Brain Complexity and Intelligence: a study of Evolutionary Robotics

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Abstract

While the correlation between Evolution (and therefore Intelligence) and increase of Brain Volume is considered evident, the difficulty in defining and quantifying Brain Complexity has been always an obstacle to study if and how much it is important. In the recent years an effort has been made to fill this gap, and the present work uses these new measures to investigate the correlation between evolution of Artificial Neural Networks and their Complexity. A Genetic Algorithm has been used to make Khepera Robots evolve in four different tasks, and the resulting Neural Networks' Complexities have been measured. Results show a significant correlation between Complexity and Fitness.

Keywords: Neural Complexity; Brain Volume; Robotics; Evolution; Genetic Algorithms; Artificial Neural Networks.

Introduction

Even admitting the unquestionable importance of brain volume in the creation of more or less intelligent beings, Darwin himself (1882) pointed out that it didn't suffice as an explanatory variable, but the increase of the brain organization had also to be taken in consideration. From then on many studies have been carried out to prove, above all, the effect of brain volume on behavior: Markina et al. (1999, 2001, 2004), for instance, proved that strains of mice selected on the basis of brain volume differ from one another in behavior (increase of stereotyped behavior and anxiety in small brain mice) but Anderson (1995) showed that neither total brain volume nor the volume of each separate brain area cause differences in learning and "reasoning" capacities; Nicolakakis et al (2003), on the other hand, studied the encephalization of bird species, proving its correlation with behavioral innovations; Poth et al. (2005) proved that in Cetaceans the ratio between grey and white matter decreases with the increase of brain volume, while ratio between brain areas changes according to the species (and its habitat); and many other studies were carried out on similar subjects.

Evolution and Brain Organization

Only in the recent years, however, interest in brain complexity and organization has risen again. Mathematical models have proved that an increase in brain volume without a more complex brain organization and modularization is impossible (Braitenberg, 2001; Kaas, 2000; Karbowsky, 2003). A substantial brain re-organization during evolution has been proved by comparing endocranial casts of different hominids (Falk, 1991; Rilling and Seligman, 2002). All the theories in this field share the idea that a better organized brain can fulfill the same functions with lesser waste of energy, which means that evolution must have favored not only an increase in brain volume, but even brain re-organization.

Neural Complexity and Artificial Neural Networks

In the recent years Tononi et al. (1994, 1996, 2003) dealt with the question of defining and quantifying neural complexity, considering the apparent dichotomy between "functional segregation" and "integration". Borrowing concepts from statistic physics, as for instance Mutual Information, they define Neural Complexity as the average Mutual Information between all the bipartitions of the "brain system" (*X*), summed on all the possible quantities of these bipartitions:

$$C_N(X) = \sum_{k=1}^{n/2} \left\langle MI(X_j^k; X - X_j^k) \right\rangle \tag{1}$$

Therefore, only those systems which are highly integrated and interconnected can show a high Neural Complexity.

Neural Complexity cannot be measured in biologic systems (neither *in vivo* nor *in vitro*), although, for instance, Van Cappellen van Walsum et al. (2003), Burgess et al. (2003) David et al. (2004) tried to estimate it starting from MEG or EEG data. Instead, Neural Complexity can be computed on Artificial Neural Networks with simple procedures[1], and it is even possible to make these artificial networks evolve with genetic algorithms, in order to analyze how complexity changes in function of evolution, which is precisely the purpose of the present work.

Experiments

The neural networks used for this work are fully recurrent networks of the Elman type (1990), that is, with a single layer of hidden neurons totally interconnected with itself. This simplification makes the networks' structure highly flexible, depending on the hidden neurons' connections' weights, and there is no need to deal directly with it: depending on how many weights are non-zero, the result will vary from structures with many feedbacks and complex dynamics to purely reactive structures, equivalent to feed-forward networks.

A genetic algorithm has then been used to make the connections' matrix evolve, with a 200 individuals' population amongst whom only the best 25 individuals have been allowed to breed. Experiments have been repeated for several amounts of hidden neurons: 4, 5, 6, 7, 9, 11, 13, 16

[1] http://www.indiana.edu/~cortex

and 20. Thus both the effect of evolution and the effect of "brain volume" on fitness have been verified.

The open source simulator YAKS (Carlsson, 1999) has been used for all of the experiments: it can simulate the behavior of Kephera robots[2] in environments with walls, light sources and movable objects. The environment setting is different for each of the four experiments, as well as the tasks assigned to robots (that are determined by the fitness function used by the genetic algorithm to select the individuals who will breed). All of the experiments have been repeated twice in order to test their reliability, given the many stochastic processes involved. As an evidence of the accuracy of the design and the resulting data, no difference could be noticed between the two repetitions.

The idea beneath these experiments is that while the evolution goes on and the systems' fitness increases, the complexity grows too: so we can say that the same evolutionary force towards a growth in complexity operate both in natural evolution and in "artificial evolution" (that is, the evolution of artificial beings).

Design

The four experiments differ only for the environment (walls, lights, objects) and the task assigned to the agents (i.e. the fitness function). The Artificial Neural Networks and the Genetic Algorithms used are the same throughout the four experiments. The reason to perform different experiments is only to see if in different tasks and environments there are the same correlations between Complexity and Fitness.

First Experiment: Navigation in a Maze. The environment is a square maze of 1m side with several walls: a Kephera robot has to navigate inside it without crashing into its walls, which would cause its immediate death. Each time the starting point and the starting direction vary randomly, and fitness has contributions both at every time and at the end of the period of life. For every instant *t* the following quantity is added:

(2) $$F_t = m_1 + m_2 - 4 \cdot abs(m_1 - m_2) - 1$$

where m_1 and m_2 represent the rotation speed of both engines, which can range between 0 (backward maximum speed) and 1 (onward maximum speed). Onward motion is so encouraged, whilst spinning is discouraged. The robot is free to navigate inside the maze using its sensors, which are stimulated by the walls' closeness.

At the end of the epoch, a quantity, proportional to the distance *d* (expressed in millimeters) between starting point and point of arrival, is added to the fitness collected during the navigation. Therefore the final function is:

(3) $$F_{tot} = 3d + \sum_t F_t$$

[2] http://www.k-team.com

Should the robot crash into a wall, its life epoch ends immediately and a value of 2000 is subtracted from the gained fitness: this value will be sufficient to select those individuals who are able to avoid obstacles, without making the function too discontinuous.

At the end of the four life epochs the achieved fitness values are summed up and the best 25 individuals are allowed to breed, generating 8 sons for each of them. In each son, each original weight is increased (or decreased) by a value randomly generated with a normal distribution.

The most evolved individuals adopt essentially all the same strategy, also in the repetition of the experiment: they move as much straightforwardly as possible until they come to a wall, then turn in the direction which involves lesser stimulation of their sensors.

Second Experiment: Search of Sources of Light. This experiment tests the integration of two sensory modalities: infrared as proximity sensors and environment light sensors for distance to light sources.

The environment is very simple: four walls compose a square with sides of 70cm, and three lights are positioned at different distances from the four vertices. This different positioning in respect to the vertices is to avoid that the agent works out a strategy based only on reaching a vertex, without using the environment light sensors.

Also in this experiment the contributes to the fitness are both added at every instant and at the end of the agent's life. At every step of the simulation the distance to the nearest source of light is calculated: if it is less than 5cm, a value of 20 is added to the fitness, otherwise the formula (2) is used. In this way the active search of light is rewarded, but also the remaining near a light, once it is found. Also in this experiment the agent dies immediately if it collides, and a value of 1000 is subtracted from its gained fitness.

If the agent arrives to its life's natural end at a distance less than 6cm from a light, it is rewarded with other 2000 "points". At the end of the four epochs the global fitness is computed and the best 25 robots are allowed to breed in the same way of experiment 1.

Third Experiment: Search of Sources of Light in a Maze. The third experiment is a more complex version of the second one: the environment is the same, but with the addition of some walls in proximity of the sources of light, walls that must be avoided to reach the lights. The fitness function is also the same, with the difference that a distance of 10 cm from the lights is rewarded at every instant (instead of 5cm) and at the end of the agent's life a distance of less than 9cm is rewarded (instead of 6cm). This is because the presence of the additional walls is otherwise a deterrent too strong in comparison with the push to find a source of light.

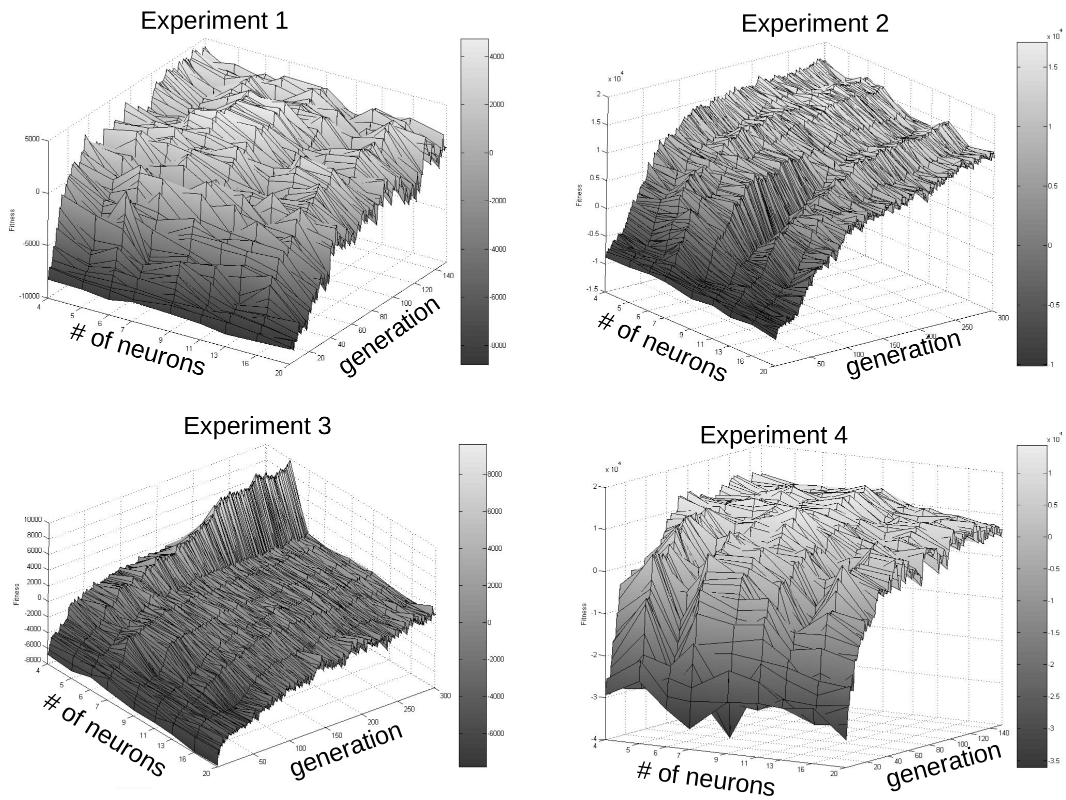

Figure 1. Average Fitness in function of the generations and number of neurons.

Fourth Experiment: Moving Objects toward a Source of Light. The fourth experiment is also inspired by the second one: in the environment there are a source of light and some scattered objects. The task in this case consists in grasping the objects and moving them near the source of light. The fitness is function of the number of moved objects and of their distance from the source of light at the end of the agent's life epoch.

Results

The most interesting analysis concerns the effect on Fitness of the number of neurons (i.e. the equivalent of the brain volume) and the Neural Complexity.

Number of Neurons. Both the Analysis of Variance and Pearson Correlation show that the number of neurons doesn't affect the Fitness of the systems ($P > .30$), in all four experiments, as also shown by Figure 1. This is definitely in contrast with all the actual theories, which consider the brain volume the most important factor for intelligence. It is worth to note that the space of solutions, given the complete recurrence of the hidden layer, is proportional to the square of the number of neurons: the advantage maybe acquired with a greater quantity of neurons is probably lost due to the increased difficulty to search optimal solutions.

Neural Complexity. Since the number of neurons is not influent, we proceeded to normalize the fitness and neural complexity measures (the computation of the neural complexity is biased by the number of neurons), to analyze the effect of Neural Complexity on Fitness, in all four experiments. As shown by Figure 2 and Table 1, in all the experiments the correlation between Fitness and Neural Complexity is significant (analogous results can be obtained analyzing the correlation between Generations and Neural Complexity). This repeatability of the results in tasks with various structures and difficulties supports our theory, and shows that the Neural Complexity Factor is always influent for the ability (i.e. "intelligence") of the systems.

Table 1. Pearson Correlations of Fitness in function of Neural Complexity.

Exp 1	Exp 2	Exp 3	Exp 4
.290(**)	.462(**)	.286(**)	.388(**)
*Significance: ** $P < 0.01$*			

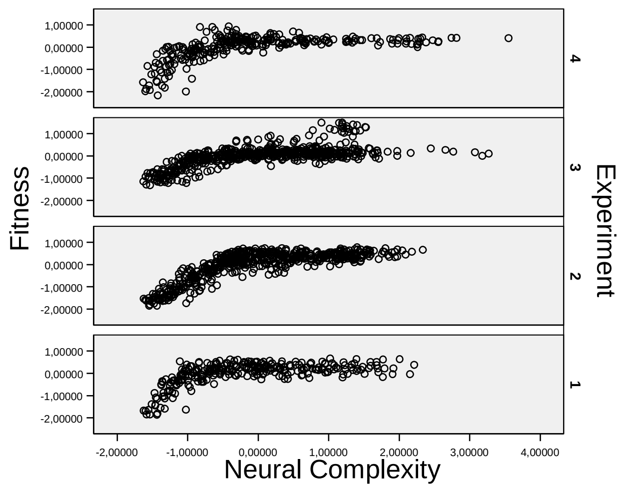

Figure 2. Variation of Fitness in function of Neural Complexity, for the various experiments.

Discussion

Although the importance of the brain volume as a fundamental factor for intelligence has been extensively studied, as well as the increase of Encephalization Quotient (Jerison, 1973) during the evolution of species, an aspect often neglected is the brain organization and complexity. The modern information technologies allow to simulate the evolution of simple "artificial brains" that control autonomous agents (robots) in environments of varying complexity, and to subsequently study every aspect of the resulting neural networks, since the complete connections matrix is available and can be analyzed in different ways.

The complexity measures used in this work have been rarely used before for mobile agents. Confronting the Fitness with the Neural Complexity computed for the Artificial Neural Networks resulting from the evolution, the most interesting result has been the discovery that also in the evolution of artificial systems operates the same force toward complexity that operates in natural evolution. There is instead no influence of the number of neurons on the agents' fitness, but must be noted that the number of neurons couldn't be modified by the genetic algorithm, therefore it is impossible to tell if the evolution would have also promoted bigger "brains". Surely, it promotes better organized and more complex brains.

Certainly much more complex researches are needed to generalize this discovery to biological systems: neural networks of various magnitudes bigger, able to learn, possibly with an ontogenesis similar to the biologic one, which control agents with richer sensory and motor systems, in more varying and complex environments.

Nevertheless, considering the available means, the present research has however achieved interesting and important results, showing a parallel between the evolution of natural and artificial systems: the force toward a greater complexity, and the correlation between complexity and "intelligent" behaviors.

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References

Anderson, B. (1995) Individual variation in cerebral cortex size and neuron number does not predict behavioral ability in the rat. *Person. Individ. Diff. 2* (18), pp. 201 - 211

Braitenberg, V. (2001). Brain Size and Number of Neurons: An Exercise in Synthetic Neuroanatomy. *Journal of Computational Neuroscience 10*, pp. 71 - 77

Burgess, A.P. & Rehman, J. & Williams, J.D. (2003). Changes in neural complexity during the perception of 3D images using random dot stereograms. *International Journal of Psychophysiology 48*, pp. 35 - 42

Carlsson, J. & Ziemke T. & Bodén M. (1999). An experimental comparison of weight evolution in neural control architectures for a 'garbage-collecting' khepera robot. *In F. Loffler, A. Mondada and U. Rückert, editors, Experiments with the Mini-Robot Khepera - Proceedings of the 1st International Khepera Workshop*, pp 31-40

Darwin, C. (1882) *The descent of man and selection in relation to sex. 2nd edn.*, London, John Murray (from http://pages.britishlibrary.net/charles.darwin)

David, O. & Cosmelli, D. & Fristona, K.J. (2004). Evaluation of different measures of functional connectivity using a neural mass model. *NeuroImage 21*, pp. 659 - 673

Elman J.L. (1990). Finding structure in time. *Cognitive Science 14*, 179–211.

Falk, D. (1991) 3.5 Million years of hominid brain evolution. *Seminars in The Neurosciences (3)*, pp. 409 - 416

Jerison, H. J. (1973). *Evolution of the Brain and Intelligence.* Academic Press, New York, New York

Kaas, J.H. (2000). Why is Brain Size so Important: Design Problems and Solutions as Neocortex Gets Bigger or Smaller. *Brain and Mind 1*, pp. 7 - 23

Karbowkski, J. (2003). How Does Connectivity Between Cortical Areas Depend on Brain Size? Implications for Efficient Computation. *Journal of Computational Neuroscience 15*, pp. 347 - 356

Markina, N.V. & Popova N.V. & Poletaeva I.I. (1999) Interstrain differences in the the behavior of mice selected for greater and lesser brain mass. *Zh Vyssh Nerv Deiat Im I P Pavlova 1* (49), pp. 59 - 67

Markina, V.N. & Salimov, R.M. & Poletaeva, I.I. (2001). Behavioral screening of two mouse lines selected for different brain weight. *Prog. Neuro-Psychpharmacol. & Biol. Psychiat. (25)*, pp. 1083 - 1109

Markina, N.V. & Salimov, R.M. & Perepelkina, O.V. & Maisky, A. I. & Poletaeva, I.I. (2004). Correlation between Brain Weight and the Pattern of Behavior Changes in Response to Ethanol Injections in Laboratory Mice. *Russian Journal of Genetics 6* (39), pp. 687 - 691

Nicolakakis, N. & Sol, D. & Lefebvre, L. (2003). Behavioural flexibility predicts species richness in birds, but not extinction risk. *Animal Behaviour 65*, pp. 445 - 452

Poth, C. & Fung, C. & Gunturkun, O. & Ridgway, S.H. & Oelschlager, H.H.A. (2005). Neuron numbers in sensory cortices of five delphinids compared to a physeterid, the pygmy sperm whale. *Brain Research Bulletin 66*, pp. 357-360

Rilling, J.K. & Seligman, R.A. (2002). A quantitative morphometric comparative analysis of the primate temporal lobe. *Journal of Human Evolution 42*, pp. 505 - 533

Tononi, G. & Sporns, O. & Edelman, G.M. (1994). A measure for brain complexity: Relating functional segregation and integration in the nervous system. *Proc. Natl. Acad. Sci. USA May (91)*, pp. 5033 - 5037

Tononi, G. & Sporns, O. & Edelman, G. (1996). A complexity measure for selective matching of signals by the brain. *Proc. Natl. Acad. Sci. USA April (93)*, pp. 3422 - 3427

Tononi, G. & Sporns, O. (2003). Measuring information integration. *BMC Neuroscience 31* (4)

van Cappellen van Walsum, A.M. & Pijnenburgb, Y.A.L. & Berendsed, H.W. & van Dijkc, B.W. & Knole, D.L. & Scheltensb, P. & Stam, C.J. (2003). A neural complexity measure applied to MEG data in Alzheimer’s disease. *Clinical Neurophysiology 114*, pp. 1034 - 1040