight adaptation of efferent-feedback fibers (similarly to what is presented in sub-section Processing cycle step 1: afferent fiber processing). The concepts and formulae apply integrally to the efferent-feedback fibers. The only difference and adjustment to be done regards the orientation of signals, which are originated at effectors and targeting the various regions of the map.

5) Processing cycle step 5: u-fibers (type 2) processing

The final step of the abstract Venn-networks processing cycle is analogous to the processing of u-fibers of type 1. The only difference is that it happens just after efferent-feedback fibers have conveyed their feedback from the effectors. Accordingly, type 2 u-fibers⁵ work absolutely in the same manner as type 1. Hence, equation 6 also holds for these fibers. As well as type 1 u-fibers, type 2 u-fibers are very important, because they can perform interregional connections of adjacent regions and far apart ones. These connections can be excitatory or inhibitory.

After this final step, the processing cycle imagined for the Venn-network architecture initiates again and is carried-out indefinitely throughout processing like in biological networks.

III. SIMULATIONS

To illustrate how simple cognitive processes can be modeled by Venn-networks, we selected volitive sensory-motor tasks and assembled instances of Venn-networks to perform them. Details of the selected biological circuitry and its artificial counterpart are now provided.

A. Pyramidal pathway and motor system – the selected circuitry

The several structures that comprise the motor system utilize distinct tracts to send or receive signals to the muscles

⁴ *Process* here again encompasses two distinct actions depending on what the network is realizing. It can be either *learning* new suitable outputs for the task or solely issuing already known ones.

⁵ Type 2 u-fibers refers to fibers that are originated on regions targeted by efferent-feedback fibers

from proprioceptors⁶. This does not imply that there is no interaction and cooperation between them. Although not completely understood yet, the mechanism of selection among the motor tracts considers aspects such as the nature of the movement to be performed, e.g. sequential, non-periodic etc. It also considers features such as the expected velocity, necessary strength, and expected performance. Altogether this will ultimately define the neuronal population(s) and route(s) to be utilized in order to generate (*i.e.* to transduce) the signal towards the muscles.

Among all motor tracts, the pyramidal, also called corticospinal tract, is the one of the most peculiar characteristics. It connects neurons adjacent to the central sulcus (posterior⁷ and anterior⁸ areas) in the cortex *directly* to the spinal cord and the cranial nerves nuclei, *i.e.* without interference from other neural circuits. Most fibers of this pathway (not all) cross to the other side of the body and are responsible for the contra-lateral motor/sensory control. Many other factors are important for the functioning of the system as well, e.g. the thickness of the fibers. Even though fiber caliber varies greatly, most of them are thin with conduction speeds situated between 5-30m/sec [1][12].

Because of its function and peculiar organization, chiefly related to voluntary movements in an almost un-modulated manner, the pyramidal pathway was used in this work as a test bed for the Venn-network.

B. Data set used

A piece of piano music was the selected source of data for training the networks in this work. Because of its simplicity, Mozart's *Sonata Facile* [9] was the one chosen. An arbitrary initial portion of the sonata generated 444 patterns that were produced by encoding the former into numeric values.

Each pattern produced by the encoding process contains distinct numeric information about flexion of all ten fingers of the piano player at a given time (regardless of their position on the keyboard). In other words, the encoding mechanism relates keystrokes within timestamp (**t**) to normalized numerical values. The convention used was 0.0; 0.5; and 1.0 to represent respectively: (a) no finger flexion, (b) the same finger flexed after a brief release of a keyboard key and (c) sustained finger flexion on a key.

C. Generalized Venn-Network Simulator

Given the need to test the ideas put forward earlier in this work and to illustrate that Venn-networks process *correctly* selected physiological scenarios, we have performed a series of computer simulations using different experimental sets-

⁶ Proprioceptors are special type of sensory receptors in the body that respond to *stimuli* from the inside of the body, e.g. the ones located in the joints and skeletal muscles.

⁷ Posterior areas to the central sulcus: *Brodman* areas 3,1,2 (or somatosensory cortex – SI, second somatosensory cortex–SII) and parts of the parietal cortex - *Brodman* area 5.

⁸ Anterior areas to the central sulcus: *Brodman* area 4 (or primary motor area – MI), and *Brodman* area 6 (or Supplementary motor area - SMA and Premotor area – PMA).

ups. All these simulations were carried out using a computer simulator specially designed and implemented by us for that purpose, the GVNS (*i.e.* *Generalized Venn-Network Simulator*) [21].

D. Using Venn-network to simulate structural-functional equivalence

1) Motivation

In various studies carried out with monkeys during mid-1980s, *Merzenich* showed the existence of changes in the topographic organization of somatosensory cortical areas due to lesion and task training [2]. He and his colleagues have shown that cortical maps are dynamically and continuously formed through competition among neighboring cortical areas. One could also conclude from their experiments that distinct arrangements of cortical areas *can* perform similar functions, *i.e.* they are functionally *equivalent*. It is important to make the distinction here between equivalence and neural plasticity. The latter is the process of neural reorganization (shown by *Merzenich's* work) whereas the former solely computes the power of distinct neural structures⁹.

In light of these arguments, we suggest that *structural-functional equivalence* is a property that must exist in artificial neural architectures. Our simulations were devised to find if Venn-networks of different structural arrangements with same number of processing units are able to:

- Learn a complex task through examples; and
- Achieve similar results despite of different layouts.

2) Network structure

We arbitrarily selected a Venn-network composed of 1,000 cortical columns (*i.e.* processing units of Venn-networks) arranged in a map of 50 x 20 (respectively width and height). Next, we simulated two different architectures in which all these units are in a unique cortical region of 1,000 units and the units are evenly partitioned into five distinct cortical regions of 200 units each.

In the first case (*i.e.* simulation of a single large “cortical” region) *one* stimulus source and *one* effector of cardinality¹⁰ *five* were utilized. In the second case (*i.e.* simulation of *five* smaller regions), *five* stimuli sources and *five* effectors of cardinality *one* were utilized. Hence, the total number of afferent and efferent connections in both cases is respectively 5,000 and 1,000.

Figure 2 shows two graphical windows produced by the GVNS, both representing distinct regional boundaries; left-hand and right hand side of the figure are, respectively, *mono* and *multiple*-region “cortex” configurations.

⁹ The concept of *equivalence* here shall not be confused with the idea supported by *Karl Lashley* – the theory of equipotentiality [5]. This theory refers to the ability of *any* intact cortical area to perform functions of others.

¹⁰ Formally, cardinality is the number of elements in a mathematical set; here cardinality of a stimuli source or of an effector can be understood, for example, as the number of fingers in one hand (in this case, the effector so to speak).

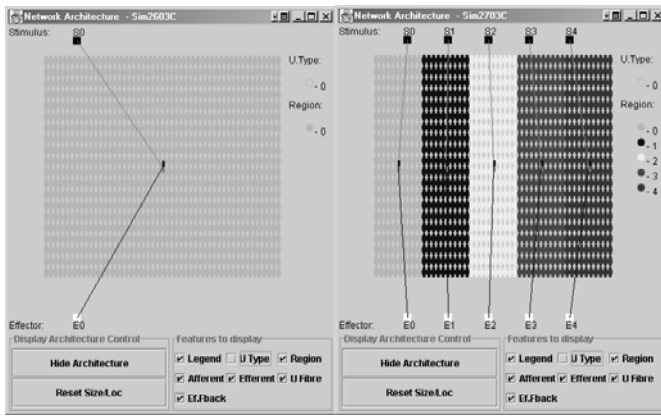


Fig. 2. Regional boundaries defined for simulations of an equivalent *mono-region* and *multiple-region*, left and right illustration, respectively. The lines connecting stimuli sources (see top of both panels of this figure) and effectors (see bottom of both panels of this figure) to the map are indications of axon bundles, *i.e.* entire pathways. Each of these pathways has as many axons as the cardinality of stimuli or effectors times the number of units connected by them in target or source region(s).

3) Simulation configuration

The two network structures simulated, featured above, were trained to perform the same finger flexion task under identical parametrical configurations. Amid all existing parameters to control the execution of simulation, *afferent learning rate* and *efferent learning rate* were the ones that produce the greatest impact on output performance of Venn-networks [20]. In a factorial varied manner and for all simulation devised here, the selected parameters assume one out of two possible values randomly selected. Thus, simulation-sets for *mono* and *multiple-region* comprise a total of four different simulations¹¹. Every simulation was repeated three times for greater accuracy, and outputs were averaged among these three repetitions. Details of values assumed by each parameter can be found in table I.

TABLE I
TRAINING PARAMETERS USED FOR SIMULATIONS OF EQUIVALENCE

Simulations (both sets)	Afferent learning rate	Efferent learning rate	Decrement afferent learning rate	Decrement efferent learning rate
A	0.1	0.05	0.6	0.9
B	0.1	0.1	0.6	0.9
C	0.05	0.1	0.6	0.9
D	0.05	0.05	0.6	0.9

Simulations A to D were devised having three processing phases each, the first phase aimed at cortical map formation (*i.e.* training of afferent connections); the second, for training of efferent connections; and the third for performance test.

The stopping criterion selected for training during all simulations of this section was a maximum average (output) error of 0.05%. This means that network training continued until this threshold was reached. In the current implementation of the simulator, *output error* is calculated at

¹¹ Two values for each of the two selected parameters gives 2² that is equal to four simulations

the end of every training epoch by averaging the error evoked in all its effectors. The last parameter different from its default value was *threshold activity* of processing units, which was set to -0.2. This was necessary in order to filter minor fluctuations observable in the map, similarly to biological systems [30]. Figures 3 and 4 show typical results for the best training networks of both architectures simulated. The three data lines correspond to three repetitions carried out for each set-up.

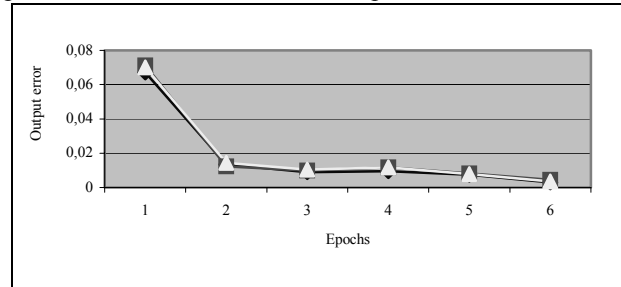


Fig. 3. Output training error evolving through training epochs over three repetitions for best training performance of *mono-region* Venn-network

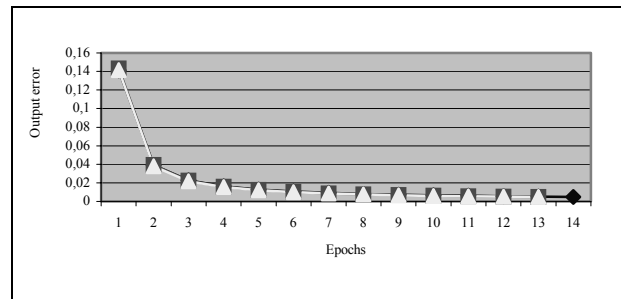


Fig. 4. Output training error evolving through training epochs over three repetitions for best training performance of *multiple-region* Venn-network

4) Results

A thorough examination was carried out namely, 24 graphics of average output error versus epochs of training. It was found that:

- All networks present a very steady decreasing learning curve no matter what parameter choice. This means that the average output error observed in the effectors of all simulations decreased smoothly as more training epochs are completed. Most importantly, this means that Venn-networks are able to efficiently learn fairly complex tasks as all learning tasks have converged, fulfilling the initial aim of this experiment.

- Simulations of *multiple-regions* invariably require more epochs to reach the stopping criterion established. This may be explained by the fact that this architecture (*i.e.* *multiple-regions*) has less synergistic effects among processing units, as all axons arriving *at* and coming *out* of the map connect independent cortical regions (*i.e.* *distinct map portions*).

- Variability of results produced across repetitions of the same simulation proved to be very small. This is an interesting feature of Venn-networks as they show themselves to be consistent when learning the same task.

5) Discussion

To illustrate the dynamical differences of the two architectures just simulated, refer to the snapshots displayed in figures 5 and 6, while the two architectures of Venn-networks are processing a given stimuli. Notice the five peaks of activations in the multi-region map of the multiple-region simulation, as opposed to a unique peak dominating the landscape of the mono-region simulation. These graphics also show how the rest of the processing units of the two maps still present small activity.

Based on these results we conclude that Venn-networks incorporate the structural-functional equivalence property sought, as they are able to learn (complex) tasks regardless of parameter-structure variation in networks of same dimensions.

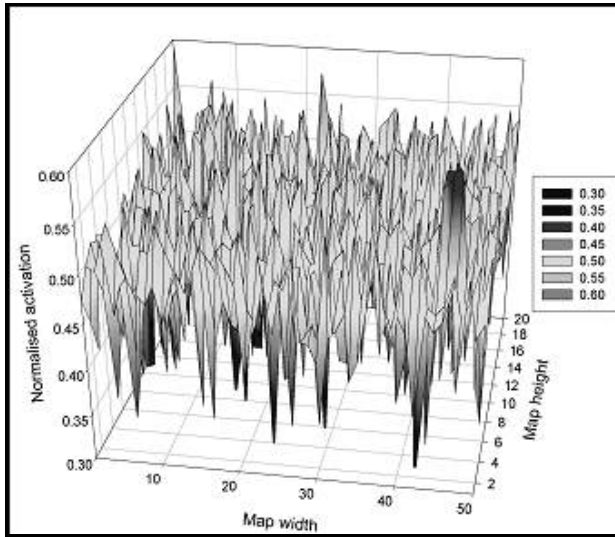


Fig. 5. Typical activation for simulations mono-region architecture

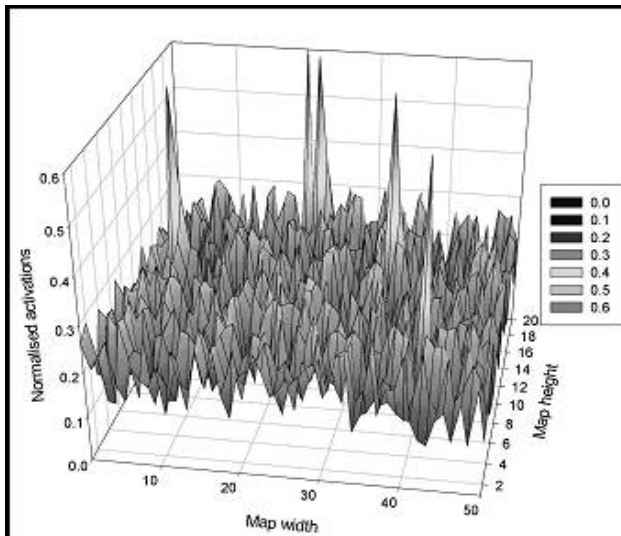


Fig. 6. Typical activation for simulations multiple-region architecture

IV. CONCLUSION

A. Results

Some features of Venn-networks, such as the ones

described below, make the proposed model different from other competitive and hybrid neural architectures (e.g. *Kohonen's* SOM [8] or *Hecht-Nielsen's* Counterpropagation [23]):

- Venn-networks have (by definition) one extra constraint in their competitive layer, *i.e.* the regions. This makes them closer to biological neural networks, and for instance distinguishable from SOM.
- Instead of considering (i) index of winner of competition or (ii) synaptic weight of competitive layer as output, Venn-networks display the inner product evoked by the competitive layer as both (1) “snapshot” of instantaneous activation (thus with aggregated meaning) and (2) input for the output supervised layer.
- The processing units have a continuous output produced by a non-linear activation function. This is different from the “winner-takes-all” (*i.e.* binary activations) as seen, for example, in counterpropagation. Because of this characteristic, map formation is non-trivial and meaningful. Moreover, as in Counterpropagation networks, the learning of Venn-networks is also very fast [22].
- Venn-networks also incorporate in a single model feedback from effectors, competition among processing units and interregional inhibition.

In spite of the difficulty of modeling any brain function, by utilizing our model, we have shown that:

- Venn-neural networks can be ‘trained’ to evoke expected behavior of complex tasks. The learning tasks of all experiments carried out have converged without requiring any *ad hoc* programmed routines or extremely complex architectures.

• At the same time all simulated tasks were satisfactorily learnt and executed by Venn-networks, the internal activity of these architectures evoked observable activations that resembled functional images (*i.e.* spatially and temporally localizable kernels of neural activity correlated to the task performed).

• The neural structure in Venn-networks does influence neural processing simulations, even though some structural differences may not be of critical importance or cannot be always easily observable.

• Functional localization, demonstrated by Venn-networks, may be suggested as an economic means of using computational resources such as ‘space’ and ‘time’. This, because less processing units are active at a single time and, thus, the overall computation can be achieved faster.

• Finally we have confirmed the hypothesis that architecture (*i.e.* network of processing elements and connectivity) influences neural processing. The simulations also show that some observable activations of the “cortex” can only happen if there is an underlying pre-set order in the circuitry.

B. Discussion

The confirmed hypothesis that structure is an active participant of computation is in-line with some research directions such as the ones carried out by *Gen Matsumoto* and his colleagues at Riken [24]. They are trying to understand the brain by reconstructing it as a non-*von Neumann* processor (*i.e.* ‘memory-based’) rather than a ‘processor-based’ device (as is the case of conventional computers). This approach implies that structure should provide the means for algorithm acquisition and execution. In Venn-networks, this ‘algebra’ is embedded in the user-defined architecture. Analogously, in biological systems, we argue that genetics may play the role of a guardian (for future generations) of a reliable substrate for correct and robust neural computation.

Even though there is some variability in the micro and macro neural structures, evolution has guaranteed a great deal of architectural uniformity in individuals of the same species. The levels of intra-species “hard-wiring” are greatly pre-established, which contrasts with what happens interspecies. This observation can be drawn from anatomical interspecies comparisons of nervous systems. In other words, most interregional (and inter-hemispheric) connections are not produced at random; rather they are genetically programmed [25]. Thus, we argue that ‘structure’ and ‘connectivity’, play a crucial role in the higher neural computational abilities of humans. Moreover, between the two, we speculate that connectivity may well be more relevant than local features because of the relative homogeneity of the former [26].

Finally, the approach adopted in this work seems to be also in line with the approach taken by other researchers such as:

- *Christopher Frith*, who suggests that when the weights in one module of the system (*i.e.* regions) are adjusted, this should not alter the functioning other modules [28]; and
- *Stephen Wolfram*, who suggests that simple units can implement complex computations when conveniently arranged [29], another suggestion of structure playing an important role in the overall processing.

C. Future work

We foresee some insightful results when processing units and connections of Venn-networks are artificially damaged for medical investigations purposes. In this scenario, Venn-networks would become a model of neurological diseases.

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