

Dynamical aspects of behavior generation under constraints

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Received: 11 October 2006 / Accepted: 25 January 2007
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Abstract Dynamic adaptation is a key feature of brains helping to maintain the quality of their performance in the face of increasingly difficult constraints. How to achieve high-quality performance under demanding real-time conditions is an important question in the study of cognitive behaviors. Animals and humans are embedded in and constrained by their environments. Our goal is to improve the understanding of the dynamics of the interacting brain–environment system by studying human behaviors when completing constrained tasks and by modeling the observed behavior. In this article we present results of experiments with humans performing tasks on the computer under variable time and resource constraints. We compare various models of behavior generation in order to describe the observed human performance. Finally we speculate on mechanisms how chaotic neurodynamics can contribute to the generation of flexible human behaviors under constraints.

Keywords Constraint satisfaction · Packing task · Dynamical systems · Chaotic neurodynamics

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Introduction

Biological brains are fundamentally pattern-forming, self-organizing systems governed by nonlinear dynamical laws Kelso (1995). It has been shown that brains use nonlinear, chaotic dynamics for the formation of perceptual categories Skarda and Freeman (1987); Accordingly, nonlinear dynamics plays a key role not only in the formation of perceptual meaning, but also in the formation of a shifting hierarchy of intentional goal states, that we observe as the action selection behavior of biological organisms Thelen and Smith (1994); Kelso (1995); Freeman (1999); Clark (1997, 1999); Harter and Kozma (2001a).

Some researchers in dynamical cognition and neurodynamics have speculated on the possibilities that complex, chaotic like dynamics may play in the role of adaptive behavior as well Skarda and Freeman (1987); Freeman (1999); Freeman et al. (2000); Kozma and Freeman (1999, 2000, 2001); West and Lebiere (2001). Chaotic dynamics have been observed in the formation of perceptual states of the olfactory sense in rabbits Skarda and Freeman (1987). Chaos provides the right blend of stability and flexibility needed by the system. Essentially, Skarda and Freeman believe that the normal background activity of neural systems is a chaotic state. In the perceptual systems, input from the sensors perturbs the neuronal ensembles and kicks them out of the chaotic background. As the result, the system transitions to a new attractor that represents the meaning of the sensory input, given the context of the state of the organism and its environment. However, the chaotic background state is not like random noise. Noise cannot be easily stopped and started, whereas chaos can

essentially switch immediately from one attractor to another. Dynamical oscillations with quick and intermittent transitions demonstrate a key ingredient in the flexible production of behavior of biological organisms. An important property of the chaotic background state is the speed with which it can adjust, dissolve and form in reaction to external events and internal pressures. Chaotic dynamics is a potential key mechanism that can explain the speed with which animals select appropriate behaviors from a seemingly infinite range of possibilities in a short time.

In the study of autonomous systems the problem of action selection plays a central role. Biological brains not only solve this problem well, but show amazing abilities to adapt to changing constraints in the task and environment. In other words, biological organisms are able to dynamically adjust to changing constraints and maintain good performance on tasks in the face of increasing difficulties. Two questions spring to mind when considering action selection as a chaotic search through an attractor landscape of intentional goal states. First of all, given the cognitive dynamical system coupled with a real-time environmental task, what are the limits imposed by the fundamental properties of neural units and their chaotic dynamics on the generation of behavior in real time? Second, how are such landscapes formed through experience with the task in order to produce good performance? This article is primarily concerned with the first question though we will provide some speculation on the second issue as well.

One way of learning more about the generation of behavior is to study people performing tasks under conditions of varying time and resource constraints. Another is to produce models of such behavior that can replicate the performance under varying conditions of limited resources. By studying the behavior of people performing tasks under constraints we can learn about their limitations in extreme conditions.

This paper is organized as follows. Section “Packing task” describes the experimental conditions involving a simplified version of the computer game Tetris. Experiments involving human players have been conducted with a variety of resource limitations, including time constraints and limited amount of available action items. Results of these experiments are described in section “Experiments with human players”. In section “Computer simulations for the packing test” we develop computational algorithms to play Tetris without human interference using two basic approaches. We train a neural network using supervised learning using examples of decisions made by humans. In an

alternative approach, we define a set of heuristic rules, whereas the computer makes its decisions based on these rules. In section “Discussion of the results” we discuss the obtained results in terms of performance of human and machine players. We interpret our findings in terms of nonlinear neurodynamics and a relationship is established between model noise and time constraints.

Packing task

To study the performance of action selection under constraints we have developed a packing task as shown in Fig. 1, which is a variant of the popular Tetris computer game Kirsh and Maglio (1992, 1994); Harter and Kozma (2001a, b); Kozma et al. (2002). In our packing task, the subject is presented with a series of 10 blocks, that appear at the top of the playing field. There are 3 basic block shapes shown in Fig. 2. In a sequence of 10 blocks which constitutes a single trial, the subject will receive different block types chosen at random. Blocks can be positioned by moving them left or right, or by rotating them clockwise or counter-clockwise. Once positioned by the subject they are dropped onto the playing field. When a block drops onto the playing field, it descends until it reaches the bottom or is obstructed in its downward fall by another block.



Fig. 1 The packing task. Blocks appear from the top and the subject rotates and moves the block before dropping it onto the playing field. The goal is to obtain as dense of a packing as possible

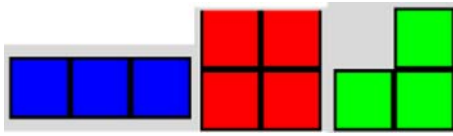


Fig. 2 The three different shape types used in the packing task

The goal of the task for the subject is to pack the shapes into the bottom of the playing field as tightly as possible. The density (d) of the packing, which is a measure of the subject's success on the task, is defined as follows:

$$d = A_{\text{block}}/A_{\text{total}}. \quad (1)$$

Here A_{block} is the area occupied by blocks, and A_{total} is defined as the product of the width of the playing field and the maximum height containing a block. For example, in Fig. 1 the playing field currently has 5 columns with 4 rows, giving $A_{\text{total}} = 5 \times 4 = 20$. Out of the area of 20, 17 cells are filled with blocks $A_{\text{block}} = 17$. This gives $d = 17/20$.

The task, simple as it might seem, is very difficult to perform optimally for a human (3 different blocks can be placed in 28 orientations with 10 blocks per trial gives a search space of 28^{10} or 3×10^{14} possible sequences). Further the task is made more difficult by the introduction of constraints that must also be considered when choosing behavior. In this article we discuss simulations of the packing task under two different types of constraints: packing resource and time.

Resources are constrained in the packing task by giving the subject only a certain number of translation/rotation resources at the beginning of a trial. For example, if a total of 15 resources are given, then the player will only be able to make a combination of 15 translations and rotations over the trial with 10 blocks. Each translation (left or right) and each rotation (clockwise or counterclockwise) expends one of the subject's resources. When the subject runs out of resources before the end of a trial, any remaining shapes simply fall at random on the playing field.

Time constraints are the second type of constraints modeled in these simulations. When a subject is playing the packing task under a time constraint, they will be presented with a block at the top of the playing field and given only a certain amount of time to position the block, for example 1 second. When time runs out, the block falls whether the subject has finished placing it.

Time and resource constraints further complicate the packing task and can make optimal play impossible. Under constraints, humans can produce suboptimal behavior and make errors in their decisions.

Clearly human experts can cope with moderate constraints but ultimately their behavior deteriorates with increasingly stringent constraints. Our goal is to study the process of deteriorating performance in the face of increasingly difficult constraints. In the next section we present experimental data collected on human subjects performing the packing task.

Experiments with human players

Overview of the experimental conditions

We performed a series of packing trials with human subjects. Subjects were asked to perform various packing trials with differing time and resource constraints. Subjects were first allowed to practice on the task until they were comfortable that they had obtained a certain level of competence. During this exercise we developed insight how people may intuitively learn and adapt when performing the packing task. These insights were used in developing the heuristic model as described in the modeling section.

In the experiments, human subjects performed the packing task at a computer terminal. The subjects controlled the position and rotation of the block to be placed by manipulating keys on the keyboard. The left and right arrows caused the block to be translated to the left or right, respectively. The up and down arrows caused clockwise and counter-clockwise rotations, respectively. These 4 actions were the only ones allowed to be performed by the subjects. In addition to the playing field itself, the subjects were given indications of the number of resources and the number of blocks they had remaining in the trial. A slight pause of a few seconds was given before the start of each new trial, and longer rest periods were given after every 30 trials.

The first set of experiments has been completed with 14 subjects. Each subject performed 30 packing trials with a 2 s time constraint, then 30 more trials with 1.5, 1.0, and 0.5 s time constraint, respectively. The time constraint set a limit on how much time they had to complete moving a block to its intended position before it was dropped. Each of the 30 trials for a particular time level consisted of performing a 10 block packing task at a different resource constraint level, which varied from 0 resources to 29 resources. The order that they received the resource constraint trials was varied randomly. So they might first perform a trial with 15 resources, then with 5 resources, etc. 0 resource trials acted as a type of control that allowed for us to

develop a minimum baseline density that happens on the packing task when blocks simply fall at random onto the playing field.

A second set of experiments has been performed by the 3 top expert players. The subjects reached this level of performance through repeated practice and experience with the task. The time constraints were varied from 1.5 to 0.5 s in 0.25 s intervals (1.5, 1.25, 1.0, 0.75, 0.5). Each time level had 30 trials with randomly varying resource constraints, similarly as in the 1st series of experiments.

Results of experiments with humans trials

Figure 3 displays the results of the human trials for the first experiment with 14 subjects. This experiment was performed mainly to determine the critical time constraint range where humans are no longer able to sustain performance because the task is happening too fast. As shown in the figure, this point appears to happen somewhere between 1.0 and 0.5 s. From our observations of the trials, 1.0 s still allowed people enough time to perform some rotations and execute their intended sequence of actions. However at 0.5 s blocks fell so fast that most of the subjects could only react minimally, usually by trying to guide the blocks to the left or right with no attempts or possibility of performing rotations.

Figure 4 shows the results of the second human trials with the 3 expert players. The main goal of this series of trials was to explore the details of the performance degradation under time constraint, in

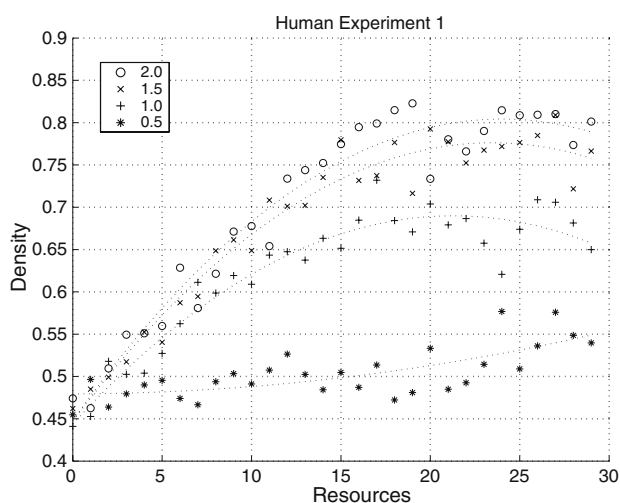


Fig. 3 Human performance on the packing task for the first set of trials. Time constraint conditions ranged from 2.0 to 0.5 s in 0.5 s intervals

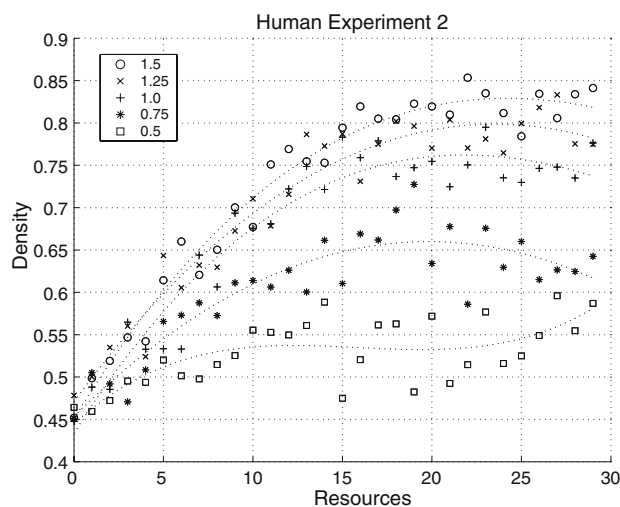


Fig. 4 Human performance in the second set of trials using 3 expert subjects. Time constraint ranged from 1.5 to 0.5 s in 0.25 s intervals

particular in the interval 0.5–1.0 s. The error rates increase significantly in this region as the length of the available time is reduced. Notice that the 3 experts outperformed on average the subjects in the first experiment.

In order to understand better the performance degradation as the function of the time constraint, we print the average results of the 3 experts as the function of the allocated time. Figure 5 displays the average density achieved by the expert human subjects in the second experiment for resource constraint levels (from 14 to 29 resources) at each of the 5 time constraints.

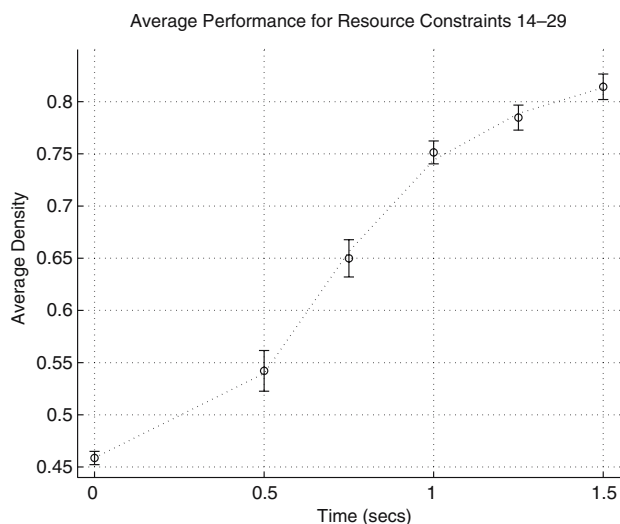


Fig. 5 Average performance achieved by expert human subjects over resource constraint conditions ranging from 14 to 29 resources. Notice the sharp drop in performance between 1.0 and 0.5 s

This figure illustrates the transition that happens as the time constraint reaches a critical level beyond which human performance drastically deteriorates.

It is seen that 1 s still allows a very good performance with a drop of about 15%. However, at 0.75 s the performance drastically drops, which indicates that a drastic change happens at this time level, which is called the critical time resource value. In experiment 1 there is a slight drop in performance between 1.5 and 1.0 s and a significant drop below 1 s. This indicates that the critical level is close to 1 s in experiment 1. On the other hand, Fig. 5 shows that the expert subjects managed to push the critical time constraint down to about 0.75 s. In the next section we develop a model to the packing task in order to interpret the above results.

Computer simulations for the packing task

The action selection mechanisms presented here aimed at modeling some aspects of biological organisms in producing behavior on the packing task under constraints. We have developed several algorithms and heuristics to perform the packing task based on various principles. Among these are neural networks based on supervised learning and an algorithm that uses heuristic rules derived from studying the behavior of people on the task. We first discuss the results from the neural network, then we present the models using heuristics.

Packing by supervised learning in neural network

The neural network based model Harter and Kozma (2001a, b) involves a multi-layer perceptron trained on examples created by human experts. These experiments were performed using the packing task with no resource limitations. Later on the question of limited resources will be addressed. For training data we had a human expert perform 50 packing trials, and we captured and encoded the input and the output of the behavior that the human produced when performing the packing task. We then trained neural networks on the data captured from the human expert, using many different configurations of number of hidden nodes and training epochs. Here the results obtained with the best trained network are presented.

We evaluated the performance of the resulting networks by having them perform the task 100 times. The average density achieved by the networks for the 100 test trials was then calculated. Table 1 shows a comparison of the best performance achieved by the networks with that of human experts (discussed in section “Experiments with human players”) and our

Table 1 Performance comparison

	Density	SD
Neural network	0.8261	0.0154
Human	0.8748	0.0314
Heuristic	0.8615	0.0087

heuristic algorithm (discussed in section “Packing by the heuristic algorithm”). The neural networks showed reasonable performance with top scores close to the those achieved by human experts. However, the networks were never quite capable of performing at the levels of human players if no resource constraints were imposed. The performance difference of the neural network was not significantly different from the others, though this conclusion is due in part to a limited amount of human experimental data.

Packing by the heuristic algorithm

We developed a set of heuristic rules to model the behavior of human decisions on the packing task under constraints. The heuristics were created by analyzing human performance on the task, described in section “Experiments with human players”. Our computer simulations using heuristics evaluate the resulting situation of dropping a given block in a particular orientation and position onto the current playing field. The heuristic evaluation takes into account factors such as the resulting contour shape of the playing field, and the creation of unfillable holes, as well as other features. These factors can be combined to evaluate the desirability of placing a block at a particular location and orientation given the current situation.

Table 1 shows that the used heuristic rules captured the essence of human decision making and a performance very close to that of an expert human has been achieved. Obviously, by further improving the rules the performance of the heuristic system, as well as that of the neural network, can be improved. However, this is not the goal of the present work. We just need some reference computer method that performs well on the packing task, so we could use it in the analysis of resource limitations.

The introduced computer algorithms (heuristic or neural) are used as a starting point in evaluating the decision making process. When performing the packing task under constraints, behavior may be modified when constraints are factored into the decision. For example, which move is considered the *best* is likely very different if there are plenty of resources available as opposed to when there are only very few resources left.

Modeling resource constraints

Resource constraints influence the behavior of biological organisms. For example, people seem to be able to intuitively adjust their behavior on the packing task to improve performance and minimize problems from running out of resources. When people have plenty of resources they freely expend those on good moves that may cost a lot. On the other hand, expert players seem to switch strategies and will select less desirable moves that help conserve resources when they perceive they are running out of them.

We have modeled this intuitive conservation of resources under conditions of constraint using a factor we call *Expectancy*. Expectancy is a measure of the expected number of resources needed on average for each block. In this case it is the number of resources that are expected to be needed for each block in order to obtain a reasonably good packing. For example, suppose that a player intuitively feels that it needs 20 resources in order to pack 10 blocks reasonably well. This means in average it expects to spend 2 moves (translations or rotations), so the expectancy is 2. Given this intuitive expectancy, it can dynamically alter the behavior during a trial in order to expend the resources wisely.

Of course we do not suggest that people consciously make such calculations while performing the packing task. However, they do intuitively develop something like an expectancy parameter through experience in performing the packing task. This intuitive feel of expected resource usage guides the subject in modifying behavior appropriately under various conditions of resource constraints that they encounter. Here we introduce an algorithm which uses a comparison of expected resource usage to actual resources remaining

as described above to help choose moves that balance between conservation of resources and optimal moves.

Figure 6 contains pseudo code for the heuristic evaluation algorithm. We used the expectancy concept as a parameter in the algorithm. The algorithm takes a given initial orientation and position of a block to be dropped, along with the current state of the environment, and it returns a resulting goal orientation and position of where it would like to drop the block. In order to compare the desirability of dropping the block in some position versus another, we measured various quantities of the environment resulting from completing a particular move. These measurements included such things as the resulting contour length of the environment after dropping the block. Another measure used was a count of the number of unfillable holes created by performing a particular move. These measures were combined to rate the desirability of all possible moves. The actual decision is influenced by the expectancy parameter and the number of resources currently remaining. If the number of resources was below the number expected to be needed, a less desirable move would be chosen in order to conserve resources.

Noise and time constraints

The second type of constraint modeled in these simulations is constraints on time. Time pressure can be added to the packing task by limiting the amount of time given the subject, from presentation of the block to when the block falls, for the subject to perform moves and rotations in order to place the block in their intended goal position. Time constraints manifest themselves as pressures to act. As time pressures are increased, behaviors may change that favor easy moves

Fig. 6 Pseudo code for the Heuristic Evaluation algorithm

- H1** Calculate list of all possible new positions and orientations $M = [P_n, O_n]$, given remaining resources R .
- H2** For each move pair $[P_n, O_n]$ in M_n .
 - H2.1** Calculate resource expenditures r_n to move from initial position $[P_i, O_i]$ to candidate position $[P_n, O_n]$.
 - H2.2** Calculate contour length l_n of resulting environment E_n after dropping block in candidate position $[P_n, O_n]$.
 - H2.3** Calculate number of unfillable holes h_n of resulting environment E_n .
 - H2.4** Score s_n the candidate move $[P_n, O_n]$.
 - H2.4.1** If expectancy times number of blocks remaining is less than remaining resources $E \times B < R$; score candidate move $[P_n, O_n]$ based solely on resulting contour length l_n and unfillable holes h_n .
 - H2.4.2** Else score candidate move $[P_n, O_n]$ using l_n and h_n but also taking into account resource expenditure r_n .
 - H2.5** Goto **H2** and evaluate next candidate move.
- H3** Choose candidate move $[P_n, O_n]$ with maximum score $\max(s_n)$ as the answer.

that are less prone to error and confusion and that can be accomplished more quickly. For example, rotations are a much more difficult manipulation to perform compared to translations, and much more prone to errors. As time pressures are increased, human players rely less and less on rotations and favor translation manipulations.

Time constraints manifest themselves in human performance in various ways, but the ultimate result is an error. This may happen because they run out of time before they complete their sequence to the intended location, or time pressures may increase the likelihood of producing an unintended behavior. We model time constraints in our simulations by introducing noise, or random errors, into the simulations. One example model of error production is to say that some percentage of the time the block does not end up in its intended goal location, but instead ends up in some other location at random. A more realistic model is to simulate the sequence of moves needed to transition from the initial location to the intended goal location and then introduce an error in that sequence. In the simulations described next, we used a simplistic model of noise as the more involved models give similar results.

Simulations with limited resources

We carried out simulations of the heuristic action selection mechanism for the packing task under constraints. We varied each of the following parameters:

- Expectancy was varied from a value of 0 to 5.0 in 0.1 increments. The chosen expectancy remained fixed for a 10 block trial.
- Resources were varied from 0 to 29. This represents the number of resources that can be expended in total for a 10 block trial. For example, 15 resources means that only a total of 15 moves and rotations can be performed for the 10 blocks in a trial.
- Noise was varied from 0 to 100% in 10% increments. As previously stated, the results presented here were obtained using a simple model of noise. Noise is intended to model the performance of subjects under increasing time constraints.

For each of the 3 combinations of parameters, 100 trials were run and the average performance on the 100 trials was calculated. Each trial consisted of a sequence of 10 blocks. All of the trials were performed on playing fields with a width of 5 cells. Performance was rated by the density of the packing achieved.

Figure 7 shows the results of the simulation for 4 values of noise: 0, 20, 40 and 60%. The 4 contour plots

display the density achieved by the algorithm for all combinations of resource constraints and expectancy at a given noise level. As noise increases, the level of performance decreases over all values of resources. Also, and not surprisingly, better performance is achieved under conditions of more resource availability.

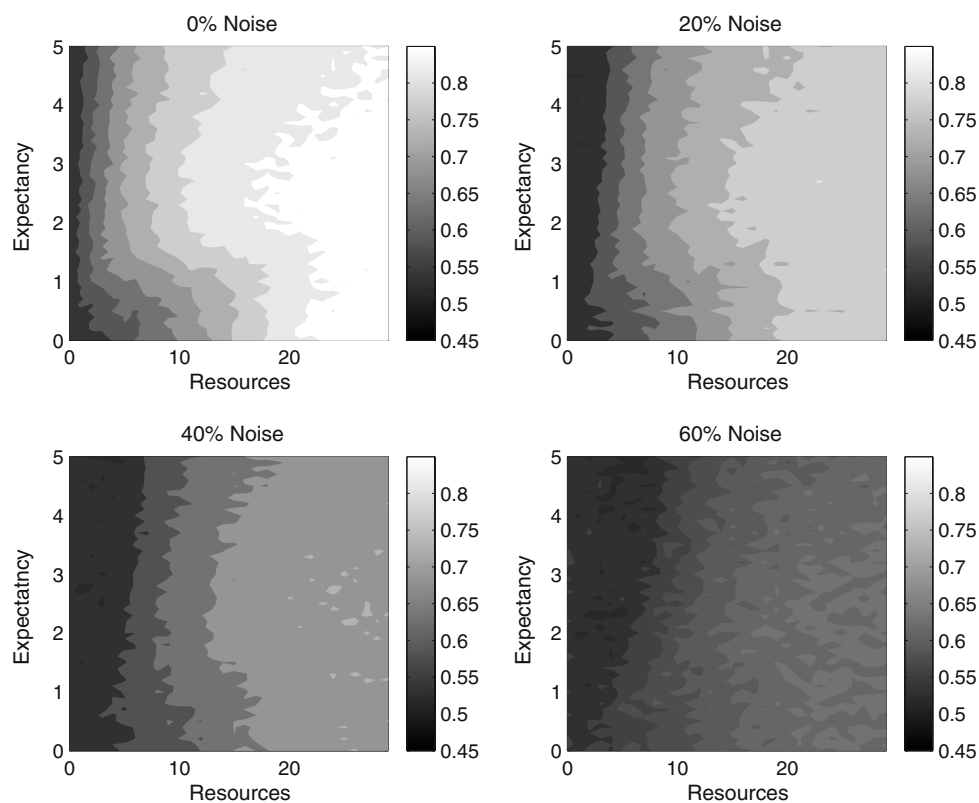
The most striking feature of the results is the prominent effect of the expectancy parameter on the performance. In particular there is a significant increase in performance around an expectancy of 2.5. This effect is most prominent at 0% noise, but is still visible at 20 and 40%. This result indicates that an expectancy parameter of 2.5 represents an optimal intuitive heuristic for decision making in the packing task under the given conditions (10 blocks per trial with a playing field of width 5). At 2.5 expectancy, the algorithm achieves a good balance between conserving resources under conditions of tight constraints and choosing good moves when possible. Expectancy values above 3 still work, however, they tend to be too conservative and performance begins to degrade. When the algorithm is too conservative it ends up with unused resources at the end of the trial.

In Fig. 8 we show a different view of the results for a single value of expectancy. Figure 8 shows the performance over all values of noise and resources for an expectancy value of 2.5. This figure reveals that resource limitations above 20 have little effect on performance, as the contour lines move parallel to the Resources axis. Decreasing the resources below 20, however, the achievable performance begins to fall. This indicates that more than 20 resources are needed in the usual case in order to achieve good packing densities on the task.

Discussion of the results

Chaotic dynamics provides a framework for understanding swift cognitive transitions during the perpetual traversal of the subject's cognitive state across the goal attractor landscape. The timing of the dynamics to find and settle into an attractor basin sets limits on the real-time performance attainable by biological brains. Pattern recognition requires distributed connectivity and state transitions involving the cortical neurons in local areas. Global state transitions are found in the spatial pattern of the phase values of the coherent oscillation with respect to the spatial ensemble average, which has the form of a cone. The apices of these cones mark the sites of nucleation of the state transitions by which the AM patterns form. Experimental evidence of phase cones and related phase transitions has been reported

Fig. 7 The computer simulation of the packing task using heuristics. This figure shows the average density achieved by the algorithm at 0, 20, 40 and 60% noise levels



first in rabbit EEGs, and later has been confirmed in human intracranial and scalp EEGs as well Freeman and Barrie (2000); Freeman et al. (2006).

In the recognition of perceptual categories, two types of emergent amplitude modulation (AM) patterns have been identified. When a stimulus is given to a system, there is a phase transition from a high

dimensional chaotic attractor to a lower dimensional wing. The first type of AM pattern occurs with a short latency immediately after the stimulus arrives. This early AM patterns represents the impact of a discriminated stimulus on the activity of the receiving cortex. The second type of AM pattern is endogenous (e.g., internally generated) and occurs with a variable latency in the time range of between 0.75 and 1.2 s Kozma and Freeman (2002).

The results introduced in this study can be given plausible interpretation in the context of dynamical systems approach to cognitive processing. Experiment concerning the packing task indicate that subjects require a well-defined minimum critical time period to complete the cognitive task with good accuracy. For a broad range of subjects this period appeared in the order of about 1 s, while a well trained expert could reduce this threshold to about 0.75 s or less. This type of dynamical behavior can be interpreted as a delayed cognitive activity due to chaotic self-organization in the brain. The critical time period can represent the minimum time that the selection and performance of intentional actions can be achieved.

Moreover, learning and experience can serve to deepen some attractors, with the effect that good goals and intentions are found and settled into more quickly. Experience on the task allows the subjects to recognize

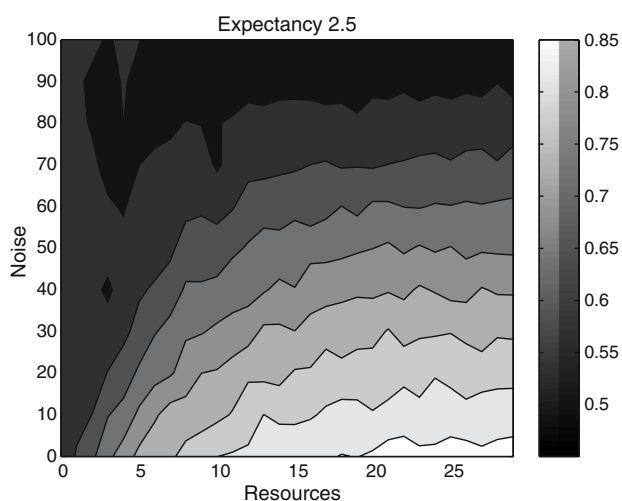


Fig. 8 Average density achieved by the algorithm for all resource constraint and all noise levels for an expectancy parameter of 2.5

and settle into the appropriate behavior attractors more quickly, and therefore push back the threshold of time constraints under which they can produce effective behavior. Our expert subjects show some evidence of this ability to extend good performance into increasingly difficult time constraint domains.

Finally, we discuss the possible connection between the computational model and the human performance under time constraints. Figure 9 indicates that there is a reasonable match between computer simulations with 10% noise and human performance with small time pressure (1.5 s). On the other hand, 70% noise

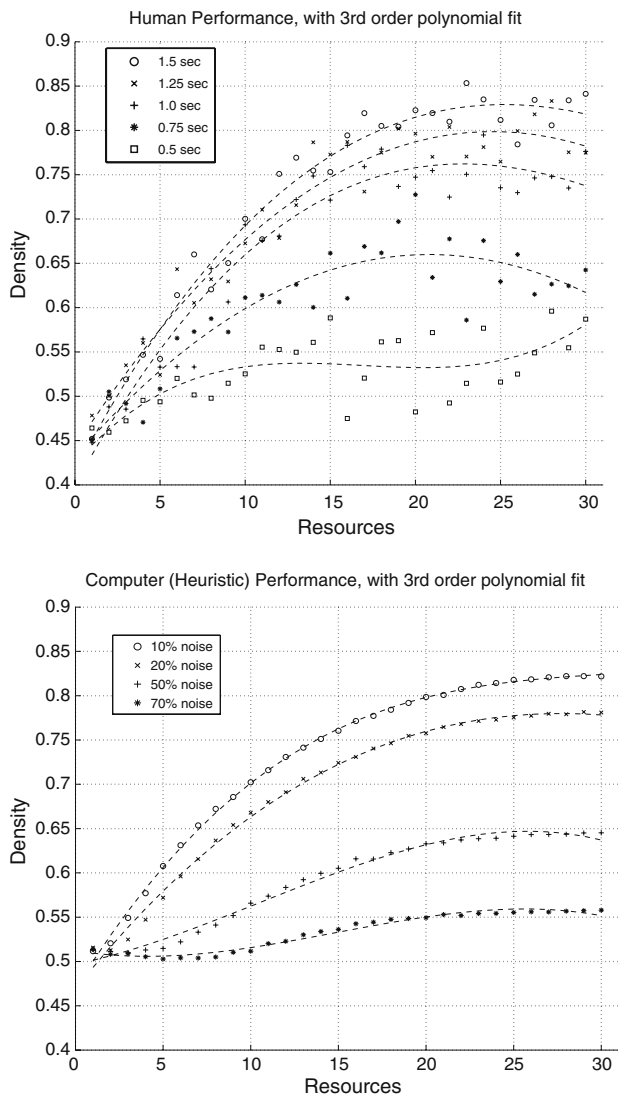


Fig. 9 Comparison of human performance (Top) with heuristic algorithm (Bottom). Human performance from the second human trials is shown for 1.5, 1.25, 1.0, 0.75 and 0.5 s time constraints in the top figure. The closest fit to these performances was achieved by the heuristic at 10, 20, 20, 50 and 70% noise levels, respectively (plotted in Bottom figure)

produces performance close to humans with very significant time pressures (0.5 s). The figure shows the human performance at the top, for time constraints of 1.5, 1.25, 1.0, 0.75 and 0.5 s, respectively on this task. The bottom portion of Fig. 9 shows performance of the computational model at noise levels 10, 20, 50 and 70, respectively. We will discuss below why we plot these particular noise levels. Visual inspection of the figure shows that our heuristic model does capture important aspects of humans performing the packing task under various resource and time constraints.

We have applied noise in our model to approximate the effects of time constraints on human subject. Figure 10 shows the relationship inferred between the time constraint value in human trials and the noise level in computer experiments. In the computer simulations, we approximated the effect of time constraints on human performance by injecting noise in the model. The introduction of computational noise did mimic important aspects of human error under time pressure, and Fig. 10 can serve as a practical tool to make the conversion between those quantities. We calculated the similarity between the human performance and the computational heuristic by comparing the sum squared error of the 3rd order polynomial fitted curve of the performance data. Table 2 shows the best calculated fits between the human and computer performance found with this method. This corresponds to data plotted in Fig. 10, where error bars indicate the sum squared error of the fit at each of the data points. Future studies are planned to analyze the role of time

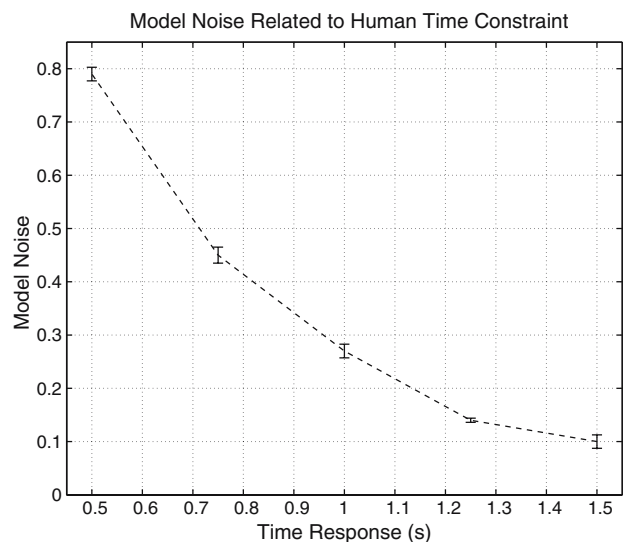


Fig. 10 Relationship between time constraint in human trials and error level in computer simulations

Table 2 Correlation of human and computational performance

Human (s)	Computer (noise) (%)	SSE
1.5	10	0.0126
1.25	14	0.0039
1.0	27	0.0128
0.75	45	0.0151
0.5	79	0.0128

and resource constraints on the formation of optimal strategies for goal oriented behavior.

Conclusions

Action selection is a central issue in the study of autonomous systems. Brains not only solve this problem well, but show amazing abilities to adapt to changing constraints in the task and environment. Biological organisms are able to maintain good performance on tasks in the face of increasing difficulties. The basic premise of our approach is that cognition is an inherently dynamic process described by complex trajectories in a high-dimensional attractor landscape. Decision making requires the reorganization of the cognitive dynamics, which would contribute to some delay in the response. Learning and experience can serve to deepen some attractors. As a result, good goals and intentions are found and settled into more quickly. Our main conclusions are summarized as follows:

- (1) We study the dynamics of decision making under constraints by evaluating the results of experiments performed by humans playing Tetris computer game. We vary a number of parameters of the experiments, including time constraints and resource constraints. Moreover, we produce models of such behavior that can replicate the performance under varying conditions of limited resources. By studying the behavior of people performing tasks under constraints we can learn about their limitations in extreme conditions.
- (2) Experiments concerning the packing task indicate that subjects require a well-defined minimum critical time period to complete the cognitive task with good accuracy. For a broad range of subjects this period appeared in the order of about 1 s, while a well trained expert could reduce this threshold to about 0.75 s or less. This type of dynamical behavior can be interpreted as a

delayed cognitive activity due to chaotic self-organization in the brain. The critical time period can represent the minimum time that the selection and performance of intentional actions can be achieved.

- (3) We have applied noise in our model to approximate the effects of time constraints on human subject. We observed that the introduction of computational noise in the models did mimic important aspects of human error under time pressure. We have derived an approximate relationship between noise level and time constraints, which can serve as a practical tool to make the conversion between those quantities. Future studies are planned to analyze the role of time and resource constraints on the formation of optimal strategies for goal oriented behavior.

Acknowledgments This work has partly supported by NASA Research Grant NCC-2-1244. Discussions with Drs. Philip Wolf and Stan Franklin were helpful and greatly appreciated. Advice by Shulan Lu concerning statistical evaluation of data is also highly appreciated.

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