Available online at www.sciencedirect.com
ScienceDirect
Cognitive Systems Research 45 (2017) 52–58
Cognitive Systems Research
www.elsevier.com/locate/cogsys

Awareness improves problem-solving performance

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Received 24 January 2017; accepted 2 May 2017
Available online 17 May 2017

Abstract

The brain's self-monitoring of activities, including internal activities – a functionality that we refer to as awareness – has been suggested as a key element of consciousness. Here we investigate whether the presence of an inner-eye-like process (monitor) that supervises the activities of a number of subsystems (operative agents) engaged in the solution of a problem can improve the problem-solving efficiency of the system. The problem is to find the global maximum of a NK fitness landscape and the performance is measured by the time required to find that maximum. The operative agents explore blindly the fitness landscape and the monitor provides them with feedback on the quality (fitness) of the proposed solutions. This feedback is then used by the operative agents to bias their searches towards the fittest regions of the landscape. We find that a weak feedback between the monitor and the operative agents improves the performance of the system, regardless of the difficulty of the problem, which is gauged by the number of local maxima in the landscape. For easy problems (i.e., landscapes without local maxima), the performance improves monotonically as the feedback strength increases, but for difficult problems, there is an optimal value of the feedback strength beyond which the system performance degrades very rapidly.
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Keywords: Consciousness; Awareness; Collective intelligence; Agent-based simulations

1. Introduction

What is consciousness for? From a biological perspective, an auspicious answer to this mind-opening question (see Blackmore (2003) for a thorough discussion of the theories of consciousness) views consciousness as a source of information about brain states – a brain's schematic description of those states – and suggests that the evolutionary usefulness of such inner eye is to provide human beings with an effective tool for doing natural psychology, i.e., for imagining what might be happening inside another person's head (Humphrey, 1999). Hence, the conception of other people as beings with minds originates from the way each individual sees himself and, in that sense, solely extraordinarily social creatures, probably humans only, would evolve consciousness as a response to the pressures to handle interpersonal relationships (Humphrey, 1999). There is an alternative, equally attractive, possibility that we may first unconsciously suppose other consciousness, and then infer our own by generalization (Jaynes, 1976). We note that the hypothesis that consciousness is closely related to social ability has been suggested in many forms by many authors (see, e.g., Baumeister & Masicampo, 2010; Carruthers, 2009; Frith, 1995; Perlovsky, 2006), but the original insight that consciousness and cognition are products of social behaviors probably dates back to Vygostsky in the 1930s (Vygotsky, 1986).

This approach, however, is not very helpful to the engineer who wants to build a conscious machine. Fortunately, the recently proposed attention schema theory of consciousness (Graziano, 2013; Graziano & Kastner, 2011) offers some hope to our engineer by positing that awareness is simply a schematic model of one's state of attention, i.e.,

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http://dx.doi.org/10.1016/j.cogsys.2017.05.003
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awareness is an internal model of attention. (The intimate connection between awareness and consciousness is expressed best by the view that consciousness is simply the awareness of what we have done or said, reflected back to us (Jaynes, 1976).) Building a functioning attention schema is a feasible software project today, which could then be coupled to the existing perceptual schemas (Murphy, 2000) to create a conscious machine. As before, the selective value of such internal model stems from the possibility of attributing the same model to other people, i.e, of doing natural psychology (Graziano, 2013).

Internal models or inner eyes keep track of processes that, within an evolutionary perspective, are useful to monitor and provide feedback to (or report on) those very same processes. This feedback can be thought of as the mechanism by which 'mind' influences matter (Graziano, 2013). Here we show that the inner monitoring can be useful in a more general problem-solving scenario. (The word awareness in the title of this paper is used with the meaning of inner monitoring.) In particular, we consider a number L of subsystems or operative agents that search randomly for the solution of a problem, viz. finding the global maximum of a rugged fitness landscape (see Section 2), and a single monitor that tracks the quality of the solution found by each agent (i.e., its fitness) and records the best solution at each time. The feedback to the operative agents occurs with frequency $p \leqslant 1$, i.e., on the average each agent receives feedback from the monitor $p \times \Delta t$ times during the time interval Δt. The feedback consists of displaying the best solution among all agents at that time, so the operative agents can copy small pieces of that solution (see Section 3 for details).

The performance of the system composed of L operative agents and a monitor is measured, essentially, by the time it takes to find the global maximum of the fitness landscape. (Since we may want to compare performances for different values of L, the actual performance measure must be properly scaled by L, as discussed in Section 3.) The relevant comparison is between the case $p = 0$ where the monitor has no effect on the operation of the system (a scenario akin to the doctrine of epiphenomenalism (Blackmore, 2003)), and the case $p > 0$ where the system receives feedback from the monitor. If the speed to solve problems has a survival value to the individuals and if that speed increases in the presence of feedback from the monitor, then one may argue for the plausibility of the evolution, as well as for the commonplaceness, of such inner-eyes-like processes in the brain.

We find that the performance of the system for small values of the feedback frequency or strength p, which is likely the most realistic scenario, is superior to the performance in absence of feedback, regardless of the difficulty of the task and of the size of the system. This finding lends support to the inner-eye scenario for brain processes. In the case of easy tasks (i.e., landscapes without local maxima), the performance always improves with increasing p, but for rugged landscapes the situation is more complicated: there exists an optimal value of p, which depends both on the complexity of the task and on the system size, beyond which the system performance deteriorates abruptly.

The rest of this paper is organized as follows. Since the tasks of varying complexity presented to the problem-solving system are finding the global maxima of rugged fitness landscapes generated by the NK model, in Section 2 we offer an outline of that classic model (Kauffman & Levin, 1987). The problem-solving system is then described in great detail in Section 3. We explore the space of parameters of the problem-solving system as well as of the NK model in Section 4, where we present and analyze the results of our simulations. Finally, Section 5 is reserved to our concluding remarks.

2. Task

The task posed to a system of L agents is to find the unique global maximum of a fitness landscape generated using the NK model (Kauffman & Levin, 1987). For our purposes, the advantage of using the NK model is that it allows the tuning of the ruggedness of the landscape – and hence of the difficulty of the task – by changing the integer parameters N and K. More specifically, the NK landscape is defined in the space of binary strings $\mathbf{x} = (x_1, \ldots, x_N)$ with $x_i = 0, 1$ and so the parameter N determines the size of the state space, given by 2^N. For each bit string $\mathbf{x}$ is assigned a distinct real-valued fitness value $\Phi(\mathbf{x}) \in [0, 1]$ which is an average of the contributions from each element i of the string, i.e.,

$$\Phi(\mathbf{x}) = \frac{1}{N} \sum_{i=1}^{N} \phi_i(\mathbf{x}), \tag{1}$$

where ϕ_i is the contribution of element i to the fitness of string $\mathbf{x}$. It is assumed that ϕ_i depends on the state x_i as well as on the states of the K right neighbors of i, i.e., $\phi_i = \phi_i(x_i, x_{i+1}, \ldots, x_{i+K})$ with the arithmetic in the subscripts done modulo N. The parameter $K = 0, \ldots, N-1$ is called the degree of epistasis and determines the ruggedness of the landscape for fixed N. The functions ϕ_i are N distinct real-valued functions on $\{0, 1\}^{K+1}$ and, as usual, we assign to each ϕ_i a uniformly distributed random number in the unit interval so that $\Phi \in (0, 1)$ has a unique global maximum (Kauffman & Levin, 1987).

The increase of the parameter K from 0 to $N-1$ decreases the correlation between the fitness of neighboring strings (i.e., strings that differ at a single bit) in the state space. In particular, the local fitness correlation is given by $corr(\mathbf{x}, \tilde{\mathbf{x}}_i) = 1 - (K+1)/N$ where $\tilde{\mathbf{x}}_i$ is the string $\mathbf{x}$with bit i flipped. Hence for $K = N-1$ the fitness values are uncorrelated and the NK model reduces to the Random Energy model (Derrida, 1981; Saakian & Fontanari, 2009). Finding the global maximum of the NK model for $K > 0$ is an NP-complete problem (Solow, Burnetas, Tsai, & Greenspan, 2000), which means that the time

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