MODELING THE TASK ENVIRONMENT: ACT-R AND THE LENS MODEL

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Human factors requires modeling techniques that capture how cognition and behavior are sensitive to environmental design. As such, techniques such as Anderson's rational analysis and Brunswik's lens model framework should be of interest to human performance modelers because they provide ways to analyze tasks and behavior as adaptive to environmental structure. We briefly describe both techniques and contrast them in the context of modeling visual search behavior. We conclude that these techniques can provide complementary resources for human performance modeling in human factors.

INTRODUCTION

A long history exists of examining human behavior and cognition as, at least partially, an adaptation to the structure of the environment (Brunswik, 1956; Gibson, 1979; Simon, 1956). This *ecological* (human-environment systems) orientation is uniquely well suited to human factors due to its ability to identify and describe barriers to successful adaptation and performance that are both internal (e.g., memory or knowledge limitations) and external (e.g., interface or automation design features). Once identified, these barriers can then serve as pointed targets for remediation by interventions such as training, selection, aiding, redesign, reallocation of function, and so on. For this reason, recent years have seen a surge of interest in ecological analysis and modeling approaches in human factors and cognitive engineering. This paper focuses on two such approaches: Anderson's rational analysis (1990) and ACT-R model (Anderson & Lebiere, 1998); and neo-Brunswikian techniques based on ecological analysis and lens modeling (see Kirlik, 2006, for a diverse collection of such models applied to cognitive engineering contexts).

Our goal here is to identify promising areas for integrating these two approaches. We hope this integration will advance prospects for developing and using computational cognitive models of human performance in dynamic, interactive contexts for engineering analysis and design (Kirlik, in press).

MODELING THE ENVIRONMENT IN ACT-R

Anderson (1990) recognized the role that environment plays in understanding human behavior when he developed his theory of rational analysis. Rational analysis is designed to provide a framework for modeling behavior as an optimization to the structure of the environment (Anderson, 1991a).

The ACT-R cognitive architecture (see Figure 1), constrained by the theory of rational analysis, consists of a detailed model of cognition that has been extensively validated in a variety of domains (Anderson and Lebiere, 1998). As depicted in Figure 1, ACT-R is an extensive and articulated model of internal cognition. The design of many of the components of this model have been informed by detailed rational analyses of how cognition may have become optimized to the structure of the external world through human evolution. However, note that Figure 1 represents the external world as a single undifferentiated entity. Our belief that more complete models of interactive cognition and behavior can be gained by integrating ACT-R with the lens model arises from the recognition that the external environment, like internal cognition, often has psychological structure that too can be articulated and modeled. In particular, we note that environments often have proximal-distal structure that is often necessary to analyze and describe in order to identify aspects of adaptive cognition that are context specific and must be learned by a performer in order to achieve successful levels of performance.

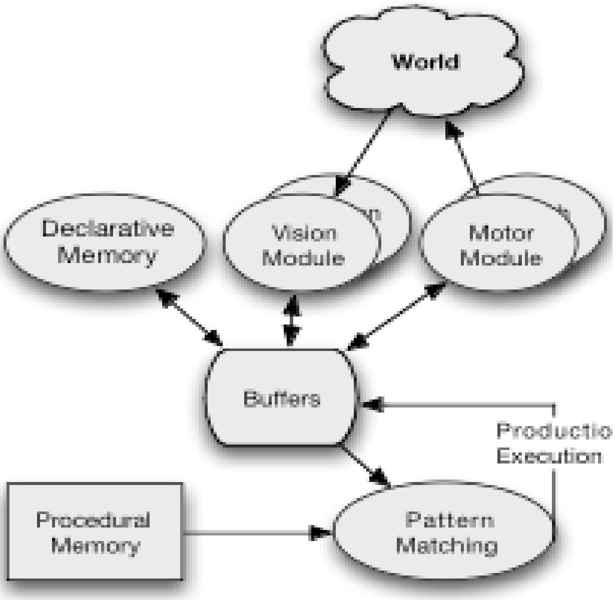

Figure 1. Overview of ACT-R

MODELING THE ENVIRONMENT USING THE LENS MODEL

When describing the contribution of the environment to rational analysis, Anderson (1991b; p. 409) stated:

> A major characteristic of the environments that are relevant to human cognition turns out to be that they are fundamentally probabilistic. Given the cues in the environment one cannot know for sure what to expect. What one can do is to start out with some weak assumptions about the environment and with experience make these increasingly strong.

In rational analysis, Anderson (1990) uses primarily Bayesian statistics to formalize the relations between proximal cues and the distal criterion or goal that must be inferred, recalled or achieved on the basis of proximal (readily available) cues. The important point to note here is that rational analyses (e.g., of memory, categorization, etc.) is motivated by evolutionary arguments and thus reflects probabilistic proximal-distal structure that has been relatively stable over the course of human evolution. Cognitive mechanisms, such as those modeled in ACT-R, can thus be viewed as embodying internalizations of these stable ecological structures.

While some aspects of adaptive behavior are indeed likely to have their origins in the operations of evolutionarily selected cognitive mechanisms, others are due to task- and context-specific adaptations to specific cue-criterion relations. Capturing this component of adaptive behavior, due to context-specific experiential learning, complements ACT-R’s attempt to capture evolutionarily optimized components of adaptive cognition.

The lens model is based on Brunswik’s probabilistic functionalism, analogous to the way ACT-R is based on rational analysis. The basic concept of probabilistic functionalism is twofold: (1) it emphasizes the relationship between the participant and the environment; and (2) the participant-environment relationship is based on uncertain relationships among the environmental variables (Cooksey, 1996).

The lens model allows one to study the complex *interaction* between the performer and the environment by creating dual symmetrical models, shown in Figure 2. The right side of the figure represents a model of the performer, while the left side is the model for the environment. In the center of the figure are the cues ($x_1 \ldots x_n$), which are shared by both the person and environment models. The cues are the pieces of information that are proximal, or readily available to the person. These cues are used to infer information about distal, or not directly observable objects and events. Lens modeling allows the comparison of how the person is using, or weighting, the cues ($r_{s,1} \ldots r_{s,n}$) with how the cues should be optimally weighted based on the environmental cue validities ($r_{e,1} \ldots r_{e,n}$). Additionally, the performer and environment are related through an overall measure of achievement (r_a). Achievement is the degree to which the person has adapted to the task criterion (environment) to the extent that environmental predictability allows. In other words, successful adaptation in the lens model is not measured in relation to performing perfectly with respect to the task criterion, but rather, it is measured as the ability to adapt to the structure of the environment given the quality of proximal cues available for doing so.

Typically, but not necessarily, measuring adaptation is accomplished by evaluating the match between the ecological validities (reliabilities) of the proximal cues and the pattern of cue weighting (usage) demonstrated by the performer. Hammond and Stewart (2001) present research demonstrating the utility of lens modeling for understanding adaptive behavior, and its limitations, in a huge variety of contexts, such as social judgment, rapport, medical diagnosis, weather forecasting, and so on. Kirlik (2006) provides research demonstrating the utility of this style of analysis, and its recent extensions, to cognitive engineering contexts such a fault diagnosis, aircraft conflict detection, adaptations of pilots to ATC clearances and taxiway geometries, browsing the world wide web, and the like.

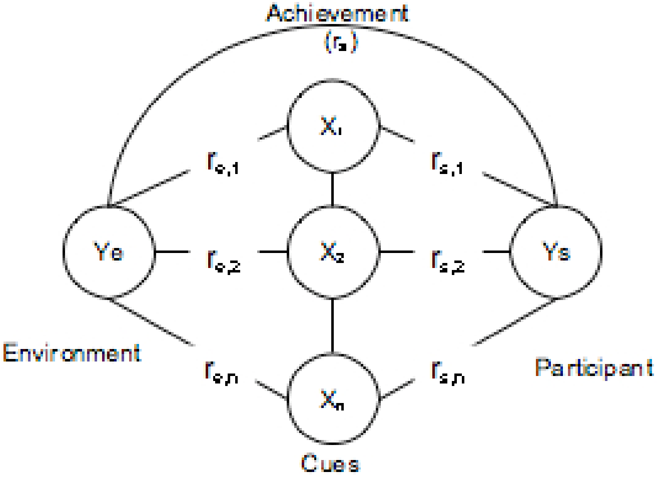

Figure 2. Brunswik's lens model

AUGMENTING ACT-R WITH LENS MODEL ANALYSIS

In order to discuss how ACT-R and Lens model analysis can provide complementary resources for human performance modeling, consider the excellent research of Salvucci (2006), who developed an ACT-R model of automobile driver behavior with control, monitoring, and decision making components. This model provided a good fit to human driver data for lane keeping, lane-changes, and curve negotiations during highway driving. The monitoring component of the driving task was described in terms of maintaining situation awareness of any vehicles around the driver’s vehicle. A random-sampling model was used to check one of four areas around the driver’s vehicle (forward, backward, left, or right) to determine if any other vehicles were present according to a set of four probabilities associated with each the four locations to be sampled.

Let us assume that we wanted to investigate whether Salvucci’s model was adaptive in terms of the frequency with which it sampled these four locations (or we wanted to test whether human sampling frequencies during driving were adaptive). This task cannot be done solely by appeal to the adaptive nature of ACT-R's cognitive mechanisms, but must also consider the structure of the driver's external environment. Where are cars more likely to appear? How quickly does this information change over time? An adaptive attention allocation mechanism would have to be finely tuned to these ecological parameters. We now discuss how a lens model approach could be used to address these issues. Although lens modeling has typically been applied to judgment and decision making tasks (Hammond and Stewart, 2001), we have recently extended the approach to model adaptive allocation of visual attention in monitoring tasks (Miller, Kirlik, Kosorukoff, and Byrne, 2004).

A LENS MODEL OF VISUAL ATTENTION ALLOCATION IN SYSTEM MONITORING

The environmental portion of the lens model of visual monitoring was developed based on previous models of visual attention allocation. Senders (1964) developed one of the first and most influential models of monitoring behavior. According to this theory, performers sample dynamic information sources to reduce uncertainty about the state of the environment. The uncertainty in the environment stems from the rate of information, or *bandwidth*, presented in displayed signals. Senders (1964) applied the Nyquist sampling theorem, which suggests that, to effectively monitor a display, it is necessary to sample a signal at two times the bandwidth (a bandwidth of W Hz would need to be sampled at a rate of 2W Hz).

Additionally, a more recent and encompassing visual attention allocation model developed by Wickens and colleagues (Wickens, Goh, Helleberg, Horrey, and Talleur, 2003), called "SEEV", suggests that attention is directed to an instrument or display based on four factors: Salience (S), Effort (EF), Expectancy (EX) (or bandwidth), and Value (V). According to this model, bandwidth and value are considered to be the "optimal" factors in guiding attention allocation. That is, for well-trained operators, these two components *should be* the only factors that drive scanning in a goal-oriented context (Moray, 1986), even though the scanning of relatively naive performers may be initially influenced by feature salience and sampling effort (Araujo et al., 2001).

Based on these models, it has typically been assumed that sampling is adapted directly *to* bandwidth. However, bandwidth is not necessarily always perfectly predictive of the meaningful events the monitor is trying to detect (e.g. when the signal travels into an unsafe region). For example, when an experienced operator is confronted with a signal that has a high bandwidth, but rarely travels into an unsafe region (i.e. alarm rate), it is unclear whether the signal will be sampled at the same frequency as a signal that has the same bandwidth but higher alarm rate. Instead of viewing signal bandwidth as directly driving sampling, we conducted an experiment to determine whether the relationship between bandwidth and alarm rate had any effect on sampling. In terms of the lens model, we investigated whether adaptation was influenced by the reliability of the proximal bandwidth cue (i.e. its ecological validity) in predicting a distal task criterion.

In our laboratory task, shown in Figure 3, participants were asked to monitor a series of four gauges whose pointers moved at various bandwidths. The goal of the participant was to detect when any pointer traveled out of bounds (an "alarm") within one second of passing the alarm threshold. For each gauge, the dark gray area is the alarm or out of bounds region and the light gray was the safe range. At the onset of each trial, the pointer (shown here at 12 o'clock) in each of the gauges would move at various bandwidths (0.5, 1.0, 2.0, or 4.0 rad/sec). Directly below the safe region on each gauge the light gray bar represents the value prescribed to the gauge. Correct alarm detections on the gauge with the widest bar were worth 8 points, the remaining gauges were worth 4, 2, and 1 point(s) respectively.

The correlation between the proximal bandwidth cue and the distal alarm rate, termed ecological validity (EV), was varied across three groups of participants (EV = 1.0, 0.75, and 0.25). EV was measured across the four gauges rather than for each individual gauge. Therefore, in the EV=1 group, the gauge with a bandwidth of 4.0 rad/sec had twice as many alarms as the gauge with a bandwidth of 2.0 rad/sec. In the EV=0.75 and EV=0.25 groups the relationship was less direct. The bandwidth and value cues were the same across all groups.

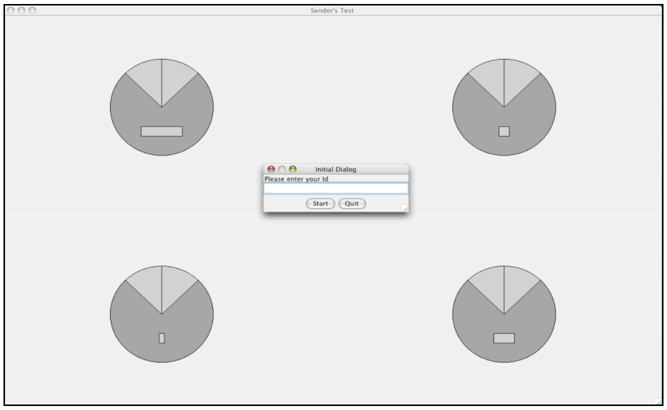

Figure 3. Sample display at trial onset. Note that this screen shot filled the screen on a Macintosh 17" flat panel studio display.

The lens model was first used to compare the correlation between the participant's observed monitoring behavior versus optimal monitoring. The participant model was measured as the cumulative dwell time for each of the four gauges over the course of the trial (% of time spent viewing each gauge). The environmental, or optimal, model was calculated based on the assumption that sampling should be proportional to the number of points that could be scored by detecting alarms on each gauge over the course of the trial. As such, the gauges that had a higher number of points, based on the product of the alarm rate and value, should be sampled more often, in proportion, than those where the product was lower. The subjective measure of dwell time was compared with the optimal dwell time to make up the achievement (r_a) component of the lens model. Figure 4 compares the optimal versus observed fixation frequencies across the three EV groups. The difference between optimal and observed sampling across the three groups suggests that EV does indeed affect sampling behavior. Also note the relatively good fit between the optimal and observed dwell times for the EV=1.0 and EV=0.25 groups, while the EV=0.75 group exhibited an almost complete lack of adaptivity. See Miller et al. (2004) for additional details.

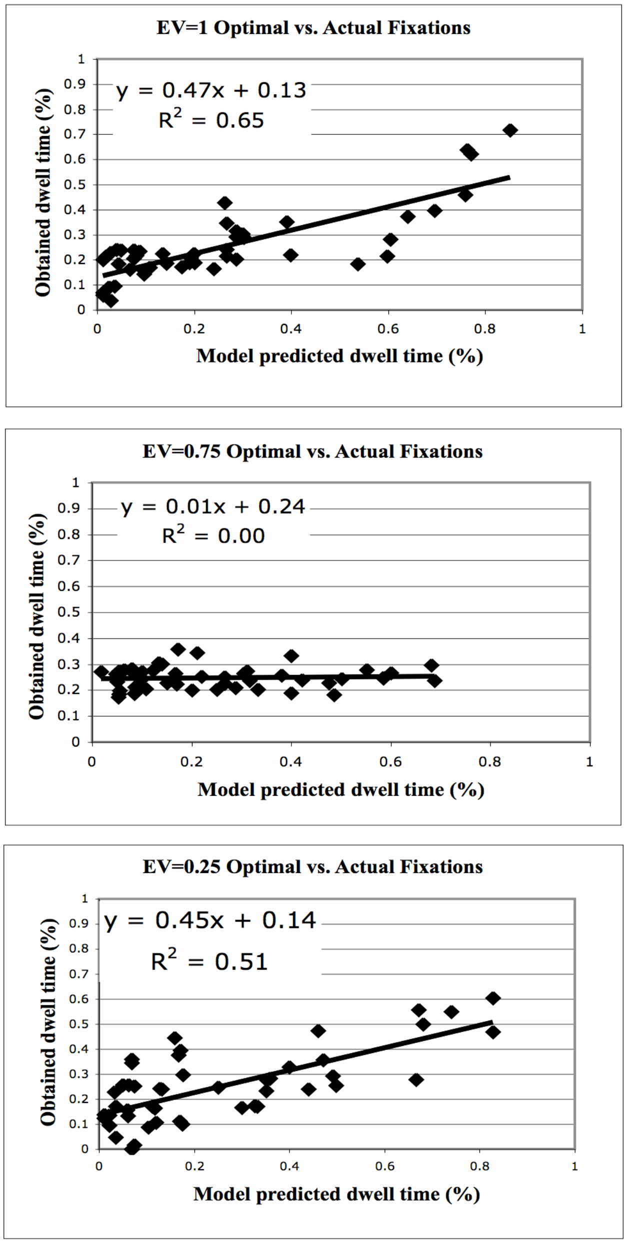

Figure 4. Model predicted versus observed dwell time.

Lens modeling was also used to examine the relation between how monitoring is subjectively influenced by the bandwidth and value cues and how the cues are objectively related to the task criterion (alarm rate). Figure 5 compares the objective versus the optimal weighting of the bandwidth and value cues for each of the three EV groups. The correlation between bandwidth and alarm rate affected how the bandwidth cue should be optimally weighted, while the optimal value weights were about the same across groups. This was expected because as the predictability of the proximal bandwidth cue decreased, participants should place less weight on the cue. Also as expected, value remained similarly predictable across conditions because the predictability of the value cue was not manipulated across groups. The observed (participant) weighting of bandwidth was similar across groups, while the value cues were weighted differently. For the EV=0.75 group, the positive weight attributed to the bandwidth cue combined with the negative weighting of the value cue provides additional evidence of a lack of adaptivity for participants in this group. Additional information and discussion of the results is provided in Miller et al. (2004).

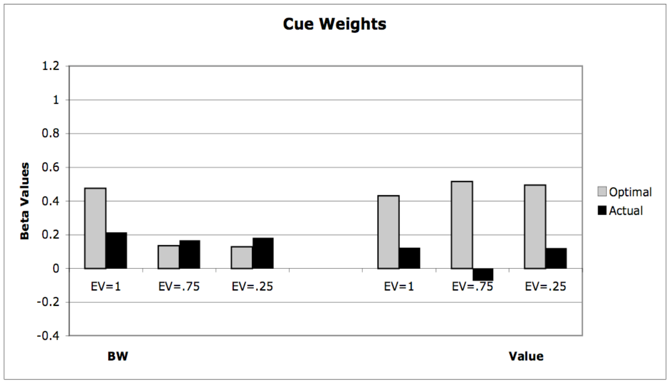

Figure 5. Lens model parameters and cue weights.

INFORMING AN ACT-R MODEL WITH LENS MODELING

To illustrate how the lens model could potentially be applied to complement ACT-R modeling, we return to Salvucci's (2006) model of automobile driver behavior as an example. Monitoring was based on maintaining situation awareness by randomly sampling, with probability *p*, one of four areas around the driver's vehicle (front, back mirror, left mirror, and right mirror). The lens model could be used to determine the optimal sampling probability for each of the four areas. Informed by Senders (1964) and Wickens et al. (2003) models of visual attention allocation, the first step would be to determine the bandwidth and value associated with each of the areas of interest. For driving, bandwidth could initially be determined from the frequency of presence or absence of vehicles in the areas of interest. Further development of the model could include identifying additional proximal or distal information such as the velocities of vehicles in the areas of interest, other drivers' intentions (e.g., turn signals) and so on. A field study or other type of ecological analysis could be used to estimate these components. The attention allocation components in the ACT-R architecture could then be tuned to attend to proximally available perceptual inputs (cues) in a manner best adapted to the task criterion of avoiding collisions.

While the existing ACT-R mechanisms describe adaptive behavior on an evolutionary time scale, the lens model allows the visual attention allocation component to be tuned to context-specific aspects of the driving task. Combining these two modeling techniques allows for an enhanced, complimentary approach to ecological analysis.

CONCLUSION

As mentioned in the introduction, several researchers have recently recognized the potential benefits of considering both rational analysis and Brunswik's ecological functionalism to provide an integrated account of embedded cognition (Byrne, Kirlik, & Fick, 2006; Gray, 2006; Pirolli, 2006). Yet, all approaches for "taking the environment seriously" in the study of cognition are not identical. In particular, we have tried to point out that, especially for modeling highly interactive behavior, rational analysis and ACT-R might have to be augmented to include techniques for explicitly modeling the manner in which cognition is adapted to context-specific environmental structure consisting of cue-criterion relations. Brunswik's lens model is one candidate framework for doing so, because this approach requires the development of explicit environmental models of this structure. Collectively, the rational analysis and lens model approaches can be used to show how the "mechanisms of cognition (can be) meshed with the external environment to form integrated cognitive systems" (Gray, 2006).

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REFERENCES

Anderson, J. R. (1990). *The adaptive character of thought*. Hillsdale, NJ: Erlbaum.

Anderson, J. R. (1991a). Is human cognition adaptive? *Behavioral and Brain Sciences*. *14*(3), 471-485.

Anderson, J.R. (1991b). The adaptive nature of human categorization. *Psychological Review*. 98, 409-429.

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

Araujo, C., Kowler, E. & M. Pavel (2001). Eye movements during visual search: The costs of choosing the optimal path. *Vision Research*, 41, 3613-3625.

Brunswik, E. (1956). *Perception and the representative design of the psychological experiments*. Berkeley: University of California Press.

Byrne, M. D., Kirlik, A., & Fick, C. S. (2006). Kilograms matter: Rational analysis, ecological rationality, and computational cognitive modeling of dynamic system control. In A. Kirlik (Ed.) *Adaptive perspectives on human-technology interaction: Models and methods for cognitive engineering and human-computer interaction*. New York: Oxford University Press.

Cooksey, R. W. (1996). *Judgment analysis: Theory, methods, and applications.* San Diego: Academic Press.

Gibson, J.J. (1979). *The ecological approach to visual perception*. Boston: Houghton Mifflin.

Gray, W.D. (2006). The emerging rapprochement between cognitive and ecological analyses. In A. Kirlik (Ed.) *Adaptive perspectives on human-technology interaction: Models and methods for cognitive engineering and human-computer interaction*. New York: Oxford University Press.

Hammond, K. R. & Stewart, T. (2001). *The essential Brunswik*. New York: Oxford University Press.

Kirlik, A. (in press). Ecological resources for modeling interactive behavior and embedded cognition. In W.D. Gray (Ed.) *Integrated models of cognitive systems*. New York: Oxford University Press.

Kirlik, A. (2006). *Adaptive perspectives on human-technology interaction: Methods and models for cognitive engineering and human-computer interaction*. New York: Oxford University Press.

Miller, S.M., Kirlik, A., Kosorukoff, A., Byrne, M.A. (2004). Ecological validity as a mediator of visual attention allocation in human-machine systems. *University of Illinois Human Factors Division Technical Report AHFD-04-17/NASA-04-6*. Available from: http://www.humanfactors.uiuc.edu/research/pubIndex.aspx

Moray, N. (1986). Monitoring behavior and supervisory control. In K. Boff, I. Kaufmann, and J. Beatty (Eds.) *Handbook of perception and human performance.* New York: Wiley.

Pirolli, P. (2006). The use of proximal information scent to forage for distal content on the World Wide Web. In A. Kirlik (Ed.) *Adaptive perspectives on human-technology interaction: Models and methods for cognitive engineering and human-computer interaction*. New York: Oxford University Press.

Salvucci, D. D. (2006). Modeling driver behavior in a cognitive architecture. *Human Factors*, *48*, 362-380.

Senders, J. W. (1964). The human operator as a monitor and controller of multidegree of freedom systems. *IEEE Transactions on Human Factors in Electronics,* HFE-5, 2-5.

Simon, H.A. (1956). Rational choice and the structure of environments. *Psychological Review*, *63*. 129-138.

Wickens, C. D., Goh, J., Helleberg, J, Horrey, W.J., and Talleur, D.A. (2003). Attentional models of multitask pilot performance using advanced display technology. *Human Factors* 45(3), 360-380.