Simulation of Contra-Lateral Inhibition Using Venn-Networks

Fernando Buarque de Lima Neto
Department of Computing Systems, Polytechnic School of Engineering, Pernambuco State University, Rua Benfica, 455 – Madalena, 50.750-410 – Recife – PE, Brazil.
Telephone: +55 (0)81 2119 3842; FAX: +55 (0)81 2119 3836; E-mail: fbln@dsc.upe.br

Philippe De Wilde
Department of Computer Science, School of Mathematics and Computer Sciences
Heriot-Watt University, EH14 4AS – Edinburgh, UK.
E-mail: p.dewilde@macs.hw.ac.uk

Abstract. This paper illustrates how a computer model, based on Venn-networks, mimics a physiological phenomenon present in brains of higher animals: *contra-lateral inhibition*. The experiments were carried out by utilizing the GVNS, i.e. Generalized Venn-network Simulator. The data-set utilized in all simulations consisted of digital representations of finger positions of a piano player when performing a *Mozart* sonata. Results show that it is possible for the referred computer model to simultaneously exhibit topological network activations while controlling a simple task such as 'moving fingers' as well as incorporating contra-lateral like inhibition.
.

Keywords: Venn-network, contra-lateral inhibition, artificial neural networks, brain modeling, brain physiology.

1. Introduction

The central nervous system (CNS) in higher animals is composed of several complex structures intertwined in a non-monotonic manner [3][4][13]. Consequently, most physiological phenomena exhibited by the CNS are of high complexity. Understanding some of the mechanisms involved in such an intricate system is vital for advances in neuroscience and artificial intelligence.

Among the so called 'dry' methods that are applied in brain studies, computer models play an important role because of the (i) reproducibility of simulations, (ii) extensibility of model-features, (iii) expandability of investigation scope, (iv) control of precision and (v) granularity of modeling.

The main objective of this work is to use the GVNS, i.e. Generalized Venn-network Simulator [7] in order to investigate its ability to mimic important properties that exist in the biological system investigated – the brain. In this paper, one specific phenomenon is investigated: *contra-lateral inhibition* [11]. All simulations carried out here are grouped and add to other investigations using Venn-networks [6][8][9]. Our new results reveal not only successful examples of this architecture's processing abilities but also, its flexibility.

With regards of *contra-lateral inhibition*, anatomical and physiological evidence indicates that some regions of the neo-cortex inhibit others via long-range fibers through the *corpus callosum* [11]. This produces an intricate tread of nervous pathways as well as a complex functional dynamics; by using Venn-networks we reproduce this peculiar mechanism of the nervous system. To illustrate this biological property we have assembled a fairly complex computational network that resembles the biological simplified circuitry of voluntary control of finger flexion in both hands. The aim was to model expected movements and production of contra-lateral inhibition at the same time.

2. Venn-network

Venn-network is an artificial neural network proposed by *Buarque de Lima Neto* in 2002 [7] together with its simulator, the GVNS. It is a biologically inspired architecture that is able to create non-linear associations between input and output spaces by utilizing a two dimensional map of processing elements (PE). Additionally, while processing, the behaviors evoked by the PEs resemble localized neural activity of cortical columns in the cortex.

In Venn-nets, each processing element can simultaneously receive an arbitrary number of connections of up to four types of fibers, which are present in the architecture. The Venn-network also allows definition of an arbitrary number of regions, which includes as many processing elements of as many different types as needed. The processing regions are the place where neural activity happens.

Following activation, the different fibers carry excitatory or inhibitory signals all around the network. This pathway is defined by the experimenter, provided that there are fiber bunches linking different regions of the network. Besides their types, fibers have other associated features such as *synaptic weights*, *delay and cardinality.* These features grant interesting and distinct behaviors to each bundle. According to their functionality, fibers are referred to as (a) afferent – those that carry incoming signals; (b) efferent – those that carry outgoing signals; (c) u-fibers – those that interconnect regions; and (d) feedback – those that carry return signals from effectors. Figure 1 contains a schematic view of the Venn-Network architecture. It has all major elements that make this kind of artificial neural network so unique, namely, different types of regions, different types of processing elements – providing the functionality of a cortical column, different types of fibers, and custom made connectivity.

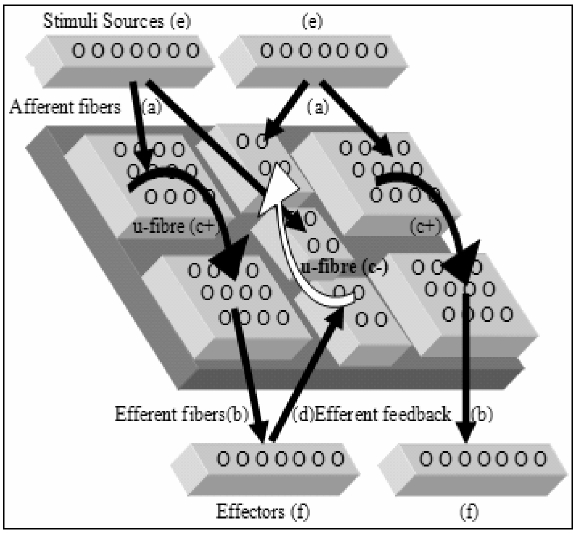


Fig. 1 – Schematic top view of the Venn-network architecture; fibers of different type are indicated by letters, namely: (a) *afferents*, (b) *efferents,* (c) *u-fibers* {both (c+) excitatory and (c-) inhibitory} and (d) efferent *feed-back*. See also regions (small rectangles) engulfing processing elements. External components: (e) *stimuli* sources and (f) *effectors* are indicated on top and bottom of the figure, respectively. Arrows are solely illustrations of user-defined bunch of fibers that link two regions (or external components) in a massively parallel manner.

3. Simulations

3.1 Experimental setup – network structure

To investigate the phenomenon of contra-lateral inhibition using Venn-networks based on physiological evidence, we select the control mechanism of voluntary movements, finger sensory-motor control. The reason for that was the relative simplicity of part of the circuitry involved. The pyramidal tract (the most important amongst all the motor pathways) connects neurons adjacent to the central sulcus (in the MI – Brodmann area 4) in the cortex directly to the spinal cord and the cranial nerves nuclei almost in an unmediated manner [11]. There, most of the fibers cross to the other side of the body, resulting in contra-lateral sensory-motor inhibition – which is seminal to the present investigation.

To match the objectives of this research, a complex network structure was devised for all simulations. The structure of the network comprises eight regions of identical size – 30 x 30 columns, divided into two "hemispheres" (four regions each), i.e. left-hand and right-hand side sensor-motor control of the simulated "cortex". It can be seen in Figure 2 that regions 0, 1, 4 and 5 lie on the left hemisphere, the other four regions: 2, 3, 6 and 7 lie on the right hemisphere. In order to help readers to compare results presented here with further ones, all simulation names *are prefixed by Sim1506.*

Throughout this investigation, due to Venn-network functionalities, all regions perform various types of specialized functions namely, motor control (regions 0 and 3), sensory processing (regions 4 and 7), inhibited-motor control (regions 1 and 2) and inhibited-sensory processing (regions 5 and 6). The Venn-network functionalities are results of the great facility to parameterize the Venn architecture, which comes down to flexile combinations of known training algorithms such as back-propagation [1] and self-organizing maps [14].

The structure of the network also has a non-trivial connectivity where all four fiber types available in the GVNS are utilized to obtain the contra-lateral inhibition phenomenon. Figure 2 displays the structure of the network utilized here. Each of the two *stimuli sources* (e.g. frontal regions of the brain) utilized sends afferents to one pair of regions (*e.g.* motor control and contra-lateral inhibited-motor control). Each of the two *effectors* (*e.g.* simulated fingers of both hands) utilized receives efferent fibers from the motor region, and simultaneously sends feedback signals to one pair of regions (*i.e.* sensory processing and contra-lateral inhibited-sensory processing). Finally, four u-fibers perform the contra-lateral inhibitory function of left-to-right and right-to-left selected regions.

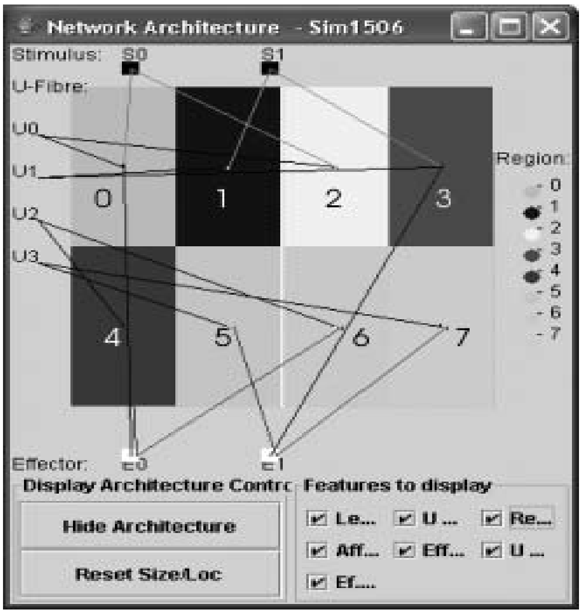


Fig. 2 – Snapshot of a GVNS window that details the network architecture defined and used for all Sim1506 simulations. Note all eight (numbered) cortical-like regions and various fiber types that comprise the model.

Another ability of Venn-networks, not explored in the present investigation, is to allow different types of processing elements within the model. Figure 3 shows that all eight regions of simulations belonging to *Sim1506* are composed of the same type of processing elements (regardless of their boundaries). This interesting ability of Venn-networks allows realistic simulations, as it is widely known that a functioning cortex is not homogeneous for cell types [11].

3.2 Experimental setup – simulation processing

All simulations carried out in this paper have four distinct processing phases. These phases are aimed at training all weights of fibers used and testing the network results. The four simulation phases were: (i) training of afferent fiber, (ii) training of efferent fibers, (iii) training of efferent feedback and (iv) testing the network performance on unseen patterns. Two repetitions were carried out per simulation set.

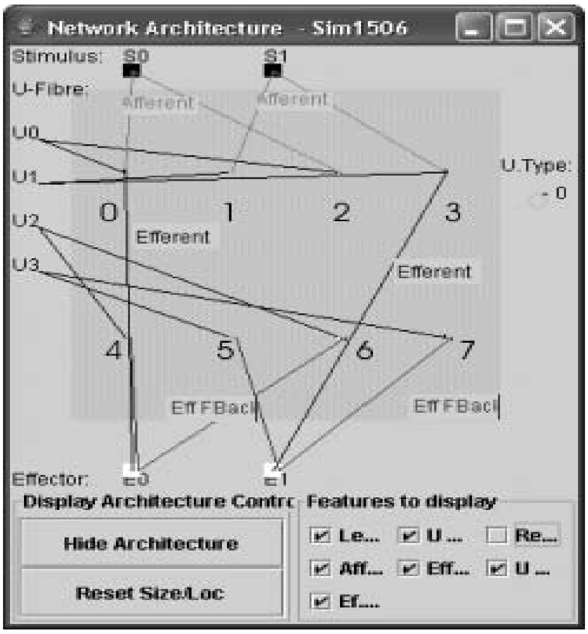


Fig. 3 – Snapshot of a GVNS window that details the processing elements defined and used for all Sim1506 simulations. Note that all PEs are of the same type (indicated as U. Type-0), regardless of region boundaries (see numbers); single lines used to illustrate fibers are simplified indications of whole sets of connections between regions – such as in real nervous pathway.

Two parameters of the model were selected *ad hoc* and varied in a two-step factorial manner for training the networks. The selected parameters were: *afferent learning rate* and *efferent learning rate*; the assigned values are indicated in Table 1.

Table 1
Parameters selected *ad hoc* to be varied during simulations Sim1506.

Simulations Sim1506	Afferent learning rate	Efferent learning rate	Efferent feedback learning rate
A	0.1	0.05	0.1
B	0.1	0.1	0.1
C	0.05	0.1	0.05
D	0.05	0.05	0.05

Other parameters different from default values of the GVNS were: decrement of afferent, efferent and efferent-FB – set respectively to 0.8, 0.9, and 0.8; neighboring – set to 1.0 for afferent and efferent-FB; and cooperation radius – set to 0.6 for afferent and efferent-FB. Learning rate values for efferent-FB were assumed to be the same used for afferent training.

3.3 Data-set used

Training patterns contain (numeric) information about flexion of all ten fingers of the piano player when performing Mozart's *Sonata Facile* [15] in a given time – regardless of their position on the keyboard. The encoding algorithm relates keystrokes within the time interval 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. An arbitrary initial portion of the sonata with 444 patterns was later used as training and testing data for the model. An example of training/testing pattern is: 0 0 0 0 1 1 0 0 0 0; this, representing left and right thumbs flexed at a given time. A comprehensive explanation on the data-set construction is provided in Buarque [7].

3.4 Training and testing

Within each of the four simulation phases, known training principles were utilized, namely, (i) training of afferent fiber – self-organizing maps [14], (ii) training of efferent fibers – back-propagation [1], (iii) training of efferent feedback – again, self-organizing maps, and (iv) testing of the network performance on unseen patterns – training patterns fed to an already formed self-organizing map.

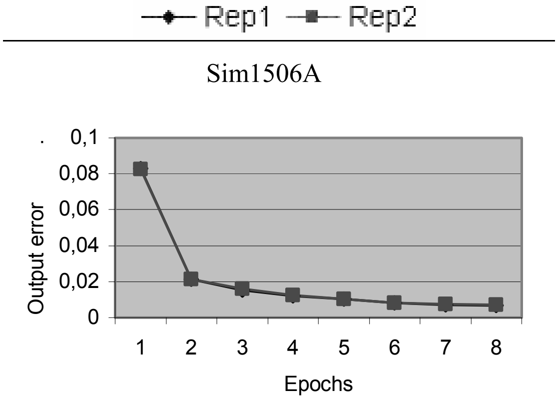
Processing of Venn-networks includes training phases 0, 1 & 2 and utilized the initial 333 patterns of the files with finger position of *left* and *right* "hands" (*i.e.* stimuli sources in the model). In addition, the testing phase (*i.e.* processing phase 3) utilized the final 111 – unseen – patterns of the same files just mentioned. The cardinality of both training and testing patterns was 5 for four all phases, as they correspond to the five fingers of the virtual hands. The stopping criteria for all four phases were: fixed number of epochs was equal to 8 for phases 0 and 1, was equal to 2 for phase 2, and one single epoch for the test phase.

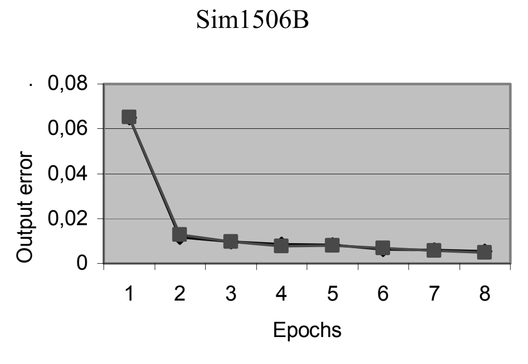
4. Results

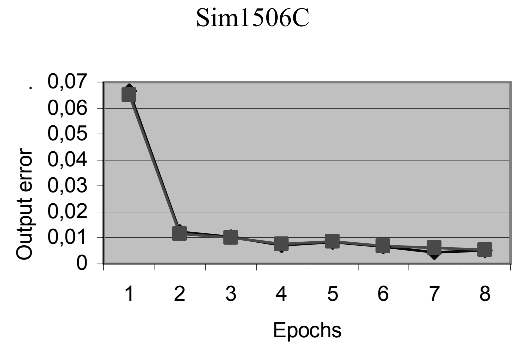
As shown in Table 2, output training errors produced by simulations Sim1506 were observed to decrease smoothly in all four simulations, reaching negligible values after eight epochs of training. Output errors are average differences between actual and desired finger position (considering all ten fingers) when *Mozart's* sonata is performed.

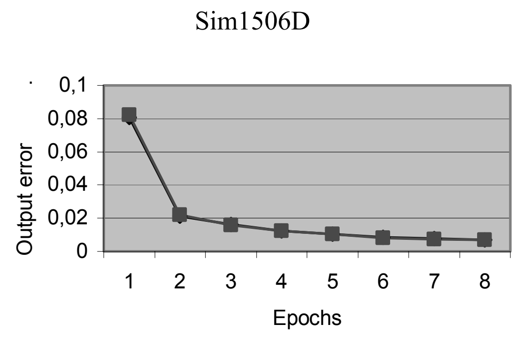
Table 2
Output error obtained by the simulated networks. The error (*i.e.* average differences between *actual* and *desired* finger positions) evolving during training epochs of Sim1506 decayed smoothly in all simulations (each two repetitions) A, B, C and D.

Output error vs. epochs of trainings









The performance on unseen values (*i.e.* data not used for training the networks) produced by Sim1506 is shown in Figure 4 and Figure 5; Sim1506C repetition 1 was the one that presented best performance. Figure 6 and Figure 7 illustrate network activities when processing a typical input, *i.e.* the activations are resulting from the *same* stimulus. The only difference is that in the latter simulation random noise and relaxation were switched-on; this is a feature of GVNS that aims to produce images that resemble functional magnetic resonance imaging [12].

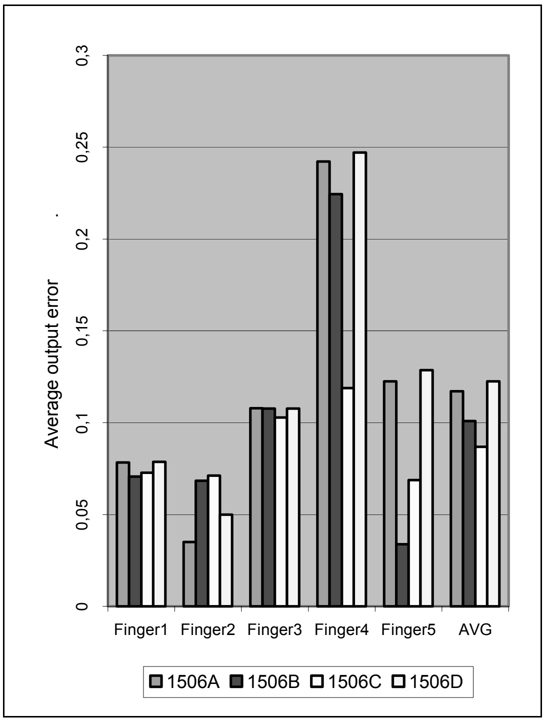


Fig. 4 – Average output error of *left* fingers across all repetitions of Sim1506

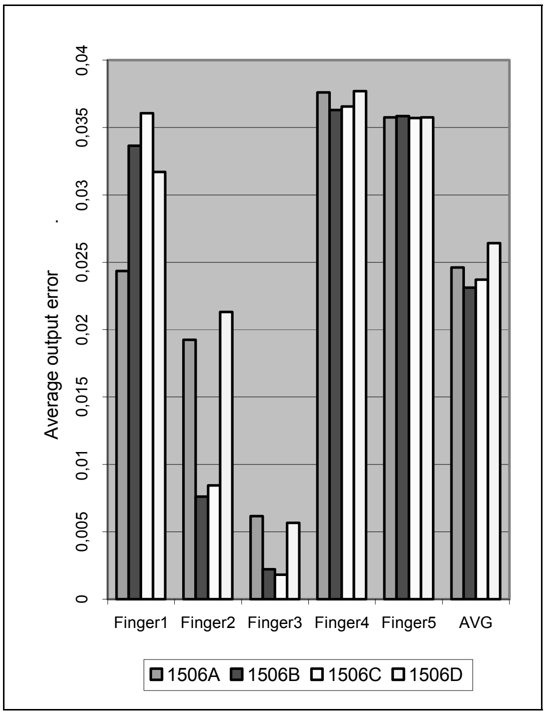


Fig. 5 – Average output error of *right* fingers across all repetitions of Sim1506

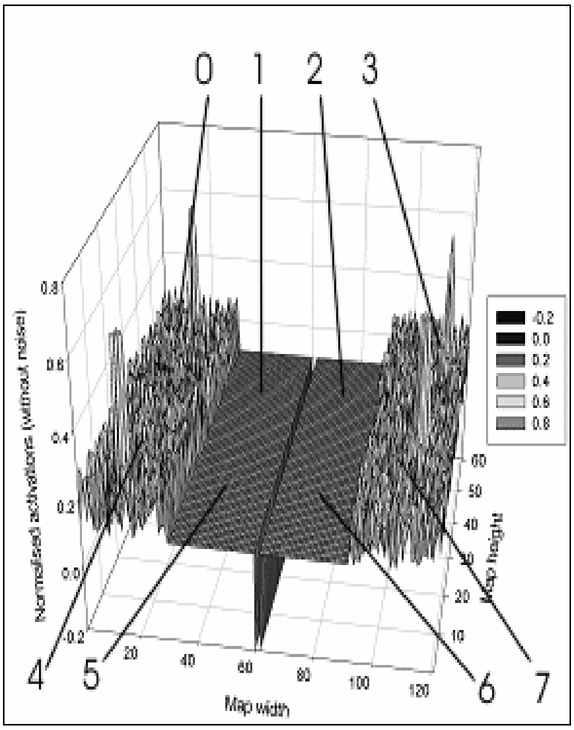


Fig. 6 – Typical activations of simulations Sim1506; it presents activations of four contra-lateral inhibitory regions (see regions indicated by numbers).

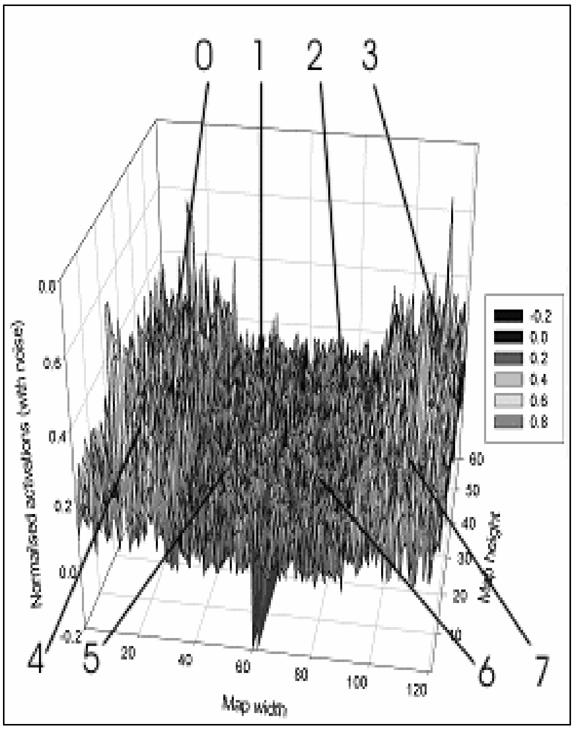


Fig. 7 – Typical activations of simulations Sim1506; the graphic exhibits activations of four contra-lateral inhibitory regions (same as above). Here including background noise added during processing (see regions indicated by numbers).

5. Conclusion

Our simulations involved training of two virtual hands using a pair of motor regions – one for each hand – as well as sensory areas, together with an equal number of areas to for investigation whether Venn models are able to evoke the contra-lateral phenomenon.

Apart from the significant differences of having more processing units (7200), regions (eight) and fibers (14 pathways), this experiment elicits results that confirm previous simpler experiments [6][8]. However, the results obtained here suggest that even in more complex configurations, Venn-networks still produce synaptic values that are coherent among similar tasks (*i.e.* same training patterns and different experimental situations).

A careful observation of results reveals an asymmetry between performances of hands. The right hand ended up better trained than the left hand. As the same data set is used in all experiments, the uneven tasks among hands are credited to be the cause of this fact. Swapping input files (hand-wise) corroborated this belief as elicited performance results were also inverted.

All facts commented above once more indicate that Venn-networks are able to control non-trivial behavior in an equivalent manner either in simple or complex configurations. Moreover, the current experiments helped us to extend this conclusion by adding to it, that this control happens even whether other internal tasks are also being processed (*e.g.* four regions contra-laterally inhibiting each other). This is an important finding and feature of Venn-networks as in the nervous system many tasks are processed in parallel [13].

The observed difference between Figure 6 and Figure 7, due to the additive noise and relaxation abilities of the GVNS, is an interesting resource that certainly makes any simulated cortical map much more realistic. This is so because real neurons do fluctuate even when not engaged in any particular task or when not receiving stimulation [10].

Finally, although only suppressed or attenuated activations are observable in regions 1, 2, 5 and 6 in Figure 6 and Figure 7, this would not happen if the model were not able to express contra-lateral inhibitions – precisely what we were set to investigate in this work. Therefore, Venn-models can mimic this physiological phenomenon observable in biology. This is because of the inhibitory action of the 'u-fibers' of Venn-models; they send signals to contra-lateral regions. These inhibitory signals are obviously preventing activities in the target regions of the u-fibers.

Acknowledgments

This work was partially supported by the CNPq – Brazilian Research Agency – under grants 200295/1998-5 and 506595/2004-8.

References

[1] D. Rumelhart, G. Hinton, and J. McClelland, Learning internal representations by error propagation, volume1, chapter 8 in [2].

[2] D. Rumelhart, J. McClelland, and PDP Research Group, (Editors) Parallel Distributed Processing: Explorations in the Microstructure of Cognition, Cambridge, MA: MIT Press, 1986.

[3] E. Kandel, The Brain and Behavior, chapter 1 in [5].

[4] E. Kandel, Nerve Cells and Behavior, chapter 2 in [5].

[5] E. Kandel, J. Schwartz, and T. Jessell, (Editors), Principles of Neural Sciences, Fourth Edition, International Edition, New York: McGraw-Hill, 2000.

[6] F. Buarque de Lima Neto, Flexion of Virtual Fingers Controlled by Artificial

Neural Networks, in Mathematics and Simulation with Biological, Economical and Musicoacoustical Applications, edited by C. D'Attellis, V. Kluev, and N. Mastorakis, WSES Press, 2001.

[7] F. Buarque de Lima Neto, Modelling Neural Processing Using Venn-Networks in Physiological and Pathological Scenarios, Ph.D. Dissertation, Dept. Electrical and Electronic Engineering, Imperial College, London/UK, 2002.

[8] F. Buarque de Lima Neto and P. De Wilde, Simulation of Ageing Using Venn-Networks, Proceedings of SBRN 2004 – 8th Brazilian Symposium on Neural Networks, edited by A. Barros, A. Araújo, H. Yehia and R. Teixeira, IEEE Computer Society: São Luis-Brazil, 2004.

[9] F. Buarque de Lima Neto and P. De Wilde, Venn-Like Models of Neocortex Patches, Proceedings of WCCI 2005 – IEEE World Congress in Computational Intelligence, edited by IEEE Computational Intelligence Society: Vancouver-Canada, 2006.

[10] I. Levitan and L. Kaczmarek, The Neuron: Cell and Molecular Biology, Second Edition, New York: Oxford University Press, 1997.

[11] P. Brodal, The Central Nervous System, Second Edition, New York: Oxford University Press, 1998.

[12] P. Jezzard, P. Matthews, and S. Smith, (Editors) Functional MRI, Oxford: Oxford University Press, 2001.

[13] P. McLeod, K. Plunkett, and E. Rolls, Introduction to Connectionist Modelling of Cognitive Processes, Oxford: Oxford University Press, 1998.

[14] T. Kohonen, The self-organizing maps in Proceedings of the IEEE 78 (1990) 1464-1480.

[15] W. Mozart, "Sonata in C major: 'Sonata facile' ", in *Sonaten fuer Klavier zu zwei Haenden nach den Quellen*, edited by C.A. Martiensen newly reviewed edition by L. Koehler and A. Ruthardt. Frankfurt: C. F. Peters Corporation, 1951.

Fernando Buarque de Lima Neto is Associate Professor in the Department of Computer Systems of the Polytechnic School of Engineering, Pernambuco State University, Recife, Brazil. He leads the Computational Intelligence research group. Dr Buarque received his PhD degree in artificial intelligence and DIC Diploma in artificial neural networks, respectively, from University of London and Imperial College-London, United Kingdom, in 2002. He received a BSc degree in computing in 1990 from Catholic University of Pernambuco-Brazil and an MSc degree in computing from Federal University of Pernambuco-Brazil in 1998. His main interests are brain inspired models of computation, intelligent decision support systems and bio-inspired robots & games. He has worked with computational models of multiple-sclerosis, stroke and aging. He proposed the Venn-model that is a novel artificial neural network able to integrate topographical representation of neural activations and functional results evoked by these activations. He also applied computational intelligence to various real world problems of decision making. Presently, He is a member of IEEE, CIS, SBC (Brazil).

Philippe De Wilde is Professor in the Department of Computer Science of The School of Mathematical and Computer Sciences, Heriot Watt University, Edinburgh, Scotland. He is a member of the Intelligent Systems Lab. Dr De Wilde received the Ph.D. degree in Mathematics and the MSc. degree in Computer Science, both in 1985 from Universiteit Gent, Belgium. His main interests are brain inspired models of uncertainty, linguistic and fuzzy uncertainty and uncertainty in dynamic multi-user environments. He has worked with dynamics of large systems. This includes neural networks models of part of the brain, and the coupling between the cerebro-vascular and neuronal networks. He also studies multi-agent systems, and how their dynamics are affected by the connectivity. Uncertainty is part of such systems, and he uses fuzzy logic and soft computing for analysing distributed systems. He is author of Neural Network Models (London, Springer, 1997, 2nd ed.). He is a member of SIAM, IEEE and an Associate Editor of IEEE Transactions on Systems, Man, and Cybernetics, Part B.