Controlling Biases in Demanding Tasks

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Abstract

Many aspects affect the way humans perform tasks, among others somebody's personality and current exhaustion level. Under varying conditions the quality of the performance is known to vary as well, for example, due to biases that occur. This paper introduces a cognitive control model addressing these aspects. It has been formally specified, tested in simulations for various scenarios, and formally analyzed.

Keywords: modeling; control; biases; task performance.

Introduction

Humans show a great variety in how they perform tasks. This variability in task performance may affect the quality of the performance. It is well-known that stress, fatigue, or high task demands can deteriorate task performance (Sanders, 1983). At the basis of these findings lies the fact that humans have a limited amount of cognitive resources. When a task becomes more demanding, these resources might become insufficient. To deal with this, humans tend to perform a task by applying cheaper cognitive reasoning steps, such as heuristics. These shortcuts often work well and might even be regarded as adaptive given their ecological validity (Gigerenzer et al., 1999). However, when the outcome of such a reasoning step deviates in a structural way from the rational outcome, it is called a bias.

The challenge addressed in this paper is to design a computational model for task performance that controls the occurrence of biases based on internal and external factors as mentioned. Various applications may benefit from such a model of human-like task performance. For example, it can be used to design virtual characters that play a role in simulations in which human aspects are important, like in realistic training environments and social games. Furthermore, such a model may help a software agent to better understand human behavior in cooperative task performance, and thus aid decision support.

In the next section various findings on human task performance are described in more detail. After this, a control approach is introduced that can generate variable task behavior. Next, this approach to control is applied to the control of biases in task execution, which results in a formally specified cognitive agent model. This model is tested in a case study, in which the agent operates in several scenarios under a variety of internal and external aspects. Finally, the model is evaluated and the research discussed.

Human Task Performance

Individual differences in cognitive characteristics entail variety in human task performance. In general some humans are more gregarious, impulsive, distractible, and less patient than others (Shields, 1983). At the same time humans manage the limited resources they have in certain ways, see e.g., (Johnston & Heinz, 1978). The allocation of cognitive resources is claimed to be flexible and under own control.

Kahneman (1973) stresses the idea that humans have a limited amount of cognitive resources. He states that there is no exact fixed amount, but that it is influenced by the arousal level of a person: the higher the arousal level, the more resources can be made available, up to a certain point. From that point on an increase in arousal may not result in an increase of available resources. McBride et al. (2007) reaffirm this and point out that humans are able to perform multiple tasks at once, as long as the total sum of processing demands does not exceed the available resources. When the total sum does exceed this level of available resources, task performance will decline (Posner & Boies, 1971).

A method humans apply to bring down the cognitive demands of a task is the use of heuristics. These rules of thumb often work well in certain types of situations. Characteristics of heuristics are, besides context dependency, their simplicity and speed. However, when they deliver incorrect or inaccurate results they are also referred to as biases, for an overview see (Wickens & Flach, 1988). Cognitive biases are known to arise especially under stress of overload conditions (Baron, 2000) and have an immediate impact on the quality of task performance.

Hancock and Warm (1989) acknowledge that demanding tasks over time do, through some kind of physiologically mediator, influence cognition. They forward the thesis that tasks themselves are the major sources of cognitive stress, which others support (e.g., Matthews & Desmond, 2002).

Model Setup and Control Approach

Our research focuses on designing a cognitive agent model that can mimic the variability in human task performance. Therefore, it possesses multiple cognitive processing components that can perform the same task. Moreover, these components vary in content, so the model can also mimic the variability in the quality of the task performance. Some components are rational and generate the output in a correct way, others represent typical biases and 'forget' to take certain factors into account. Components that perform biased processing require less processing resources than rational ones, but they may generate incorrect outputs.

Furthermore, the model possesses a control method to determine which of the cognitive processing components may become active to generate a required output, see Figure 1. On the top level, above the dashed line, the control processes are shown, distinguished from the component processing. Input for this control process is coordination information about the various components and their input-output connections. The output of this control level is control information on which components should become active. Each component has two input layers: one for coordination information (the upper square at the left side of the component), and one for data information (the lower square). Output is also generated at both levels, depicted by the squares at the right side of a component.

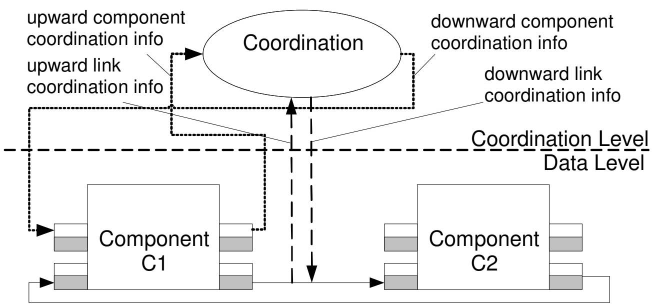


Figure 1: Control Approach

The cognitive agent model decides which component(s) may become active based on the current external, as well as internal states. A major constraint is that the required processing resources of the to-be-selected components have to lie within the available processing resources.

As discussed above, cognitive biases arise in human task performance under overload conditions. Since the model is about mimicking human (biased) task performance, the same principle should hold for an agent incorporating the model. The idea is that, when faced with high task demands, the agent will be motivated to operate on a high cognitive processing level. Over time, this will result in it becoming exhausted, which entails less available processing resources. The latter will affect the control decisions made. More specifically, when the agent becomes more exhausted, components with lower processing costs will be chosen, which usually implies a higher level of biases.

Formal Analysis

The cognitive agent model is expected to show certain behavioral properties as discussed above. Here such properties are identified and formalized, enabling automated verification. The first property relates task demand to biases.

HTDtoHB Higher task demand leads to higher biases.

This global property can be related to more local properties relating task demand to exhaustion, exhaustion to selection of less demanding components, and less demanding components to biases.

HTDtoHX Higher task demand leads to a higher exhaustion level.
HXtoLDC Higher exhaustion level leads to less demanding components.
LDCtoHB Less demanding components lead to higher biases.

The relationship between these behavioral properties is:

HTDtoHX & HXtoLDC & LDCtoHB $\Rightarrow$ HTDtoHB

For formalization of these properties a reified temporal predicate logical language was used; e.g. (Galton, 2006). Expressions are built on atoms referring to state properties, time points, and traces. The properties can be formalized by comparing for one given trace the levels (of task and component demand, exhaustion level and biases) to certain bounds, or by comparing these levels in a relative manner in two traces. The following abbreviations are used:

aboveduring(γ, t, D, a(V), M) ≡ $\forall t1, V1\ [\ t \leq t1 \leq t+D\ \&\ at(\gamma, t1, a(V1)) \Rightarrow V1 \geq M$
belowduring(γ, t, D, a(V), M) ≡ $\forall t1, V1\ [\ t \leq t1 \leq t+D\ \&\ at(\gamma, t1, a(V1)) \Rightarrow V1 \leq M$
aboveleadstoabove(γ,D1, a(V), M1, E, D2, b(V), M2) ≡
$\forall t$ [aboveduring(γ, t, D1, a(V), M1) $\Rightarrow$ aboveduring(γ, t+E, D2, b(V), M2)]
aboveleadstobelow(γ,D1, a(V), M1, E, D2, b(V), M2) ≡
$\forall t$ [aboveduring(γ, t, D1, a(V), M1) $\Rightarrow$ belowduring(γ, t+E, D2, b(V), M2)]
belowleadstoabove(γ,D1, a(V), M1, E, D2, b(V), M2) ≡
$\forall t$ [belowduring(γ, t, D1, a(V), M1) $\Rightarrow$ aboveduring(γ, t+E, D2, b(V), M2)]
ishigherduring(γ1, γ2, t, D, a(V) ≡
$\forall t1, V1, V2\ [\ t \leq t1 \leq t+D\ \&\ at(\gamma1, t, a(V1))\ \&\ at(\gamma2, t, a(V2)) \Rightarrow V1 \geq V2\ ]$
higherleadstohigher(γ1, γ2, D1, a(V), E, D2, b(V)) ≡
$\forall t$ [ishigherduring(γ1, γ2, t, D1, a(V)) $\Rightarrow$ ishigherduring(γ1, γ2, t+E, D2, b(V))]
higherleadstolower(γ1, γ2, D1, a(V), E, D2, b(V)) ≡
$\forall t$ [ishigherduring(γ1, γ2, t, D1, a(V)) $\Rightarrow$ ishigherduring(γ2, γ1, t+E, D2, b(V))]

Based on these, properties are formalized as follows:

HTDtoHBwithin(γ, D1, M1, E, D4, M4)

If in a trace γ for some time duration D1 the task demand is higher than M1, then after some delay E for some time duration D4 biases are higher than M4.

aboveleadstoabove(γ, D1, taskdemand(V), M1, E, D4, biaslevel(V), M4)

HTDtoHBbetween(γ1, γ2, D1, E, D4)

If in trace γ1 for some time duration D1 the task demand in γ1 is higher than the task demand in γ2, then after some time delay E, for some time duration D4 biases in trace γ1 are higher than biases in trace γ2.

higherleadstohigher(γ1, γ2, D1, taskdemand(V), E, D4, biaslevel(V))

HTDtoHXwithin(γ, D1, M1, E1, D2, M2)

If in a trace γ for some time duration D1 the task demand is higher than M1, then after some delay E1 for some time duration D2 the exhaustion level is higher than M2.

aboveleadstoabove(γ, D1, taskdemand(V), M1, E1, D2, exhaustionlevel(V), M2)

HTDtoHXbetween(γ1, γ2, D1, E1, D2)

If in trace γ1 for some time duration D1 the task demand in γ1 is higher than the task demand in γ2, then after some time delay E1, for some time duration D2 the exhaustion level in trace γ1 is higher than the exhaustion level in trace γ2.

higherleadstohigher(γ1, γ2, D1, taskdemand(V), E1, D2, exhaustionlevel(V))

HXtoLDCwithin(γ, D2, M2, E2, D3, M3)

If in a trace γ for some time duration D2 the exhaustion level is higher than M2, then after some delay E2 for some time duration D3 the demand of selected components is lower than M3.

aboveleadstobelow(γ,D2, exhaustionlevel(V), M2, E2, D3, componentdemand(V), M3)

HTDtoHXbetween(γ1, γ2, D2, E2, D3)

If in trace γ1 for some time duration D2 the exhaustion level in γ1 is higher than the exhaustion level in γ2, then after some time delay E2, for some time duration D3 the demand of selected components in γ1 trace is lower than the demand of selected components in trace γ2.

higherleadstolower(γ1, γ2, D2, exhaustionlevel(V), E2, D3, componentdemand(V))

LDCtoHBwithin(γ, D3, M3, E3, D4, M4)

If in a trace γ for some time duration D3 the demand of selected components is lower than M3, then after some delay E3 for some time duration D4 the biases are higher than M4.

belowleadstoabove(γ,D3, componentdemand(V), M3, E3, D4, biaslevel(V), M4)

LDCtoHBbetween(γ1, γ2, D3, E3, D4)

If in trace γ1 for some time duration D3 the demand of selected components in γ2 is lower than in γ1, then after some time delay E3, for some time duration D4 the biases in trace γ2 are higher than the biases in trace γ1.

higherleadstolower(γ1, γ2, D3, componentdemand(V), E3, D4, biaslevel(V))

Automated verification of these properties has been performed against generated simulation traces.

Dynamical System Models Used

In the next section the overall executable cognitive agent model is described. It includes some computational models in dynamical system style (based on difference / differential equations), which are introduced in this section.

The model is based on literature from cognitive science and human factors research. Hancock and Meshkati (1988) define mental workload as: 'The operator's evaluation of the attentional load margin (between their motivated capacity and the current task demands) while achieving adequate task performance in a mission-relevant context.' An elaboration on their figure illustrating this principle is shown in Figure 2.

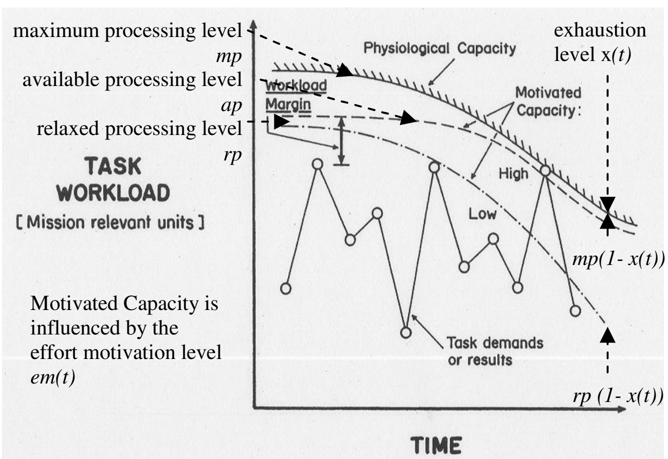


Figure 2: Cognitive processing levels over time

Basic concepts used in our model are:

$x(t)$	the exhaustion level at t
mp	maximal cognitive processing level if no exhaustion exists
rp	relaxed cognitive processing level if no exhaustion exist
$td(t)$	the externally determined task demand at t
$ptd(t)$	the internally perceived task demand at t
$em(t)$	the effort motivation level at t
β	parameter determining source of effort motivation
$ap(t)$	the available processing level at t
$cp(t)$	the current processing effort at t

The exhaustion level $x(t)$ is assumed to be normalized between 0 (no exhaustion) and 1 (complete exhaustion). As exhaustion affects possible processing levels, the maximal cognitive processing level at some time point t is taken to be $mp\ (1 - x(t))$, and the relaxed cognitive processing level $rp\ (1 - x(t))$; this is illustrated in Figure 2. The incoming external task demand td is transferred to the internal perceived task demand ptd by dividing it by the current maximal processing level ($mp\ (1 - x(t))$. When the result is above 1, it is set to 1 which ensures that the perceived task demand lies between 0 and 1. The perceived task demand and exhaustion level determine based on a personality characteristic parameter β what the current effort motivation level $em(t)$ is, with a value between 0 (no motivation) and 1 (totally motivated). This level in return determines the current available processing level $ap(t)$, which influence the maximal processing effort $cp(t)$. Below these processes are described in more detail.

Exhaustion First, the model for the level of cognitive exhaustion $x(t)$ over time is introduced. The exhaustion for a next time point depends on the current processing effort, but also on the current exhaustion, which is built up in the past. The assumption is that exhaustion increases proportionally to the amount by which the current cognitive processing effort $cp(t)$ exceeds the level indicated by $rp\ (1 - x(t))$. When the current processing effort is lower than this value, exhaustion decreases proportionally, until 0 is reached. Furthermore, the factor γ is used to fine-tune the model.

$$\Delta x \;=\; \gamma\ \frac{cp(t) - rp\ (1 - x(t))}{mp}\ \Delta t$$

$$x(t+\Delta t) \;=\; \begin{cases} x(t) + \Delta x & \text{if } \quad x(t) + \Delta x > 0 \\ 0 & \text{else} \end{cases}$$

Effort Motivation At time t the cognitive effort motivation level influences the processing level at which the agent maximally operates. A personality characteristic parameter β is introduced that indicates in how far the motivation for effort is externally driven through the perceived task demand (indicated by $\beta = 1$), or internally driven by the exhaustion level (indicated by $\beta = 0$). The effort motivation $em(t)$ is determined as follows.

$$em(t) = \beta\, ptd(t) + (1 - \beta)\ (1 - x(t))$$

Available Processing Level Given the motivation indicator the cognitive processing level made available $ap(t)$ is determined as follows. If the motivation is 1, the maximal possible processing level $mp\ (1 - x(t))$ will be the processing level made available. If the motivation is 0, the available processing level is the relaxed processing level $rp\ (1 - x(t))$, which is always proportional to $mp\ (1 - x(t))$. The general model for the processing level made available is:

$$ap(t) = (em(t)\ mp + (1 - em(t))\ rp)\ (1 - x(t))$$

When $cp(t) = ap(t)$ is taken (i.e., the processing level made available is fully used), the three models for $x(t)$, $em(t)$ and $ap(t)$ above can be combined to obtain a single (but complex) difference or differential equation model for $x(t)$, given the chosen values $cp(t)$ for the current processing effort over time.

Overall Cognitive Agent Model

This section describes the overall design of the cognitive agent model, incorporating the dynamical models of the previous section. To evaluate whether the model indeed dynamically adjusts its task performance in a way similar to humans, it has been designed in a formal, executable format. The model includes various cognitive components and control knowledge about them. In addition, it is able to observe the world, form goals, and execute actions. The model's execution cycle is as follows:

Determine Observations: The agent observes the world and forms beliefs about what it sees.

Determine Goals: Based on beliefs, it forms goals with priorities.

Determine Task Demand: Based on the formed goals, their priorities, and the cognitive processing level that is required to reach them in the optimal way, the task demand is determined.

Determine Perceived Task Demand: The perceived task demand is deduced from the real task demand (see section above).
Determine Effort Motivation Level: see section above.
Determine Available Processing Level: see section above.

After these processes the agent starts the selection process of the cognitive processing components to be executed.

Determine Executability of Components: First, it determines which components are eligible for execution, i.e. that they can actually produce outputs when selected. For this it checks for each component whether all the input it requires is available.

Determine Relevance of Components for Goals: Next, it determines which components are relevant for which goal:

∀g ∀c ∀k ∀cr ∀kr ∀x
If goal(g) & component_has_output (c, g) &
component_requires_processing_level(c,k) & component_has_output (cr, g)
component_requires_processing_level(cr,kr) &
¬∃co ∃ko (component_has_output (co, g) &
component_requires_processing_level(co,ko) & ko > kr)
component_has_executability(c, 1) & exhaustion-level(x) &
b = 1 – | (1 – k / kr) – x |
then component_has_relevance_for_goal(c, g, b)

This process entails that the relevance of a component *c* for a certain goal *g* that it has as its output, depends on the current exhaustion level *x* and the existence of a most expensive component *cr* that has goal *g* as its output. The rational behind this process is that the most expensive component is the best (most rational) component to reach *g,* and is preferred when there is no exhaustion (receives a relevancy of $1 - | (1 - kr/kr) - 0| = 1$). However, the more exhausted the agent is, the more it prefers the cheaper components over the expensive ones. For example, when *x* is 0.3, *cr* only receives a relevancy of 0.7, while *c*, given it requires a lower processing level, e.g. 4 instead of 6, receives a relevancy of $1 - | (1 - 4/6) - 0.3| = 0.97$. If a component does not have a certain goal as one of its outputs, its relevance for that goal is 0.

Determine Priority of Components: The priorities of the components for the various goals are determined by multiplying their relevancy for a goal with the priority of that respective goal.

Determine Components to be Activated: This is done by considering all possible groups of components for which it holds that 1) they have a priority greater than 0; 2) they are not relevant for the same goal; 3) their output does not make the goal of the other irrelevant. Furthermore, 4) their combined required processing level is below, or equal to, the available processing level. The components that are selected for execution are the members of the group with the highest total priority, which is formed by the sum of the priorities of the components.

Determine Activated Components: The components that are selected for activation are executed.

Determine Current Processing Effort: The current processing effort that the executing components deliver is determined.

Update Exhaustion Level: Given this current processing effort, the exhaustion level is updated, see the previous section.

As long as observations are made, the agent keeps controlling its process as indicated. When there is no task demand the agent relaxes, resulting in decreased exhaustion.

Simulation Experiments

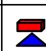
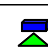
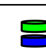
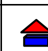
To evaluate the cognitive agent model, simulation experiments were performed in LeadsTo (Bosse et al, 2007), which is especially developed to model executable temporal properties. For the evaluation a simple classification task was chosen. Although simplified, it is representative for the kinds of tasks future software agents might perform, e.g. in training simulations of military air-traffic-controllers. The task entails the correct classification at every execution cycle of the objects (none, one or two) then present in the world. The classification of an object entails assigning it to one of the bins present in the environment. Objects have two properties, namely a color (red, blue or green), and a shape (cube, cylinder or triangle). This results in nine possible objects that can be classified. Bins also have two properties; they can either fit red, blue, green, or all colors and cube, cylinder, triangle, or all shapes. For the current scenario's it is assumed that these 4 bins are present:

Bin 1: fits red cubes	Bin 2: fits blue objects
Bin 3: fits any colored triangles	Bin 4: fits all objects

The general goal of the task is to classify objects, but also to do this as precise as possible. The assignment of an object to a bin whose properties it exactly matches has the highest preference. Furthermore, partial classifications are desired above an assignment to the most general bin. So in the current scenario, the best classification of the red cube is assigning it to bin 1, followed by an assignment to bin 4. A blue triangle can be assigned to bin 2 just as well as to bin 3; bin 4 however is less desired.

To test the behavior of the cognitive agent model over time, four scenarios were developed. They all incorporate the same bins, but the objects present in the world over time differ. In the scenario named *1 object*, one object is present at every execution cycle. The similar principle holds for the scenario named *2 objects.* For scenarios named *low demand* and *high demand* the amount of objects varies, see Table 1 for an overview. Each scenario takes 9 time steps.

Table 1: Objects present in world over time

	1	2	3	4	5	6	7	8	9
low demand									
high demand									

During the execution cycle of the model, the agent first observes the world and forms beliefs about the properties of the available objects and bins. Then it derives new goals from the top level goal classify_all_objects as follows:

∀x ∀p
If goal(classify_all_objects)
goal_has_priority(classify_all_objects, p)
belief(object, x)
then goal(belief(classification_type_of,x, total))
goal_has_priority(belief(classification_type_of,x, total), p/3 * 1.1)
goal_satisfied_when(belief(classification_type_of,x,total),
belief(classified,x))
goal(belief(classification_type_of,x, partly))
goal_has_priority(belief(classification_type_of,x, partly), p/3)
goal_satisfied_when(belief(classification_type_of,x, partly),
belief(classified,x))
goal(belief(classification_type_of,x, not))
goal_has_priority(belief(classification_type_of,x, not), p/3 * 0.9)
goal_satisfied_when(belief(classification_type_of,x, not,
belief(classified,x))

So for every object the agent forms three classification goals, with varying priority. These priorities express the agent's preferences for the various types of classifications.

The task demand for the current task is determined by the combined task demand of the present objects. Objects entail task demand because they cause goals with priorities.

$$\text{task\_demand} = \Sigma \{ \text{mp} * \text{p} \mid \text{goal(g)} \wedge \text{goal\_has\_priority(g, p)} \wedge \text{maximum\_required\_processing\_level\_for\_goal(g, mp)} \}$$

For the current task this entails that a single object delivers a total task demand of 5.06667. This results in a constant task demand for the scenarios *1 object* and *2 objects*; 5.06667 and 10.1333 respectively. For scenarios *low* and *high demand* the task demand varies, see Figure 3.

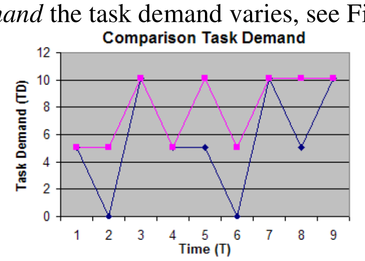


Figure 3: Task demand for scenario's *low demand* (blue diamonds) and *high demand* (pink squares)

Above it was described how, based on the goals and the priority of components for these goals, the cognitive agent model determines which components execute. Besides the components themselves, it also uses control knowledge over these components, e.g. about their inputs, outputs, and required processing level. The latter value is deduced from the number of required inputs of the component.

The following shows the process of a rational component in the form of an executable temporal rule:

If	then
HoldsAt (belief(object,x), t) HoldsAt (belief(bin,y), t) HoldsAt (belief(has_shape,x,s), t) HoldsAt (belief(fits_shape,y,s), t) HoldsAt (belief(has_color,x,c),t) HoldsAt (belief(fits_color,y,c), t)	HoldsAt (belief(classified_as,x,y), t+1) HoldsAt (belief(classified,x), t+1) HoldsAt (belief(classification_type_of,x, total), t+1)

This component requires a processing level of 6 and has a bias level of 0. Besides rational components, biased ones are present with a different process but a same output, e.g.:

If	then
HoldsAt (belief(object,x), t) HoldsAt (belief(bin,y), t) HoldsAt (belief(has_shape,x,s), t) HoldsAt (belief(fits_shape,y,s), t)	HoldsAt(belief(classified_as,x,y), t+1) HoldsAt(belief(classified,x), t+1) HoldsAt(belief(classification_type_of,x, total), t+1)

This component also deduces a belief about a total classification, but forgets to take the colors of the object and the bin into account. The final result might be correct, but might also be incorrect. This second component requires a processing level of 4 and has a bias level of 4/6, because the most expensive processing requires a level of 6; see the previous section on the relevance of components.

Last, various parameters present in the model are assigned a fixed value to arrive at an executable version. For the current task the maximal processing level *mp* is set to 10 and the relaxed processing level *rp* to 7. It is assumed that the agent is not exhausted at the beginning of the task. Furthermore, parameter γ, with which the granularity in exhaustion level over time can be tuned, is set to 0.3.

Each scenario was executed twice, once with personality value 0.7 (motivation primarily determined by external task demand) and once with value 0.3 (motivated primarily determined by internal exhaustion level).

Simulation Results

Scenario 1 object In this scenario the cognitive agent model classified each object in a perfect way for both personalities. Since there is a maximum of one object at each execution, the maximal possible current processing level (for the red cube classification) lies at 6. This is below the relaxed processing level, set at 7, and thus no exhaustion occurs.

Scenario 2 objects In this scenario the two objects ensure a constant high task demand of 10.1333. This results in a constant perceived task demand *ptd* of 1, which causes both agents to make more than their relaxed processing level available. Therefore the effort of the selected processing components often lies above the relaxed processing level *rp (1 - x(t))*, causing the agent to become exhausted, which in turn influences the available processing level, see Figure 4.

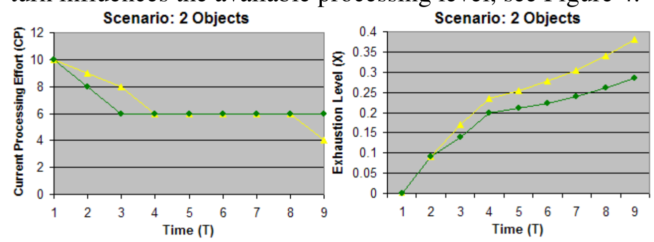


Figure 4: Current processing effort and exhaustion level for personality 0.7 (yellow triangles) and 0.3 (green dots)

The agent with personality value 0.7 will, given the *ptd* of 1, make more processing level available than the agent with personality value 0.3. This is beneficial at first; more available processing level entails that more demanding, so less biased, components can execute. However, due to this higher effort level this agent becomes exhausted quicker. This results in that it over time actually has less processing level available, which result in the selection of cheaper and thus more biased components, see Figure 5a.

Scenarios low and high demand In the scenarios *low* and *high demand* the numbers of objects that are available at each execution cycle vary, see Table 1. The variety in the task demand, see Figure 3, clearly determines the variety in current processing effort, see Figure 5b. This in turn influences the exhaustion level and bias level, see Figure 6.

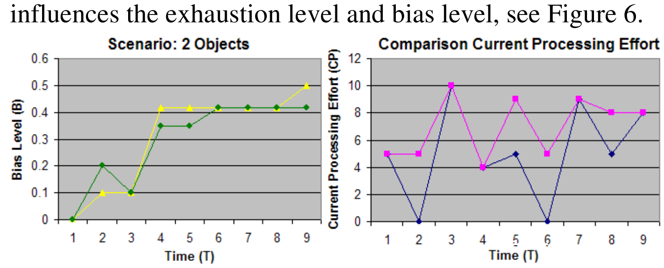


Figure 5: (a) Bias level for personality value 0.7 (yellow triangles) and 0.3 (green dots) in the *2 objects* scenario (b) Current processing effort for the *low demand* (blue diamonds) and *high demand* (pink squares) scenarios

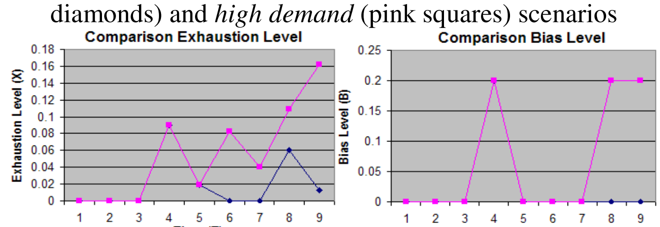


Figure 6: Exhaustion and bias level for the *low* (blue diamonds) and *high demand* (pink squares) scenarios

The increase in bias level has its impact on the quality of the task performance. Table 2 sums for personality value 0.7 the percentage of false classifications averaged over all objects present. As an example: this percentage is 75 percent when the agent blindly assigned an object to any bin, since it is correct for bin 4, which is one of four bins.

Table 2: Percentage of mistakes for personality value 0.7

Scenario	1	2	3	4	5	6	7	8	9
1 object	0	0	0	0	0	0	0	0	0
2 objects	0	0	50	25	37.5	25	12.5	37.5	62.5
lowdemand	0	0	0	50	0	0	0	0	0
highdemand	0	0	0	50	0	0	0	100	75

Verification

Formalized properties, such as those presented earlier, have been automatically verified against a number of simulation traces, such as discussed above. As an example, property HTDtoHBwithin has been verified and shown to hold for all four traces for the following values for the duration and bound parameters: D1=100, E=100, D4=100, M1=8, M4=0.2. Notice that one execution cycle of the model takes a 100 time steps. Moreover, the property HTDtoHBbetween that compares two traces was also verified and shown to hold for the *low demand – high demand* scenario pair as well as the *1 object – 2 objects* scenario pair for the values: D1=100, E=100, D4=100.

Discussion and Conclusion

This paper presented a cognitive agent model capable of dynamically adapting its behavior to the external, as well as its internal state. Related research with a similar goal focuses on integrating emotions, arousal, and motivation in cognitive systems, but no similar approach can be found. Closest to this work is the work of Ritter et al. (2006) that implements various theories of stress and their effect on behavior (some considered biases). However, the implemented factors were local, fixed and no temporal aspect is incorporated. One theory they did not implement is that tasks themselves are stressors (the approach taken in this paper). About this they state "we recognize that modeling tasks as stressors is an interesting and important next step in the effort to model the effects of stress."

The dynamical cognitive agent model was tested for various task scenarios in simulations. A formal analysis of properties of the model has been performed, including automated verification of the identified properties against simulation traces, indeed showing the behavior as expected.

For a number of choices that were made for the case currently presented, also alternative choices could have been made, e.g., for the choice of parameters for the maximum en relaxed processing power in relation to the required processing level of components. It is expected that the values of the parameters depend on the application context. Based on the requirements of the behavior that the model should show, these can be adapted as to provide a best fit.

The model's main contribution is that it offers a mechanism to control the appearance of biases in a wide variety of tasks, but even stronger, on multiple levels of the task execution. The current paper solely addressed the controlling of biases appearing in cognitive components processing beliefs. The processes from observations to beliefs and from beliefs to goals were fixed. These processes may just as well be subject to biases under stress. A biased determination of priorities of goals can also have serious effects on task execution. In future work the control of these processes will be added to the current model.

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