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18

Including Human Variability in a Cognitive Architecture to Improve Team Simulation

Frank E. Ritter and Emma Norling

1 INTRODUCTION

When sophisticated models of human behavior are used in synthetic environments or video games, they typically attempt to capture normative behavior by providing homogenous agents from a cognitive architecture. A recognized shortcoming of this approach is that in reality people do not always behave in exactly the same manner: no matter how well trained a person might be, there are always instances when they deviate from what is prescribed by their training. Even when following doctrine, there can be considerable variability across individuals (Pew & Mavor, 1998; Ritter et al., 2003). This variability, even after differences in knowledge are removed, arises both from individual differences, where different abilities can lead to marked differences in behavior, and also from behavior moderators – internal and external factors, typically related to time, that moderate individual differences, compounding the effect of individual differences. As well as having a considerable impact on individual behavior, such variability will also strongly influence team and organizational performance.

Much of organizational theory and practice is designed to study individual differences and their impact on team performance, however most existing cognitive architectures create homogenous models unaffected by time. Some social simulation models do explore the impact of individual differences (e.g., cooperative versus non-cooperative agents in Axelrod, 1997; and papers in NAACSOS Conferences), but in such cases, the differences are usually modeled at a coarse level, or simply as differences in knowledge alone. As discussed below, more subtle individual differences can have considerable impact on teams and larger organizational units. COJACK, the architecture introduced in this chapter, is designed to model individual differences and variability in a psychologically plausible manner, facilitating simulation of such phenomena.

After very briefly reviewing how individual differences can modify teamwork in Section 2, in Section 3 we provide examples of architectures that support modeling variability. In Section 4 we then discuss the types of variability that should be supported by architectures, briefly outlining how this can be achieved. Finally, we conclude with a discussion of how these considerations have influenced the design of COJACK, and issues that will affect other architectures.

2 HUMAN VARIABILITY AND ITS INFLUENCE ON TEAMWORK

Several areas of research have long recognized that human variability plays an important role in team dynamics, and that different combinations of team members will have considerable impact on the overall performance of teams. In social psychology, the Myers–Briggs personality test often is used to study how team composition affects team performance. In the area of human factors research, for example, numerous authors in this book and in McNeese et al.'s (2001) book examine how team member's information processing capabilities will modify team performance and attempt to design optimal teams based on tasks and team member capabilities.

In management science, Belbin (1993) identified nine "team roles" for members of management teams, where each role type contributes in different ways to the team. These roles are based on a range of factors, including cognitive ability and personality factors. For a team to perform well, it must contain a balance of these roles. He also notes that some individuals do not obviously fit in one particular role, but that this can be a strength or weakness depending on how the individual reacts to it. It can mean that this person is flexible and able to take on different team roles as the need arises, but it can also mean that the individual is not a good "team player." Belbin's work focuses on management teams. Other sources of human variability will be important for other types of teams. For a team engaged in physical work, the perceptual/motor ability of individual team members will make them more or less suited to particular roles. The performance of team members will also be constrained by the abilities of others – for example, a team traveling together cannot progress together any faster than its slowest member.

3 VARIABILITY IN EXISTING COGNITIVE ARCHITECTURES

There are considerable differences in the types of variability supported by existing cognitive architectures. Here we briefly outline some of the architectures that provide lessons in this area.

3.1 ACT-R, Soar, and CLARION

Like almost all cognitive architectures, ACT-R, Soar, and CLARION (Chapters 2, 3, and 4 in this book) support modeling individual differences as differences in knowledge. There have been several efforts to extend Soar and ACT-R to incorporate further aspects of variability, and CLARION can be used in this way (Chapter 6 by Naveh & Sun). In Soar, Chong (e.g., 1999) has started to include moderators such as fear, but his models do not allow for changes in the influence of the moderators over time: the models start and stay fearful. The work by Gratch and colleagues (e.g., Gratch & Marsella (2004); and Chapter 9 here) incorporates a model of appraisal that updates the agent's emotional state over time. A model of teamwork has been developed in Soar (STEAM: Tambe, 1997), but human variability has not yet been explored within STEAM to our knowledge.

The most recent version of ACT-R (5.0) includes a model of perception and action with noise parameters that can be increased to cause more variation, in addition to the cognitive parameters provided by previous versions. There have been a few projects that have attempted to include more aspects of individual differences (e.g., Daily, Lovett, & Reder, 2001) and the body and its effects on cognition (Jongman, 1998; Ritter, Avraamides, & Councill, 2002), but none of these have also examined teamwork.

3.2 Other Cognitive Architectures

There are several other architectures that support human variability (e.g., Epic: Meyer, Glass, Mueller, Seymour, & Kieras, 2001). We only review a few examples here. PSI (Dörner, 2003), one of the more complete, includes a body and a sense of time, in addition to parameters related to individual differences. These two aspects play an important role in modeling human variability. PSI's behavior in a complex task has been compared with human behavior (Detje, 2000), demonstrating that models and humans need a complex task with several subtasks to express variability – if there is only one task, the model cannot give up on that task, or prefer a different task. The human data in this complex task showed that the behaviors and behavior orders varied across individuals. Finally, varying the drives and individual parameters in the model gave rise to different types of behavior. MAMID (Hudlicka, 2004) is a similar architecture that starts to model the effects of moderators on cognition but extends this to model the effects on leadership; PMFserv includes moderators and has been used to model crowd behavior (Silverman, 2004).

Sloman (2000) has argued the need to include emotions in human modeling, and has developed the Sim_Agent toolkit to explore these types of architectures (Sloman & Logan, 1999). The use of this toolkit has illustrated that there is a wide range of differences to explore. Social science simulations such as appear at the NAACSOS Conference model teams, but have tended either not to model cognition in detail or else not to model variability. There are no doubt further exceptions.

4 ADDING SUPPORT FOR HUMAN VARIABILITY

Human variability can be viewed as consisting of three types of variability. The first type is inherent individual differences of abilities, such as working memory capacity. The second and third types represent external and internal factors that cause an individual to vary their behavior over time (Ritter, 1993). A variety of reviews have been undertaken that provide support for modeling these differences, including Boff and Lincoln's general review (1988), and Silverman's (2004) focused survey.

This section summarizes the types of parameters that we propose to start to model individual differences and to support modeling behavioral moderators, and is taken from a more detailed review (Ritter & Norling, 2003).

4.1 Individual Differences

Our initial survey identified approximately sixty architectural parameters that have been studied because they give rise to individual differences that can be broadly classified into four groups: cognition, perception, action, and physiology. Although this parameter set is not exhaustive (it would certainly be possible to find many more parameters that influence human reasoning and action), we believe that this set is a sufficient initial set to capture the main elements that contribute to human variability. We briefly describe each group, presenting examples to illustrate how they can influence agent behavior.

4.1.1 *Cognition*

The parameters that we have selected to capture variability in cognition are primarily taken from ACT-R 5.0 (Anderson et al., 2002). This parameter set has been extensively validated. In addition to these parameters, we have identified a number of higher-level parameters affecting cognition, such as the number of parallel tasks that can be maintained. We have included a few personality variables such as acquiescence. Ultimately, however, we believe, these higher-level effects should arise from the effects of lower level parameters.

4.1.2 *Perception*

The majority of simulated environments provide most perceptual data as visual data, sometimes also including sound. Here we focus on visual perception. A similar parameter set has been developed for aural perception.

TABLE 18.1. *Example parameters of visual perception. Defaults are taken from the literature. Suggested standard deviations, in parentheses, in most cases are estimated.*

Parameter	Default	Description
Saccade time	120 ms (10 ms)	Time taken to move the eye to a new location.
Fovea size	3 deg. (0.2 deg)	The size of the cone of vision for which full visual detail is available.
Visual working memory	3 (0.5)	The number of items that can be stored in the visual buffer.

Table 18.1 provides several examples. These parameters (and the mechanisms that they influence) are assumed to be separate from other cognitive mechanisms. This approach treats perception as impenetrable, in that cognition is assumed not to modify how perception works (Pylyshyn 1999). This assumption is useful because it makes it easier to create cognitive agents. There are already suggestions that this approach is too modular when taken to this extreme, and should only be seen as a useful working hypothesis.

4.1.3 *Action*

Existing models that have typically included motor output have often done so at the level of hand movements and typing (e.g., ACT-R/PM: Byrne, 2001; EPIC: Meyer et al., 2001; SegMan: St. Amant & Riedl, 2001; Sim-eyes and -hands: Jones, Ritter, & Wood, 2000; Norling & Ritter, 2001; Ritter et al., 2000). The more accurate models include parameters to modify both speed and accuracy. Speed particularly is not constant over time, with variance under standard conditions that can itself be affected by moderators.

The fine-grained level of mouse and keyboard inputs does not, however, correspond to the level of detail provided by the simulation environments in which many agents will operate. The architecture should also provide support for movement at other levels of granularity, such as walking. Parameters and mechanisms for gross motor movements are likely to be particularly important for modeling fatigue, both as a variable that is influenced by moderators, but also because motor output over time increases fatigue.

4.1.4 *Physiology*

Physiological parameters are necessary to represent fundamental aspects of the agent's body. Initial settings will represent individual differences. They will also help implement the effects of other moderators and time. Many physiological aspects of a body may influence the agent via their interaction with other parameters rather than or in addition to directly influencing the reasoning/action of the agent. As such, they can themselves be seen as behavior moderators. For example, heart rate and blood pressure influence how quickly stimulants are taken up and then excreted.

Parameters we have included in this set include heart rate, blood pressure, body temperature, and levels of various naturally occurring hormones (such as cortisol). One of the difficulties of including these parameters at this stage is that the effects of many of these variables on cognition have not been extensively studied particularly with models in mind, giving us limited data to work with (Silverman, 2004). As a result, it is likely that the initial versions of architectures will contain only placeholders for these parameters, without attempting to capture their full influence. They do, however, provide useful suggestions for further research.

4.2 Behavior Moderators

Extending Ritter's (1993) earlier analysis, we have grouped behavior moderators and the variables to implement them into three classes: external (arising outside the entity), internal (arising from internal changes in the entity), and task-based (arising from processing). Task-based moderators can be seen as a special sub-class of internal moderators. They have important implications for modeling behavior, so we keep them separate.

4.2.1 *External Moderators*

External moderators are external events or conditions that affect the entity's behavior. These include things such as temperature, noise, and time of day. The range of external moderators that *could* be modeled is extensive, but the choice of moderators to include will depend on the model, the task to be performed, and most importantly, the perceptions that are available from the model's environment.

External moderators influence the agent's body, and will have to be implemented as changes to intermediate, physiological parameters that are time dependent. The effect of temperature, for example, is a cumulative function. These parameters can then be used to moderate cognitive parameters.

4.2.2 *Internal Moderators*

Internal moderators are those that arise out of changes within the individual, especially over time. Variations in the values of the entity's parameters can themselves lead to variations in other parameters. Task-based moderators (discussed next) are a special sub-class of internal moderators. Other types of internal moderators include changes in physiology with time (e.g., caffeine) and sleep and fatigue-related factors.

Chemical moderators such as caffeine are, in a way, like external moderators. These moderators originate outside the body, but it is their effect

on the body (and subsequently on the brain) that produce the changes i behavior. Typically, an initial dose is ingested, which may take some tim to be absorbed, and then over time the chemical is excreted. The level c the chemical affects various aspects of cognition, perception, and action.

4.2.3 *Task-Based Moderators*

Task-based moderators are those associated with the information bein processed and the passage of time. Most cognitive architectures assum that their mechanisms are fixed across time; however, there are many ele ments of the task that can moderate behavior, including time itself. Sampl task-based moderators include boredom, fatigue, and appraisal/emotiv moderators. We know, for example, that performance on a vigilance tasl drops 20% over as little time as an hour (Boff & Lincoln, 1988, Ch. 7.403).

4.3 Including Variability for Team Studies

Differences across individuals and over time within an individual are im portant when studying team performance. Obviously, some of the param eters that we have identified will have more of an impact on teamworl than others. For some of the lower level parameters, their influence o teamwork may be indirect and not yet known. However, many behaviora differences arise from the interaction of parameters and moderators, s consideration must be made before discarding any particular paramete The effect of reaction time, for example, on teamwork, appears to be littl studied, yet Gratch and Marsella (2004 and Chapter 9 in this book) repor reaction time as important for interpreting social agent cognition. In th absence of better measures, those parameters that are most clearly under stood should be implemented first, providing a framework for testing th implementations of less studied or more complex parameters.

5 MODELING TEAM AND ORGANIZATIONAL EFFECTS OF INDIVIDUAL DIFFERENCES

We present here an overview of COJACK, a project to create a cognitiv architecture that supports human variability. It is based on the lessons fron the architectures reviewed and uses the parameter set we have develope (Ritter & Norling, 2003). Many aspects of this architecture will also b important in other cognitive architectures in the future.

5.1 The Development of COJACK

COJACK is based upon an existing agent programming language, JACK (www.agent-software.com.au). As JACK is a Belief-Desires-Intention (BDI)-based language, its core constructs correspond to folk psychologica

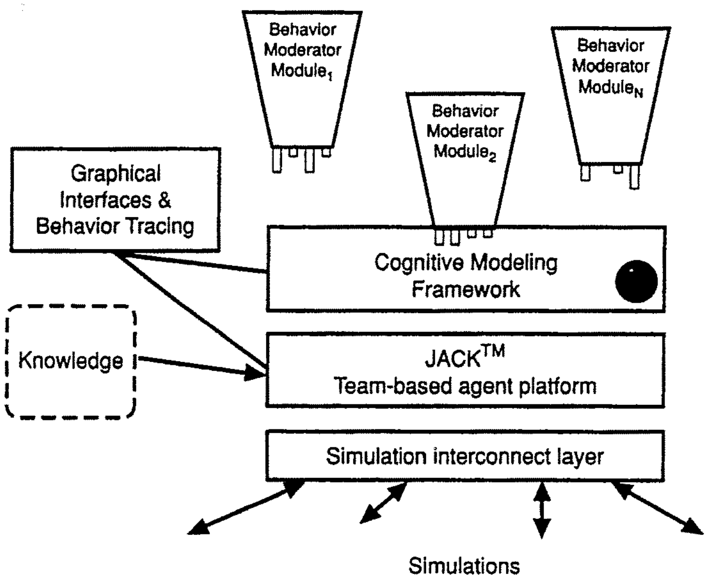

FIGURE 18.1. Schematic of the COJACK cognitive agent-based architecture.

concepts. This level of representation facilitates both knowledge capture from the experts to be modeled and understanding the models that are developed (Norling & Sonenberg, 2004). JACK provides a level of abstraction useful for knowledge acquisition and model understanding; COJACK fills in the details needed to support variability. We aim to maintain the usability of JACK while supporting cognitive plausibility.

COJACK is a software overlay for JACK that supports individual differences through the set of parameters outlined earlier, and behavior moderators via active modifications to these parameters. These parameters vary across time in a particular individual, as well as across individuals. Finally, COJACK is tied to the environment through a simulation interconnect layer, which remains an important aspect of modeling (Ritter, Baxter, Jones, & Young, 2000). COJACK's implementation has been tested with a model of serial subtraction, a task commonly used to stress subjects. Figure 18.1 provides a schematic of COJACK. This framework includes constraints on its processing mechanisms. These processes degrade with time on task (or are refreshed with rest).

The behavior moderator modules, which look like a type of key in the figure, represent different settings of these parameters, including how the parameters influence each other and how fast they change with time.

Currently, settings are designed to be used in isolation to modify the cognitive architecture as an overlay, but in time they will interact to produce cumulative effects. This merging will be limited by our attention as well as the paucity of data of how multiple moderators interact.

Graphical interfaces and traces will be supported though the cognitive modeling framework as well as the base agent architecture. These displays and traces are necessary for debugging and for explanation to users.

5.2 The Addition of a Simulated Body

Cognitive aspects alone are not enough to support human-like variability; the interactions between perception/action/physiology/cognition are important. Several architectures have included parts of bodies, particularly perception and action, but it is time to start to include further parameters related to a body, such as reservoirs related to sleep and energy (as in PMFserv and PSI). The full range of interactions between physiology and cognition are not yet understood, but capturing more of these effects will prove important.

5.3 The Importance of Time and Usability

Few existing cognitive architectures alter their behavior because of changes in physiology with the passage of time. However, the effects of nearly all of the important moderators considered here (e.g., fatigue, stimulants) change as time passes. Architectures that wish to model such moderators will have to include the effects of time, and modify their bodies and information processing mechanisms accordingly.

Modeling these additional physiological processes and time will require that some attention be paid to usability. The overlays will have to be clear, with their effects included in model traces, and to be inspectable because these parameters will intentionally vary across individuals, with time, and with initial settings. The overlays will draw on research that most cognitive modelers are not familiar with. All these factors will make the models harder to use, ironically, making models more like the humans they are meant to simulate.

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