The Role of Constraints and Dynamic Mechanisms in Behavior Generation

Derek Harter, Robert Kozma and Srinivas Achunala
Department of Computer Science
University of Memphis
Memphis, TN 38152
`[dharter|rkozma|sachunala]@memphis.edu`

Abstract

Biological brains are capable of adaptive behavior to sustain performance on tasks in the face of increasingly difficult constraints. Precisely how this performance is achieved, especially under demanding real-time constraint, is an important problem in the study of cognition. Brains are embedded in and constrained by their environments. The brain/environment pair together form a coupled dynamical system that mutually influence and react to one another. We can begin to understand how such performance is achieved by studying real behavior on constrained tasks, and modeling this behavior. In this article we present a task with varying conditions of time and resource constraint. We present data collected on humans performing the task under such constraint. We compare models that we have developed of this behavior generation to human performance. Finally we speculate on some of the mechanisms of chaotic neurodynamics that may be involved in the flexible generation of behavior under constraint.

Keywords
Constraint satisfaction, packing task, dynamical systems, chaotic neurodynamics

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$\sim$5400 words; 19 refs; 10 figures; 1 table

1 Introduction

The fundamental question for all biological organisms comes down to what should be done next (Franklin, 1995). In the study of autonomous agents this has come to be known as the **action selection** problem. Biological brains not only solve this problem well, but show amazing abilities to adapt to changing constraint in the task and environment. In other words, biological organisms are able to dynamically adjust to changing constraint and maintain good performance on tasks in the face of increasing difficulties.

Biological brains are fundamentally pattern-forming, self-organizing systems governed by nonlinear dynamical laws (Kelso, 1995, pg. 26). It has been shown that nonlinear, chaotic dynamics are used in the formation of perceptual categories in biological brains (Skarda & Freeman, 1987; Kozma & Freeman, 2000). We believe that such dynamics are not only essential 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 & Smith, 1994; Kelso, 1995; Freeman, 1999; Harter & Kozma, 2001a; Clark, 1999, 1997).

Some researchers in dynamical cognition and neurodynamics have speculated on the possibilities that more complex, chaotic like dynamics may play in the role of adaptive behavior (Skarda & Freeman, 1987; Freeman, 1999; Freeman, Kozma, & Werbos, 2000; Kozma & Freeman, 1999, 2000, 2001a; West & Lebiere, 2001). Chaotic dynamics have been observed in the formation of perceptual states of the olfactory sense in rabbits (Skarda & Freeman, 1987). Skarda and Freeman have speculated that chaos may play a fundamental role in the formation of perceptual meanings. 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 from the chaotic background, and the result is that the system transitions into a new attractor that represents the meaning of the sensory input, given the context of the state of the organism and its environment. But the normal 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. This type of dynamics may be a key property in the flexible production of behavior in biological organisms.

Two questions spring to mind in this view of action selection as the chaotic search through an attractor landscape of intentional goal states. First of all, given that this is a 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. Secondly, 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.

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 may be a key mechanism that helps to explain the speed with which appropriate behaviors can be selected from among a seemingly infinite range of possibilities in such a short time.

One way of learning more about the generation of behavior is to study people performing tasks under conditions of varying time and resource constraint. Another is to produce models of such behavior that can replicate the performance under varying conditions of limited resources. By studying the external performance of people performing tasks under such constraint we can begin to learn about their limitations in extreme conditions. Studying behavior under such conditions can also give us insights into the developmental progressions people undergo when learning to perform on a novel task.

2 Packing Task

To study the performance of action selection under constraint we have developed a packing task as shown in Fig. 1, which is a simplified variant of the popular tetris computer game (Kozma, Harter, & Achunala, 2002; Harter, Kozma, & Franklin, 2001; Harter & Kozma, 2001a, 2001b; Kirsh & Maglio, 1992, 1994). 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.

Insert Figure 1 here

Insert Figure 2 here

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 of their packing, which is a measure of the subjects success on the task, can be calculated simply by dividing the area filled in with blocks with the total area. For example, in Fig. 1 the playing field currently has 5 columns with 4 rows in height for a total area of 20. Out of that area of 20, 17 cells are filled with blocks. Therefore in the figure, the current density of the packing is 17 / 20 or 0.85.

The task, simple as it might seem, is still too 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 3x10^{14} possible sequences). Further the task is made more difficult by the introduction of constraint that must also be considered when choosing behavior. In this article we discuss simulations of the packing task under two different types of constraint: 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 the subject is given 15 resources, they will only be able to make a combination of 15 moves and rotations over the whole 10 block trial. Each horizontal movement (left or right) and each rotation (clockwise or counter-clockwise) expends one of the subjects 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 constraint are the second type of constraint 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 in their intended position and orientation or not.

Time and resource constraint further complicate the packing task and make optimal play impossible. Under such constraint, systems are forced to produce behavior in noisy conditions and under uncertain information. But even under such unfavorable conditions, biological systems are capable of maintaining performance levels in the face of increasingly difficult constraint.

In the next section we present some data collected on human subjects performing the packing task. In section 4 we present computer simulations of behavior producing systems performing under time and resource constraint in the packing task. Finally we compare our simulations with the human data and discuss the implications of our research for dynamical models of action selection in autonomous agents.

3 Human Trials

3.1 Overview of the Experimental Conditions

To develop our models of the parameters that people may intuitively learn and adapt when performing the packing task, we performed a series of packing trials on human subjects. Subjects were asked to perform many packing trials, with differing time and resource constraint. Subjects were first allowed to practice on the task until they were comfortable that they had obtained a certain level of competence.

In the experiments, 14 computer science graduate students 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. A session of 30 trials took about 20 minutes.

In the first set of experiments we ran all 14 subjects. Each subject performed 30 packing trials with a 2.0 second time constraint, then 30 more with a 1.5 second time constraint, and similarly for 1.0 and 0.5 second time constraint. 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 for them. 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.

The second set of experiments had a similar set up as the first one. In the second set we ran 16 experiments using 3 subjects. The time constraint has been varied from 1.5 to 0.5 seconds in 0.25 second intervals (1.5, 1.25, 1.0, 0.75, 0.5). Each time level had 30 trials with a different resource constraint as in the previous experiment. The 3 subjects who performed the 16 experiments were players who had achieved a high level of proficiency on the packing task, obtaining better performance on average than other players. The subjects reached this level of performance through repeated practice and experience with the task.

3.2 Results of Human Trials

Fig. 3 displays the results of the human trials for the first experiment. 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 for them to process. As shown in the figure, this point appears to happen somewhere between 1.0 and 0.5 seconds. Dash lines indicate spline interpolation of the experimental points for each time constraint, separately. From our observations of the trials, 1.0 second still allowed people enough time to perform some rotations and execute their intended sequence of actions. However at 0.5 seconds blocks fell so fast that 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.

Insert Figure 3 here

Fig. 4 shows the results of the second human trials performed by 3 expert human players. We designed these trials to study the details of the performance transition in the critical region between

1.0 and 0.5 seconds. In the region between 1.0 and 0.5 seconds the human subject is sometimes able to complete their intended moves, but not always. Also error rates increase drastically in this region. Notice that the 3 expert level subjects performed better on average over the subjects in the first experiment. In fact, the subjects in this experiment have gained enough proficiency to push the critical time constraint level to a smaller value. In experiment 1 there appears to be a small drop in performance between 1.5 and 1.0 seconds. The expert subjects performed noticeably better at the 1.0 second time constraint level. They managed to push the critical time constraint down to somewhere at or below the 0.75 second constraint.

Insert Figure 4 here

Fig. 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 constraint. This figure illustrates the transition in performance that happens as the time constraint reaches a critical level beyond that of human brains to cope with.

Insert Figure 5 here

4 Computer Simulations

The action selection mechanisms presented here are meant to model some aspects of biological organisms in producing behavior on the packing task under constraint. In particular, we model the selection of an intended goal position for a block using a neural network or a set of heuristics.

We have developed several algorithms and heuristics to perform the packing task based on various principles. Among these are neural networks based on backpropogation learning and an algorithm using heuristics derived from studying the behavior of people on the task. We first discuss the results from the neural network simulations and then present the models using heuristics.

4.1 Neural Network

The neural network based model (Harter & Kozma, 2001b, 2001a) involves a multi-layer perceptron trained on examples created by human experts. These experiments were performed using the packing task with no resource limitations. For training data we had a human 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 trained a number of multi-layer, feed-forward neural networks on the data captured from the human expert, using many different configurations of number of hidden nodes and training epochs. The results shown here have been obtained using the NNs with the best performances.

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 players (discussed in section 3) and our heuristic algorithm (discussed in section 4.2). 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.

Insert Table 1 here

4.2 Heuristic Algorithm

We now move on to experiments performed under varying conditions of time and resource constraint. We developed a set of heuristics in order to model the behavior of humans on the packing task under constraint. The heuristics were created by analyzing human performance on the task, described in section 3. 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.

The heuristic evaluation of intended goal positions is used as a starting point in the decision making process. When performing the packing task under constraint, behavior may be modified when the constraint is factored into the decision making process. For example, which move is considered *best* may be very different if there are plenty of resources left as opposed to when there are only very few resources left.

Expectancy and Resource Constraint Resource constraint can influence the behavior producing mechanisms in biological organisms. 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. For example when people have plenty of resources they freely expend resources on good moves that may cost a lot of resources. However, people 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 you intuitively feel that you need 20 resources in order to pack 10 blocks reasonably well. Another way of looking at this would be that you expect to expend, on average, 2 resources for each block in order to obtain a good packing. Given this intuitive expectancy of 2 resources per block, you can dynamically alter your behavior during a trial in order to expend your resources wisely. If you have 5 blocks left to pack you would expect to need about 10 resources. If you actually have 15 resources left you would feel fairly safe in choosing the move you think best, even if you have to expend 5 resources in order to execute it. However, if you only had 8 resources instead, you might think twice about expending 5 resources on a move and instead pick a slightly worse move that helps to conserve resources.

Of course we don't believe 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 constraint that they encounter. Our algorithm 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.

Fig. 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 resulting environment from performing a particular move. These measurements included such things as the resulting contour length of the environment from 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 of which move to choose could be influenced by the expectancy parameter and the number of resources currently remaining to the program. 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.

Insert Figure 6 here

Noise and Time Constraint The second type of constraint modeled in these simulations is constraint 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 constraint manifest themselves as pressures to act. As time pressures are increased, behaviors may change that favor easy moves 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 constraint manifest themselves in human performance in various ways, but the ultimate effect is to induce an error. By an error, we mean that the subject fails to move and position the block to their intended goal location. 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 constraint 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. In the more realistic model, each move in the sequence may be erroneously executed. Also the sequence of moves can be stopped before completion, with increasing probability depending on the number of moves in the sequence.

In the simulations described next, we used a simplistic model of noise as the more elaborated model gives similar results.

Overview of the Experimental Conditions We carried out simulations of the heuristic action selection mechanism for the packing task with constraint. 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 constraint.

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.

5 Discussion of the Results

5.1 Results of Computer Experiments

Fig. 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 constraint 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.

Insert Figure 7 here

The most striking feature of the results are the prominent difference that the expectancy parameter can make in performance. In particular there is a great increase in performance around an expectancy of 2.5, which is most prominent at 0% noise but is still visible at 20 and 40%. An expectancy parameter of 2.5 represents an optimal intuitive heuristic for decision making in the packing task as we have set it up (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. Fig. 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 relatively little effect on performance. If the number of available resources, however, drops below 20, the achievable performance diminishes significantly. This indicates that more than 20 resources are needed in the usual case in order to achieve good packing densities on the task.

Insert Figure 8 here

5.2 Comparison of Human Trials and Computer Simulations

Next, we speculate on the possible connection between our computational models and human performance under time constraint. Fig. 9 indicates that there is a reasonable match between computer simulations with 10% noise and human performance with small time pressures (1.5 sec available). On the other hand, 70% noise produces performance close to humans with very significant time pressures (0.5 sec). We believe that our heuristic model does capture some aspects of humans performing the packing task under various conditions resource and time constraint.

Insert Figure 9 here

Fig. 10 shows the inferred relationship between the time constraint value in human trials and the noise level of computer experiments. In the computer simulations, our intention has been to approximate time constraint by induced error level introduced in the computer algorithm. This figure shows that, if there is indeed a relationship between the error level and the performance error, then it can be described by a S-shape like curve as shown in Fig. 10. Further experimental studies and computer simulations are to be conducted to understand the nature of this relationship.

Insert Figure 10 here

We have used noise to model the effects of time constrains. It remains to be seen if a more realistic action selection model, using chaotic dynamics to generate behavior, can model not only the performance levels and timings of human behavior, but also the kinds and types of errors produced by humans.

6 Conclusions and Future Perspectives

Viewing action selection as the self-organization of a goal attractor landscape has several implications. The timing of the dynamics to find and settle into an attractor basin sets limits on the real-time performance possible by biological brains. However, 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 for subjects to recognize and settle into good behavior attractors more quickly, and therefore push back the threshold of time constraint 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.

The time to recognize and fall into a goal attractor is a critical feature of performing tasks under real time constraint. In the recognition of perceptual categories, two types of emergent amplitude modulation (AM) patterns have been identified (Kozma & Freeman, 2001b, 2001a, 1999, 2000). 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 750 and 1200 ms.

The second type of emergent pattern represents the act of categorization of the input stimulus. The type II pattern is the result of recognition of stimuli meaningful in the current situation to the organism.

We believe that the same type of pattern formation works in the emergence of intentional actions from the entorhinal cortex. In this case, the dynamics provide the action selection mechanism for recognizing and choosing among strategies and goals for the organism. The time period of around 750 ms. represents the minimum time that the selection and performance of intentional goal actions can be achieved. Through learning in real time tasks, people can push their performance up to this limit, but the fundamental dynamics of the brain dictates that intentional goals cannot be formed in time frames less than this period needed for the formation of type II AM patterns.

Future studies will be conducted to analyze the role of time and resource constraint on the formation of optimal strategies of goal oriented behaviors. In particular, experiments are planned to investigate the relation between actions and EEG activity in humans.

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Table 1: Performance Comparison

	Density
Neural Network	0.8261
Human	0.8748
Heuristic	0.8615

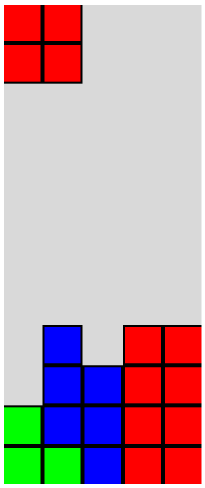

Figure 1: The packing task. Blocks appear from the top and the subject rotates and moves the block before dropping it onto the playing field. The goal is to obtain as dense of a packing as possible.

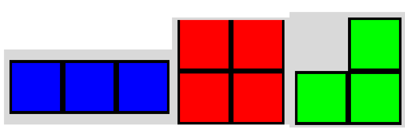

Figure 2: The three different shape types used in the packing task.

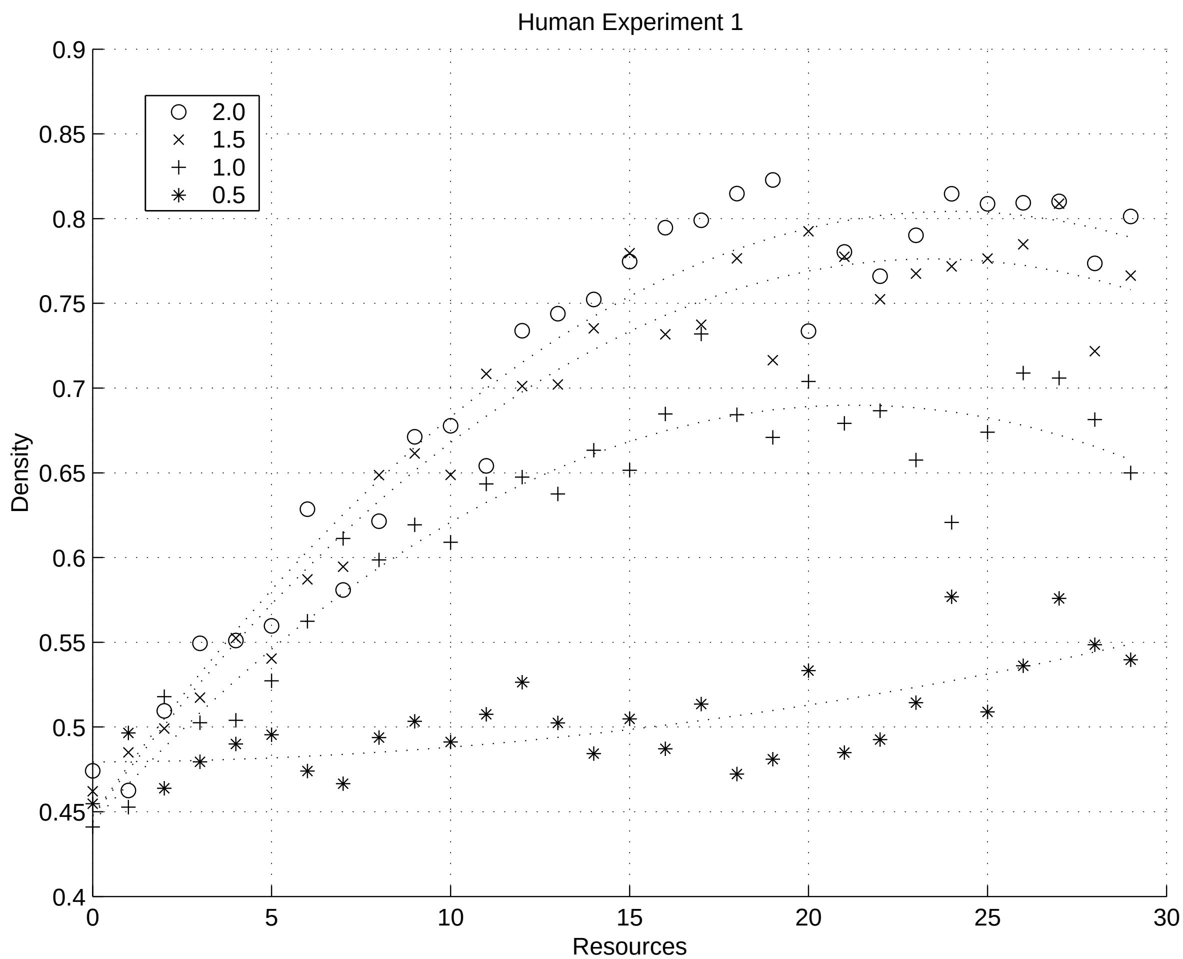

Figure 3: Human performance on the packing task for the first set of trials. Time constraint conditions ranged from 2.0 to 0.5 seconds in 0.5 second intervals.

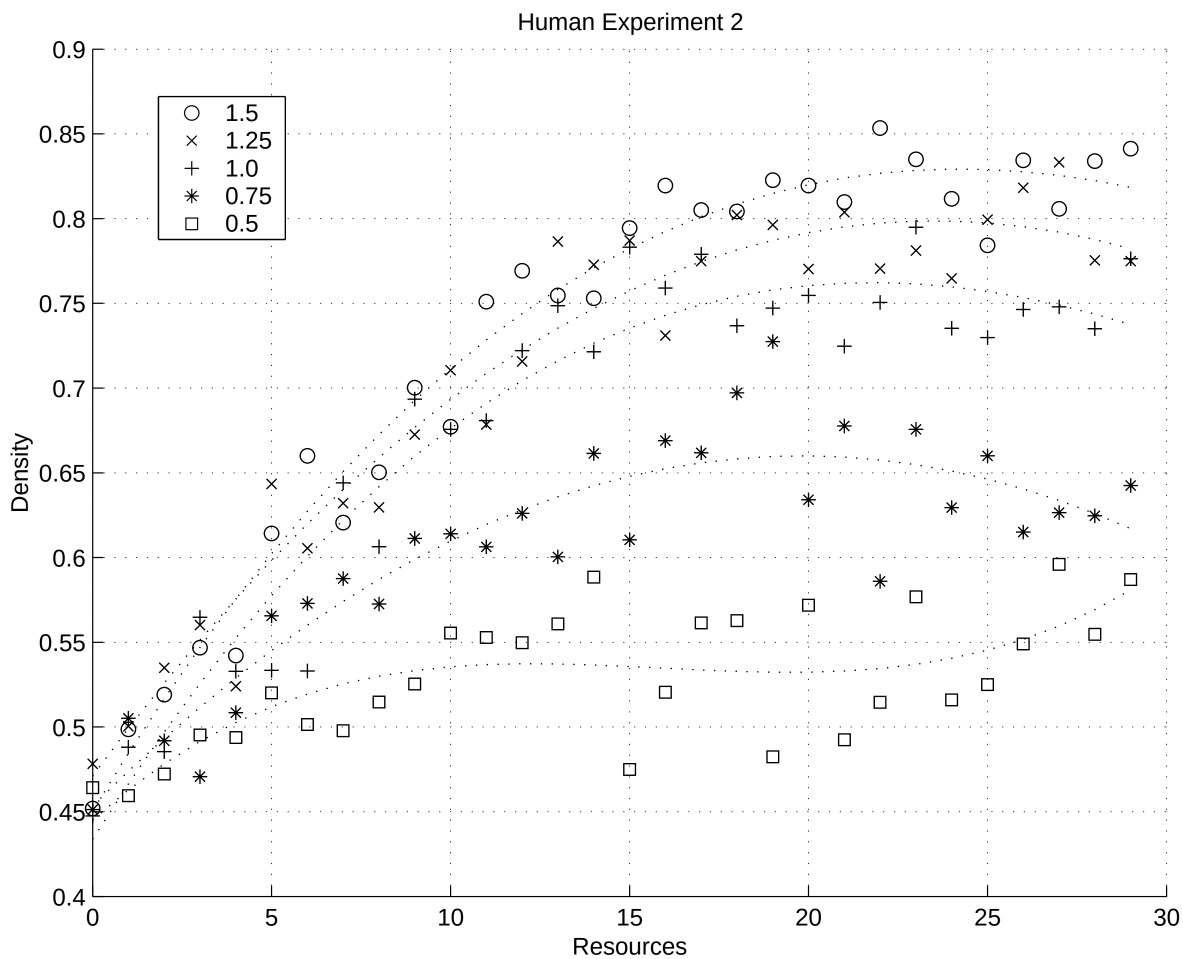

Figure 4: Human performance in the second set of trials using 3 expert subjects. Time constraint ranged from 1.5 to 0.5 seconds in 0.25 second intervals.

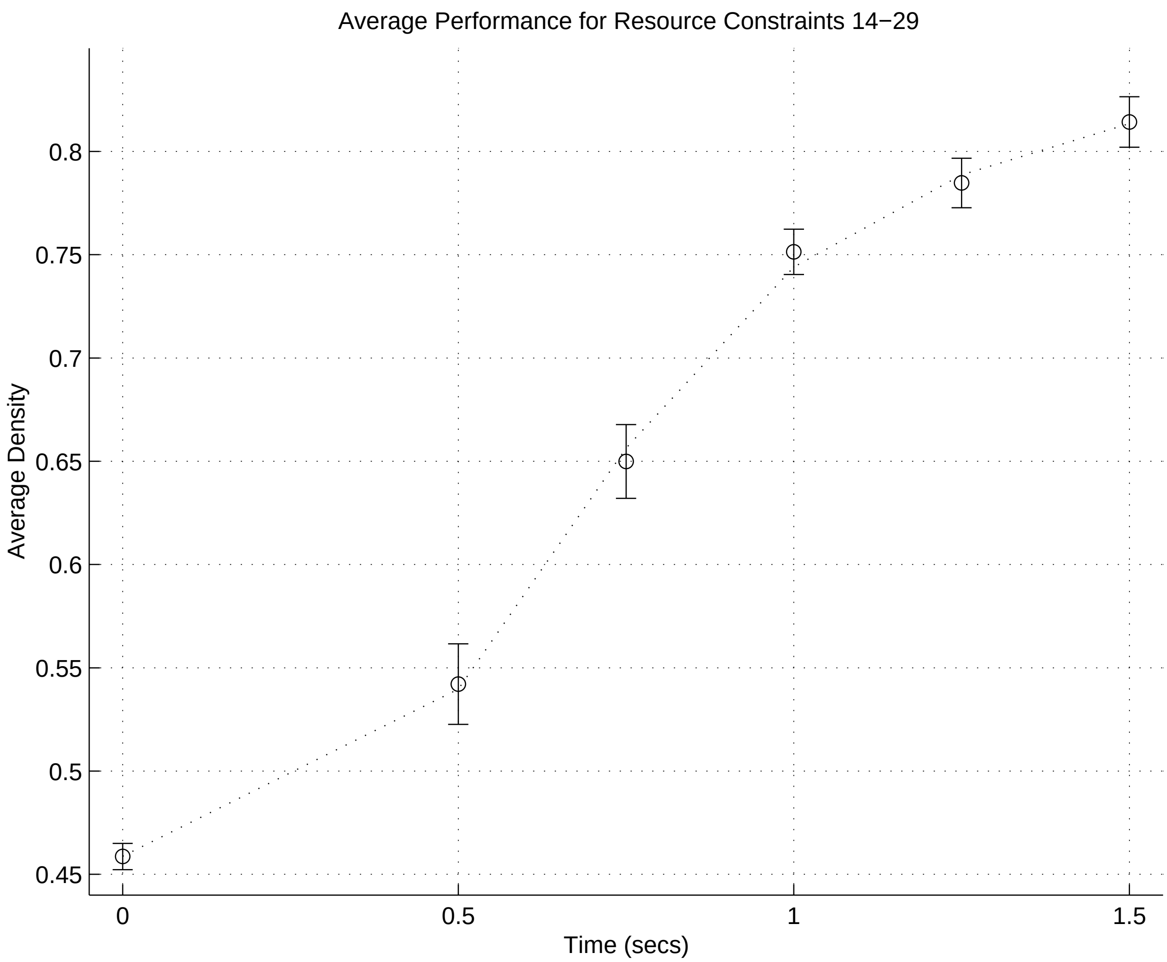

Figure 5: Average performance achieved by expert human subjects over resource constraint conditions ranging from 14 to 29 resources. Notice the sharp drop in performance between 1.0 and 0.5 seconds.

Algorithm: Heuristic Evaluation (H)
Given an expectancy E, remaining resources R, remaining number of blocks B type of block T, an initial position of the block P_i and an initial orientation O_i, and an environmental configuration of previously dropped blocks E_i, determine a new position P_n and new orientation O_n to drop the block onto the field.

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.

Figure 6: Pseudo code for the Heuristic Evaluation algorithm.

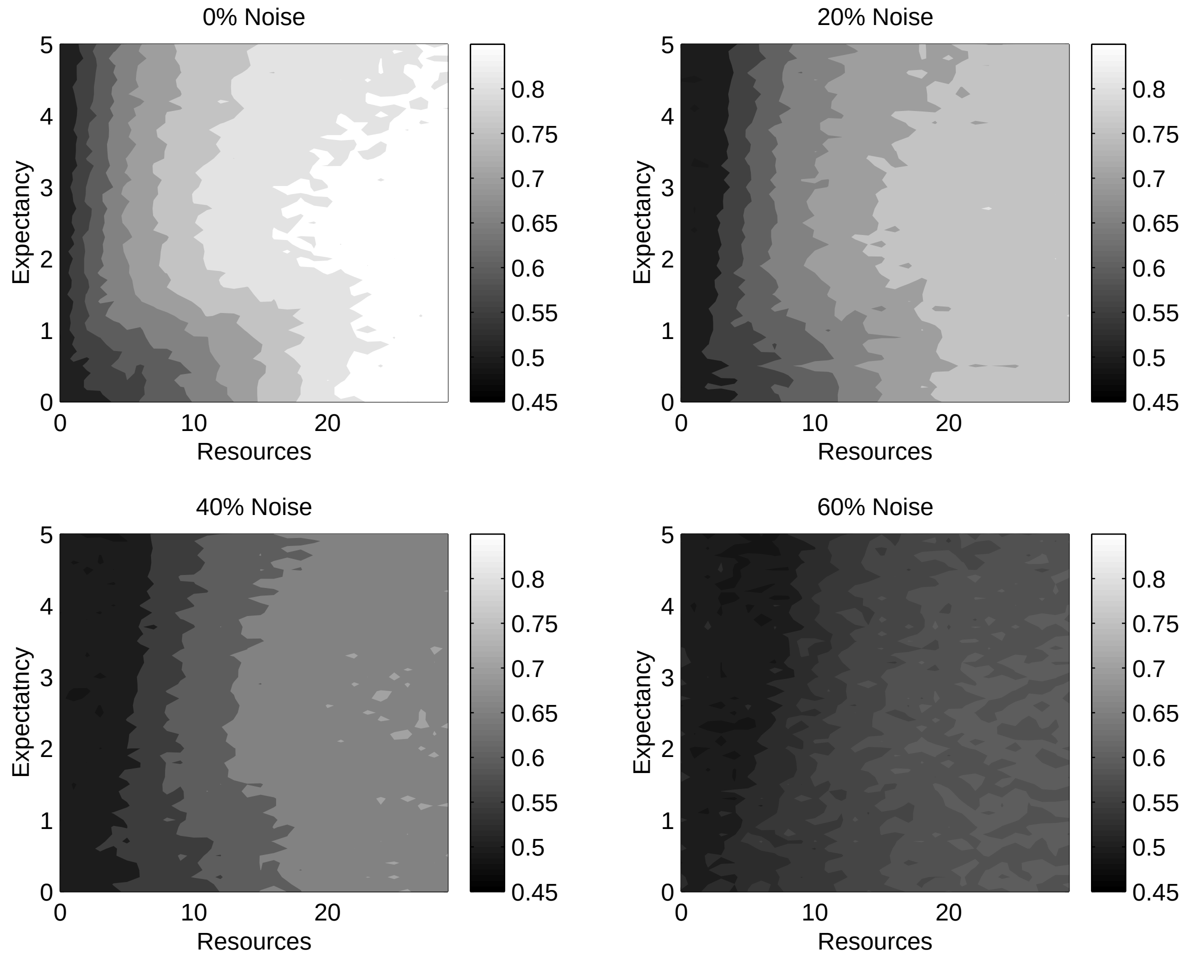

Figure 7: The computer simulation of the packing task using heuristics. This figure shows the average density achieved by the algorithm at 0,20,40 and 60% noise levels.

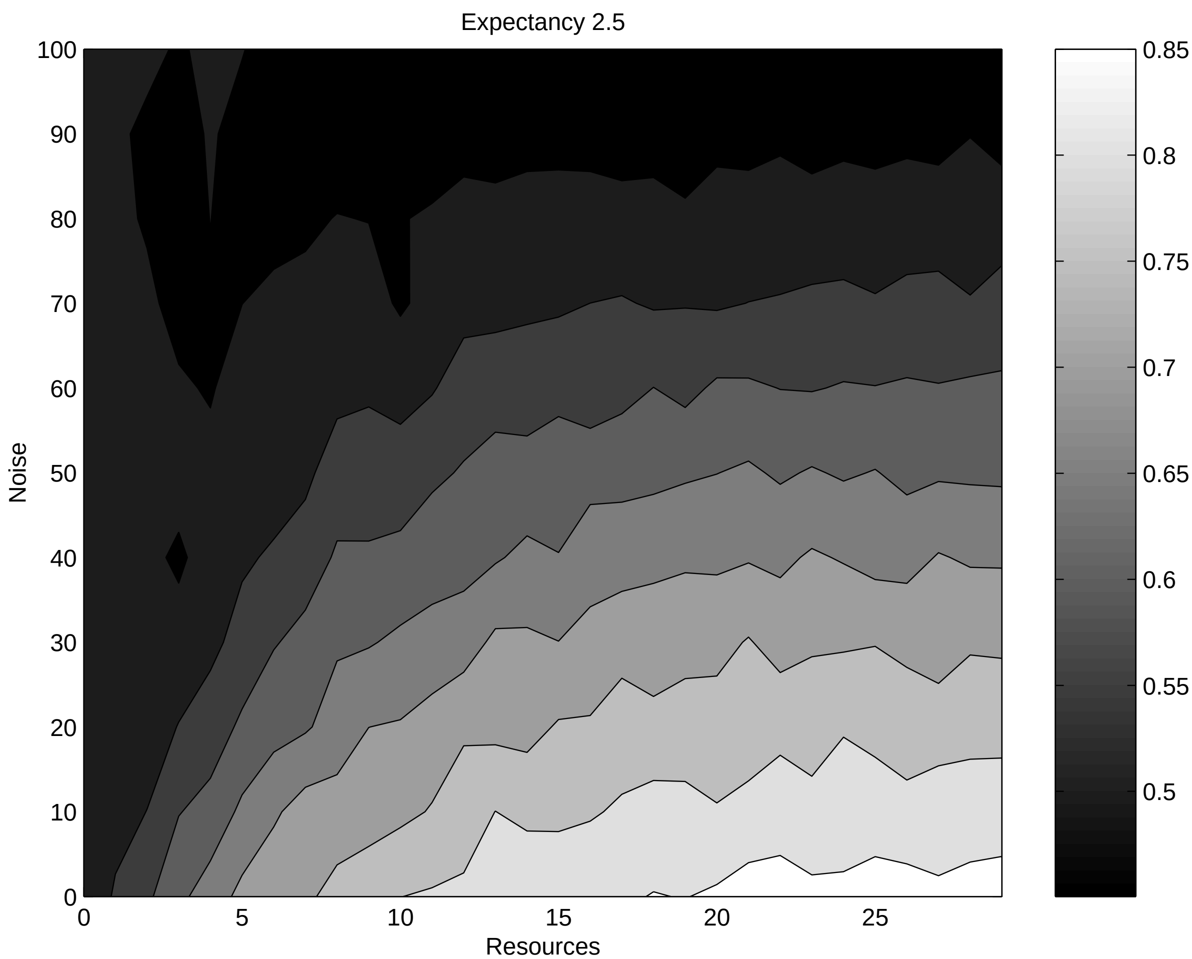

Figure 8: Average density achieved by the algorithm for all resource constraint and all noise levels for an expectancy parameter of 2.5.

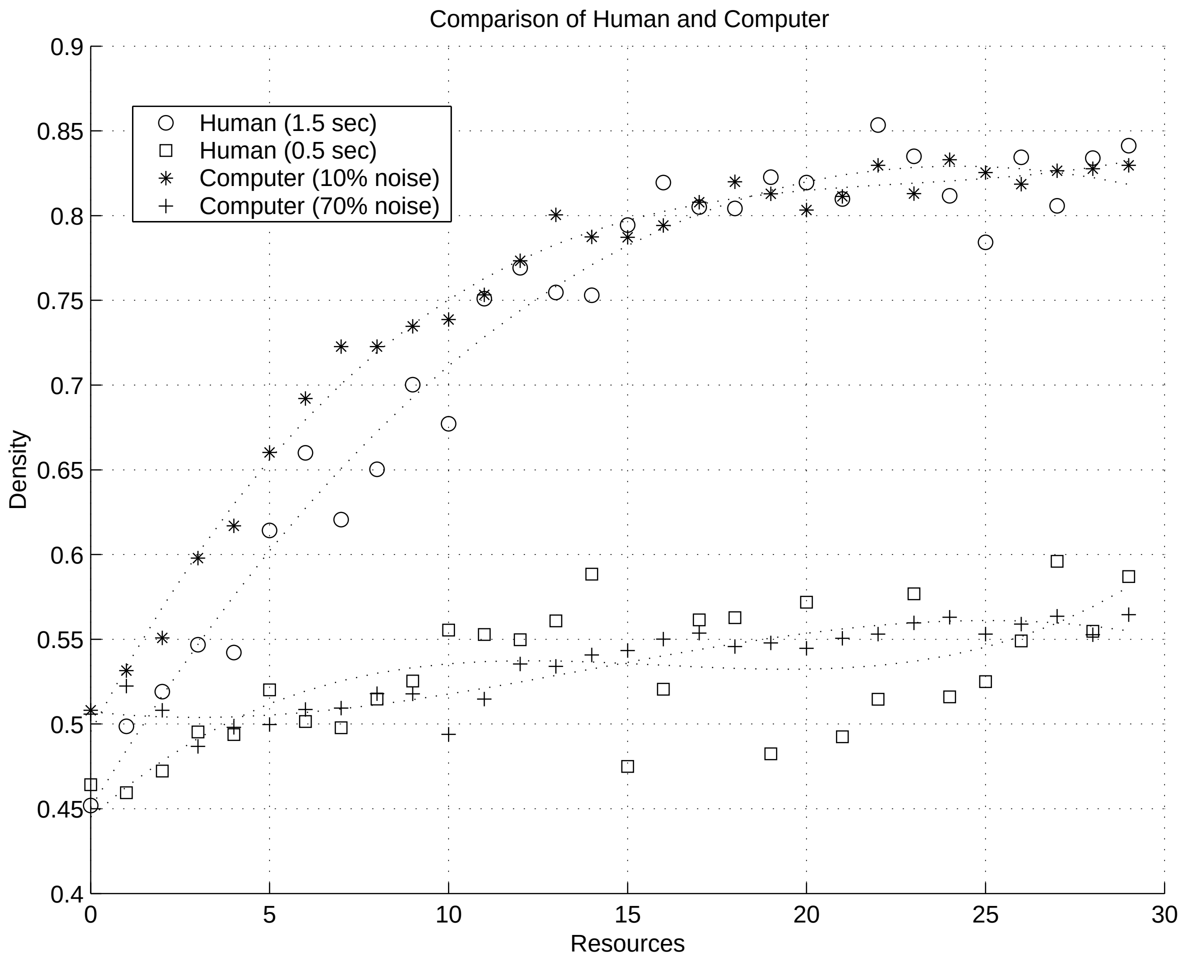

Figure 9: Human performance from the second human trials for 1.5 and 0.5 seconds. We compare this to the computer simulation of action selection at 10% and 70% noise levels.

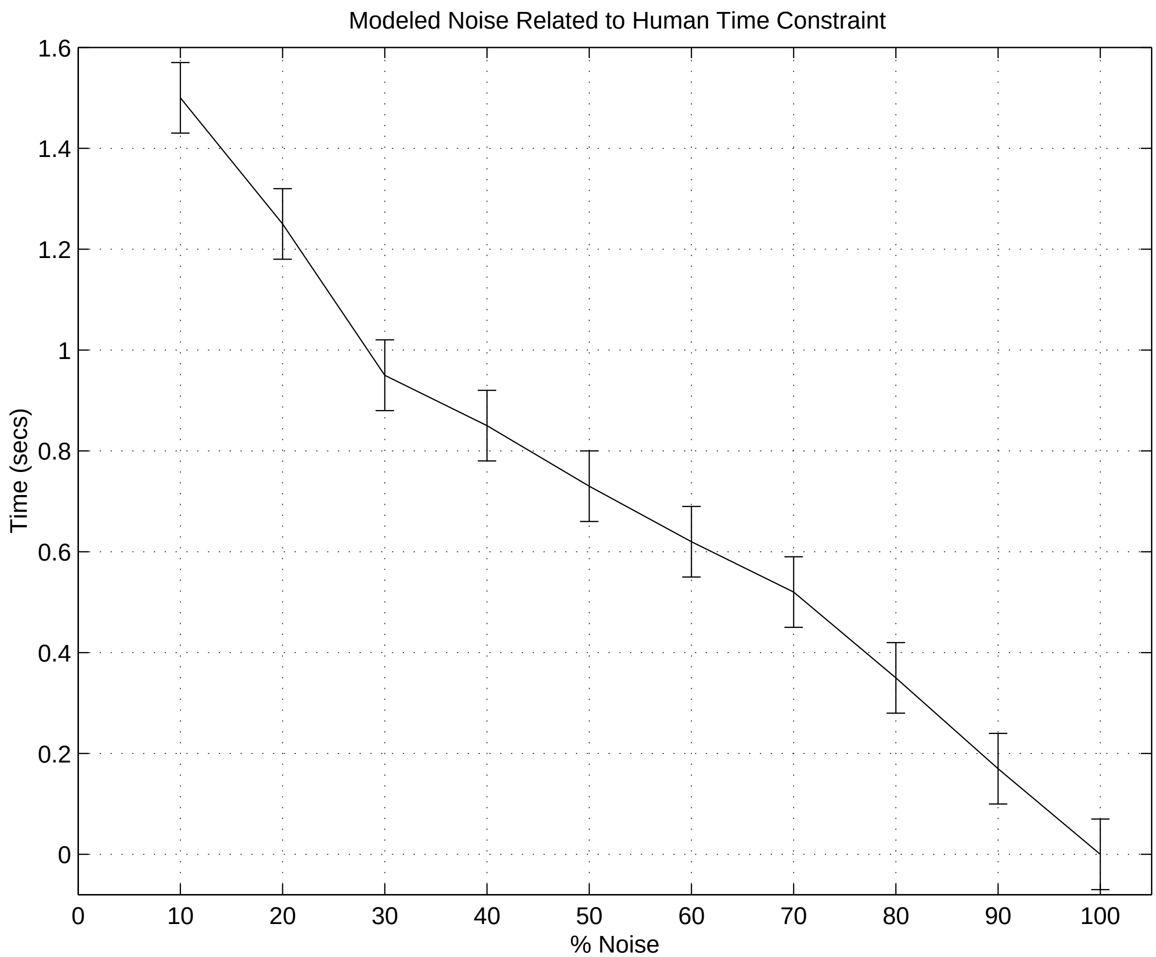

Figure 10: Relationship between time constraint in human trials and error level in computer simulations.