Workshop on ACT-R Models of Human-System Interaction, Mesa, AZ, January 2002. www.dtic.mil/AFRL/afrl.html

Modeling the Effects of Two Behavior Moderators in ACT-R

Frank E. Ritter 1, Marios N. Avraamides 2, Isaac Councill 1, Karen S. Quigley 3, Laura Cousino Klein 4, Michael D. McNeese 1, Dirk Van Rooy 1, Michele McClellan Stine 4, and Isabella M. Rodrigues 4

1 School of Information Sciences and Technology,
Penn State, University Park, PA 16802
2 Department of Psychology
Penn State, University Park, PA 16802
3 Department of Psychiatry
University of Medicine and Dentistry of New Jersey, Newark, NJ 07103
and
VA Medical Center
New Jersey Health Care System
East Orange, NJ 07018
4 Department of Biobehavioral Health
Penn State, University Park, PA 16802

ritter@ist.psu.edu

Abstract

Simulating the effects of behavior moderators within a cognitive architecture is essential for building cognitive models that can realistically capture the full range of human performance. We demonstrate that some of these effects can be modeled by varying parameters of the cognitive architecture and some by modifying the knowledge that is built into the models. As an example of implementing the two approaches, we present an ACT-R model that performs serial subtraction under varying levels of task-appraisal and with and without anxiety realized as worry. The model also includes caffeine which is not discussed in the present article. The interested reader is directed to Ritter, Quigley, Klein, McNeese, Van Rooy, Councill, Avraamides, Stine, and Rodriguez (submitted).

Introduction

The last two decades of cognitive research have been marked with the increased popularity of cognitive architectures. Architectures such as Soar (Laird, Newell, & Rosenbloom, 1991), ACT-R (Anderson & Lebiere, 1998) and EPIC (Kieras & Meyer, 1977) have emerged, thus implementing Newell s (1973; 1990) call for unified theories of cognition. Cognitive architectures have successfully produced a vast number of computational models that simulate human performance on various tasks.

Despite the remarkable success of cognitive models, substantial effort has been devoted to improving the architectures themselves. Indeed, recent improvements have allowed researchers to model tasks that were not possible before. For example, the introduction of ACT-R/PM (Byrne & Anderson, 1998) and its assimilation in the latest incarnation of ACT-R have allowed the design of models that can interact with the world via virtual eyes, hands, ears, and mouths.

In spite of such exciting developments, cognitive architectures are still far from achieving the ultimate goal of integrating all the pieces of knowledge that exist about the functioning of the cognitive system. Particularly, we believe that one aspect of the cognitive system has been almost totally ignored by cognitive modelers: cognitive activity is often moderated by factors that are not directly related to the ongoing task. Cognitive modelers seem to ignore that factors such as noise, temperature, stress, excitement and so on, can interact with our cognitive processes and dramatically change how we perform a given task. We argue that modeling the effects of such behavior moderators will lead to more accurate and realistic simulations of human cognition. Including behavior moderators is imperative for cognitive models to be used as surrogate users (e.g., in military simulations) or models that might lead to important decisions and changes in policies.

An example of a potentially influential model is the driving model of Salvucci (2001). This model showed that while dialing on a cell-phone resulted in driving-performance decrements, using a voice interface did not produce any severe effects. While the implication from this result is quite clear, it should be noted that the model is not a complete model of human behavior on the road as it does not take into account the various external factors (e.g., heavy traffic on the road, low visibility etc.) or internal states of the individual (e.g., angry mood, feeling sleepy etc.) that can be quite influential in this task. While using the voice-key did not by itself exert any effect on driving performance, it could have interacted with other factors to produce detrimental effects. Because we believe that behavior moderators can exert strong effects that can potentially alter both the efficiency and the strategies used for performing a cognitive task, we argue that they should be taken more seriously in modeling efforts.

The goal of the present paper is to describe two approaches that can be adopted by modelers interested in including the effects of behavior moderators in their models. We then present an ACT-R model that was designed to implement these two approaches.

Modeling behavior moderators

Designing a computational model to simulate human performance is a two-step procedure. First, a cognitive architecture must be chosen. The architecture provides the task-independent and relatively constant aspects of cognition, thus constraining the model by specifying the mechanisms that will govern its workings. Second, starting knowledge set has to be provided. Building a model is in essence equivalent to providing task-specific procedural and declarative knowledge to the architecture. For example, a model that solves arithmetic problems must have the knowledge to perform arithmetic operations and a number of arithmetic facts stored in its memory. We argue that the effects of behavior moderators can be modeled by modifying either the mechanisms provided by the architecture or the knowledge that is available to the model. The model we discuss provides an example of how behavior moderators can be built into cognitive models with these two approaches.

The serial-subtraction model

Our model of serial subtraction was built using the ACT-R 4.0 cognitive architecture (Anderson & Lebiere, 1998). It performs a serial subtraction task often used to study behavior under stress. That is, it begins with a large 4-digit number and it repeatedly subtracts from it a specified 1 or 2-digit number. The model s declarative knowledge consists solely of arithmetic facts and goal-related information, and its procedural knowledge by rules to retrieve subtraction results from memory. Figure 1 presents the graphical interface of the model.

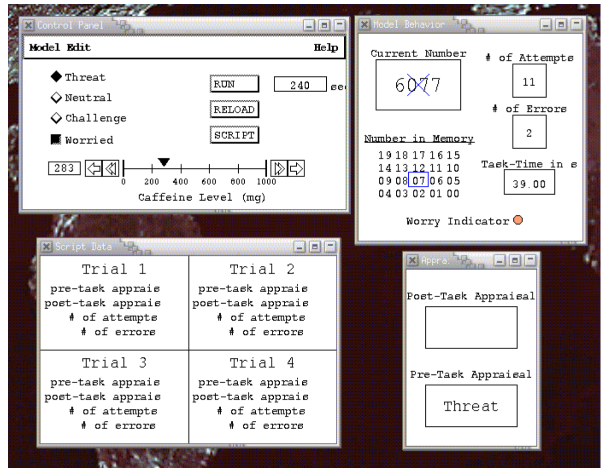

Figure 1: The graphical interface of the serial subtraction model.

Varying architectural parameters

The behavior moderator we chose to include in the serial-subtraction model is task-appraisal (Lazarus, 1966; Lazarus & Folkman, 1984). Task-appraisal is considered an internal moderator as it represents an individual s subjective evaluation of a stressful event. Based on the evaluation, appraisal can be of a challenging or a threatening form. A challenging appraisal is formed when the individual deems her abilities high enough to cope with the stressful event, while a threatening appraisal arises when the stressfulness of the task is judged to surpass the coping abilities of the individual.

Task-appraisals can be distinguished into pre-task appraisals and post-task appraisals based on whether they are formed before or after the execution of the task. Empirical evidence suggests a link between the form of task-appraisal and performance on arithmetic tasks such as the serial-subtraction task we use in our model. While threatening appraisals have been associated with fewer solution attempts and poorer performance, challenging appraisals have been related with better performance and more solution attempts than neutral situations (Kelsey, Blascovich, Leitten, Schneider, Tomaka, & Wiens, 2000; Quigley, Barret, & Weinstein, in press). We have attempted to model these effects by varying the values of three parameters that are provided by the ACT-R architecture. Two of these parameters are involved in the conflict resolution process, that is, the process based on which ACT-R decides which rule will fire when more than one matches the goal of the system.

The first parameter modified was the value of the goal, which represents how much time ACT-R is willing to spend attempting to achieve the goal. The value of the goal has been previously associated with the level of motivation (Belavkin, Ritter, & Elliman, 1999). As Belavkin et al. pointed out, when the value of the goal is high the system performs the task as if it is in a state of high motivation; that is, it strives to achieve the goal regardless of the costs involved. We varied the value of the goal to reflect differences in motivation levels between the two forms of task-appraisal. Specifically, the parameter was increased from its default value when the task was performed under a challenging appraisal and was decreased when appraisal was threatening.

The second parameter is the noise parameter, which represents the level of randomness present at conflict resolution (rule choice). This parameter has been previously varied to capture the irrationality present in the though process of children (Jones, Ritter, & Wood, 2000). We have increased the default value of this parameter to provide greater stochasticity in the strategy selection process under a threatening appraisal state, and decreased it to model a clear-head in the case of challenging appraisals.

In addition to these two parameters, we varied the value of the source activation parameter. This parameter reflects the amount of attentional resources and has been previously used to model individual differences in working memory capacity (Lovett, Reder, & Lebiere, 1999). Previous research has associated the amount of attentional capacity with the stressfulness of the task (Hancock, 1989). To simulate a reduction of attentional capacity under stressful situations, we have decreased the default value of source activation when the task was performed under a threatening appraisal. On the other hand, we increased the value of source activation to model a state of increased attentional capacity in the case of a challenging appraisal.

Model Performance

By varying the default values of these three parameters of the ACT-R architecture we have been able to model the effects of the pre-task appraisal moderator. Post-task appraisal is also included in the model, which simply inherits the parameters of pre-task appraisal at the end of each running cycle. Data suggest that it is not this simple, there is almost a resetting that occurs such that the appraisals are not exactly the same (Task 1 post is not identical to Task 1 pre). This simplification is a working assumption that can be refined later.
As can be seen in the top two sections of Table 1, the model produces a pattern of results that is similar with that reported at the group level in an empirical study using the same serial-subtraction task (Tomaka, Blascovich, Kelsey, & Leitten, 1993). The model tends to undershoot the human data but it reproduces the better performance and the increased number of solution attempts when the task is performed in a state of challenging appraisal. The model of worry is taken up next.

Table 1: Comparison of model with human data

Pre-task appraisal	Number of	CH		TH		NE
Simulation	attempts	50	>	41.2	<	47.3
(N=10)	correct	48.4	>	37.8	<	44.8
Simulation with Worry	attempts	39.2	>	32.5	<	35.8.
(N=10)	correct	37	>	29.5	<	33.2
Tomaka et al. (1993)	attempts	61	>	46		n.a.
	correct	56	>	42		n.a.

Note Human data taken from Tomaka et al. (1993); < and > denote significant differences at the p<.01 level, N= number of simulation runs, CH=challenging appraisal, TH=threatening appraisal, NE=neutral

Modifying the model s knowledge

The previous section described how we modified parameters of the cognitive architecture to capture the effects of task-appraisal in our serial-subtraction model. However, we believe that moderators can be built into cognitive models without varying the values of architectural parameters. Instead, the knowledge provided to the model can be modified to incorporate the effects of behavior moderators. As an example, we have used the same serial-subtraction model and we have modified its knowledge to simulate the effects of worry on performance. We define worry as the anxiety that is specific to the task to be performed. Because our task is of an arithmetic nature, worry may be equivalent to the term math anxiety that is used by Ashcraft and Kirk (2001).

Previous research has associated math anxiety with performance decrements on somewhat complex arithmetic tasks. Particularly, lower accuracy and longer latencies have been observed in solving arithmetic problems that involve a carry operation, such as multicolumn addition (Ashcraft & Faust, 1994; Faust, Ashcraft, & Fleck, 1996). Ashcraft and Kirk (2001) suggest that the effect of math anxiety on arithmetic performance is caused by an on-line reduction of working memory resources. In line with Eysenck and Calvo s (1992) processing efficiency theory, they propose that math anxiety produces intrusive thoughts that compete with the main task for cognitive resources. Because of this, the amount of cognitive resources that remains available for the arithmetic task is diminished under high math anxiety. Indeed, participants with high levels of math anxiety report the presence of such intrusive thoughts when solving arithmetic tasks (Faust, 1992, cited in Ashcraft & Kirk).

We have simulated the experience of intrusive thoughts by modifying the knowledge of the serial-subtraction model to enable the model to worry .

Specifically, we added into the model s procedural knowledge a simple rule that can fire any time while the model is performing the serial-subtraction task[1]. In essence, math anxiety is modeled as a secondary task that is performed concurrently with serial subtraction. Due to the serial nature of rule-firing in ACT-R, whenever the worry rule fires, it results into a slowing down of the execution of the subtraction task. In addition to producing an increase in total solution time, the occasional firing of the worry production affects the content of working memory. Because the processing of the main task is halted when the worry rule fires, there is more time for task-relevant declarative information to decay from working memory. The decay of memory information produces more frequent retrievals of inappropriate arithmetic facts. This results into performance that is more errorful when the task is performed under high anxiety conditions.

Model performance

When the model performs the serial-subtraction task with math-anxiety turned-on , it makes more errors and takes more time. To the best of our knowledge, there are no available data that examine the effects of math anxiety on performance in a serial subtraction task. Therefore, we have not yet compared directly the performance of our model with human data. Nevertheless, the model seems to capture the effects reported by studies that use multicolumn addition (e.g., Ashcraft & Kirk, 2001). The lower section of Table 1 shows the average performance of our model with math-anxiety turned on and off under the three different levels of task-appraisal.

Conclusions

The cognitive model that we have presented implements the two approaches we suggested for modeling the effects of behavior moderators. First, we have varied parameters that are provided by the ACT-R architecture to model performance under different task-appraisals. Second, we have modified the knowledge of the model to simulate the influence of math anxiety.

In both cases we were able to produce the pattern of results that are documented by empirical research, by using very simple techniques that could be easily adopted and used in cognitive models of other tasks. We believe that a greater number of moderators should be explored and their effects should be modeled by using reusable techniques that can be shared among modelers.

Including the effects of behavior moderators into computational models of cognition will give power to cognitive modelers as it will provide them with the capability of designing models that can capture more realistically human behavior. The design of high-fidelity models is particularly important for models that can be used for training purposes (e.g., in military simulations).

Furthermore, we believe including more behavior moderators in cognitive architectures would attract more researchers toward the cognitive modeling community. Non-modelers who are interested in the cognitive structure of behavior moderators may seize the opportunity of using cognitive models to form and validate more precise theories and test complex interactions that are too costly to test with empirical studies. Testing empirically more than a handful of moderators requires excessive amounts of time, human resources, and very diverse expertise. As a result, psychologists typically focus on examining the effects of 1 or 2 behavior moderators in isolation from all other moderators because their interaction are difficult to predict using verbal theories. Using cognitive modeling will allow researchers to examine a greater number of moderators—especially if good care is taken for creating reusable models and test complex effects. Predictions and bold hypotheses can be formed and tested in a cognitive model before investing resources into complex experiments. Moreover, the level of concreteness that cognitive modeling entails would allow these researchers to draw more confident conclusions about the effects of behavior moderators. This is because, in contrast to verbal theories, cognitive models require explicit specification of all mechanisms that are involved in performing a task. Consequently, building model to simulate the effect of a moderator on performance will force the researcher to specify in non-vague terms how exactly the moderator produces its effect.

In summary, we argue that a closer examination of behavior moderators from the perspective of cognitive modeling will provide important advantages for both cognitive modelers and traditional researchers. The present article has sketched examples of how the effects of moderators can be inserted into computational models with the goal of stimulating research in this important area.

Acknowledgments

This project was supported by the US Office of Navy Research, award number N000140110547 and by the Space and Naval Warfare Systems Center, San Diego. The views expressed in this article do not necessarily reflect the positions or the policies of the U.S. Government, and no official endorsement should be inferred.

[1] The worry rule always matches the current goal and fires when it is selected by the conflict resolution process.

References

Anderson, J., R, & Lebiere, C. (1998). *The atomic components of thought.* Mahwah, NJ: Erlbaum.

Ashcraft, M., H, & Kirk, E., P. (2001). The relationships among working memory, math anxiety, and performance. *Journal of Experimental Psychology: General, 130*(2), 224-237.

Belavkin, R., Ritter, F. E., & Elliman, D. (1999). Towards including simple emotions in a cognitive architecture in order to fit children's behaviour better. In Erlbaum (Ed.), *Proceedings of the 1999 Conference of the Cognitive Society, 784.* Mahwah, NJ.

Byrne, M., & Anderson, J., R. (1998). Perception and action. In J. Anderson, R & C. Lebiere (Eds.), *The atomic components of thought* (pp. 167-200). Hillsdale, NJ: Erlbaum.

Eysenck, M., W, & Calvo, M., G. (1992). Anxiety and performance: the processing efficiency theory. *Cognition and Emotion, 6*, 409-434.

Hancock, P., A. (1989). A dynamic model of stress and sustained attention. *Human factors, 31*(5), 519-537.

Jones, G., Ritter, F., E, & Wood, D., J. (2000). Using a cognitive architecture to examine what develops. *Psychological Science, 11*(2), 93-100.

Kelsey, R. M., Blascovich, J., Leitten, C. L., Schneider, T. R., Tomaka, J., & Wiens, S. (2000). Cardiovascular reactivity and adaptation to recurrent psychological stress: The moderating effects of evaluative observation. *Psychophysiology, 37*, 748-756.

Kieras, D., E, & Meyer, D., E. (1997). An overview of the EPIC architecture for cognition and performance with application to human-computer interaction. *Human-computer interaction, 12*(4), 391-438.

Laird, J., E, Newell, A., & Rosenbloom, P., S. (1991). Soar: An architecture for general intelligence. *Artificial Intelligence, 47*, 289-325.

Lazarus, R. S. (1966). *Psychological stress and the coping process*. New York: McGraw-Hill.

Lazarus, R. S., & Folkman, S. (1984). *Stress, appraisal and coping*. New York: Springer Publishing.

Lovett, M., C, Reder, L., M, & Lebiere, C. (1999). Modeling working memory in a unified architecture: An ACT-R perspective. In P. Shah & A. Miyake (Eds.), *Models of working memory:Mechanisms of active maintenance and executive control* (pp. 135-182). New York, NY: Cambridge University Press.

Newell, A. (1973). You can't play 20 questions with nature and win. In W. G. Chase (Ed.), *Visual Information Processing*: Academic Press.

Newell, A. (1990). *Unified theories of cognition*. Cambridge, MA: Harvard University Press.

Pew, R., W, & Mavor, A., S (Eds.). (1998). *Modeling human and organizational behavior*. Washington, D.C: National Academy Press.

Quigley, K. S., Barret, L. F., & Weinstein, S. (in press). Cardiovascular patterns associated with threat and challenge appraisals: Individual responses across time. *Psychophysiology*.

Ritter, F. E., Quigley, K. S., Klein, L. C., McNeese, M. D., Rooy, D. V., Councill, I., Avraamides, M. N., Stine, M. M., & Rodrigues, I. M. (submitted). Including the effects of pretask appraisal and caffeine in the ACT-R cognitive architecture: Creating a dynamic architectural overlay.

Salvucci, D., D. (2001). Predicting the effects of in-car interface use on driver performance: an integrated model approach. *International Journal of Human-Computer Studies, 55*, 85-107.

Tomaka, J., Blascovich, J., Kelsey, R. M., & Leitten, C. L. (1993). Subjective, physiological, and behavioral effects of threat and challenge appraisal. *Journal of Personality and Social Psychology, 65*(2), 248-260.