Culturally-Affected Human Behavior Modeling and Its Applications to Serious Games

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AI systems can be divided into two categories, those that seek to think/act rationally and those that seek to think/act like humans (Russell and Norvig 2003). The systems that have rational behavior as their goal don't attempt to account for the social factors that influence human behavior in many ways. Even the systems with human-like behavior as their goal, such ACT-R (Anderson et al. 1995) and Soar (Laird, Newell, and Rosenbloom 1987), generally focus on either passing the Turing Test or detailed aspects of cognition and/or models of neural physiology. There are very few AI systems that attempt to account for the social influences on human behavior. Three possible examples are PsychSim (Pynadath and Marsella 2005), Silverman's Performance Moderators Functions (Silverman 2001) and PGREDS (Franceschini et al. 2004).

The goal of the Culturally Affected Behavior (CAB) effort at the University of Southern California's Institute for Creative Technologies (ICT) is to develop a computational approach for representing, encoding, and using cultural knowledge modularly at the individual and aggregate level. Unlike most of the research in sociology, anthropology and psychology, the cultural models and representations the CAB effort seeks to develop will be integrated into AI behavior generation algorithms and virtual environment simulations. This requires that our approach to cultural modeling be computational in order to be implemented as part of a human behavior model. One of the primary challenges of the CAB effort is to create a representation that is easy to author and modify as well as being able to support changes to an AI character's cultural model without reauthoring that character's entire behavior set. The CAB project addresses this challenge by trying to modularize the cultural model into a chunk of knowledge that affects the AI agent's appearance, reasoning and behavior but, to the extent possible, is separate from the rest of the agent's behavior model. Culture obviously has a deep and pervasive influence on behavior and the extent to which cultural knowledge can be modularized is a central research challenge of the CAB effort.

Beyond the rational vs. human-like distinction, AI systems can also be characterized by the forms of information they take as input, their internal reasoning mechanisms, and the forms of behavior they output. Two examples are agent-based AI architectures, such as Soar and ACT-R, and automated planning systems (Ghallab, Nau, and Traverso 2004). Agent architectures take as input knowledge about a domain (often encoded as rules) and perceptions of the local environment, reason by rule matching and forward and/or backward chaining, and output atomic actions to be performed in the environment. Automated planning systems take as input an initial world state, a goal world state, and a list of available actions or operators, reason primarily through state or plan-space search, and output a plan (sequence of actions) that will achieve the goal state from the initial state. One approach to designing a culturally-influenced behavior generation system is to consider what cultural information should be included in the inputs to the system (knowledge and sensors), how that information should influence the reasoning, and what cultural information needs to be included in the outputs of the system. In addition, it is vital to consider the authoring process that generates the system inputs. As shown in Table 1, inputs will include cultural descriptors for the entity (ethnicity, religion, political affiliation, economic status, nationality, age, gender, languages spoken), a modular culture model which includes both high-level parameters and detailed culture-specific behavior, and information about the cultural context of the entity's environment. These cultural inputs will have influences on how the entity reasons (goal selection, beliefs, attitudes, emotions, biases…) and the range of actions considered by the entity. Cultural influences on the entity's reasoning will be indirectly observable through their effect on the generated behavior (i.e. what action or plan is output by the system) and directly observable as the actions and plans themselves will be culturally annotated to modifying execution (based on social conventions, target language, dress, local gestures, diet, etc.).

Table 1: Inputs, reasoning techniques, and outputs for AI behavior generation systems.

	Inputs	Reasoning	Outputs
Agent-based systems	• Knowledge • Perceptions	• Rule matching • Forward chaining • Backward chaining	Atomic Actions
Automated planning systems	• Initial state • Goal state • Operators	• State-space search • Plan-space search	Plans
Cultural	• Entity's cultural	• Cultural	Cultural

influence	descriptors • Modular culture model • Cultural context of the entity's environment	influences on reasoning:	influences on actions including annotations on actions and plans for use during execution

Culture has been defined as the collective programming of the mind that separates one group of people from another (Hofstede, 1994). Previous research on culture in the fields of psychology, sociology and anthropology falls into two general categories. Researchers such as Hofstede (Hofstede 1994) attempt to identify a small set of high-level cultural parameters (such as power distance, individualism, masculinity, uncertainty avoidance, long-term orientation) which characterize a culture. This is effectively the cultural equivalent of the Meyers-Briggs personality test (Myers 1962). Other researchers (DiMaggio, 1997) focus on very detailed aspects of culturally-influenced behavior such as greetings and polite/impolite gestures. Unfortunately it isn't feasible to derive the low-level details of culturally-influenced behavior solely from the high-level cultural parameters. Hofstede's five dimensions of culture just don't contain enough information to derive, for example, the fact that in Muslim countries women should not initiate a handshake when greeting a man. However, Hofstede's masculinity dimension (which is generally very high in Muslim countries) could be used as an indicator that there are culturally-important details involved in a woman greeting a man. This dimension might also suggest that Hindu cultures, which have similar masculinity values, might share many details in this area with Muslim cultures. Thus the high-level theories can provide useful indicators and parallels that could reduce the authoring challenge inherent in creating cultural behavior “modules” that encode the details of culturally-influenced behavior. At the very least the high-level theories should point to areas of behavior which are likely to have culturally-specific aspects and/or suggest commonalities between different cultures which might suggest that detailed cultural information can be reused.

ICT has two ongoing efforts, the Virtual Human project and the ELECT BiLAT immersive training application, which are good examples of applications that might take advantage of these cultural behavior modules. From the perspective of the Virtual Human system (Rickel et al. 2002) and Appraisal Theory (Scherer, Schorr, and Johnstone 2001) on which the system is based, culture primarily influences the way in which the virtual human will assess the current situation and the details of the virtual human’s interactions with humans (and other virtual humans). For example, a virtual human with the Iraqi culture module loaded will react to being offered alcohol very differently than a virtual human with the German culture module loaded. In this context even a secular Iraqi culture module will differ from a more religiously motivated Iraqi culture model. Thus the Virtual Human system already has built in some of the dimensions of control that the cultural behavior module can use to modify behavior. Examples of these dimensions of control include goal selection and assessment, language, vocabulary, facial expressions and gestures.

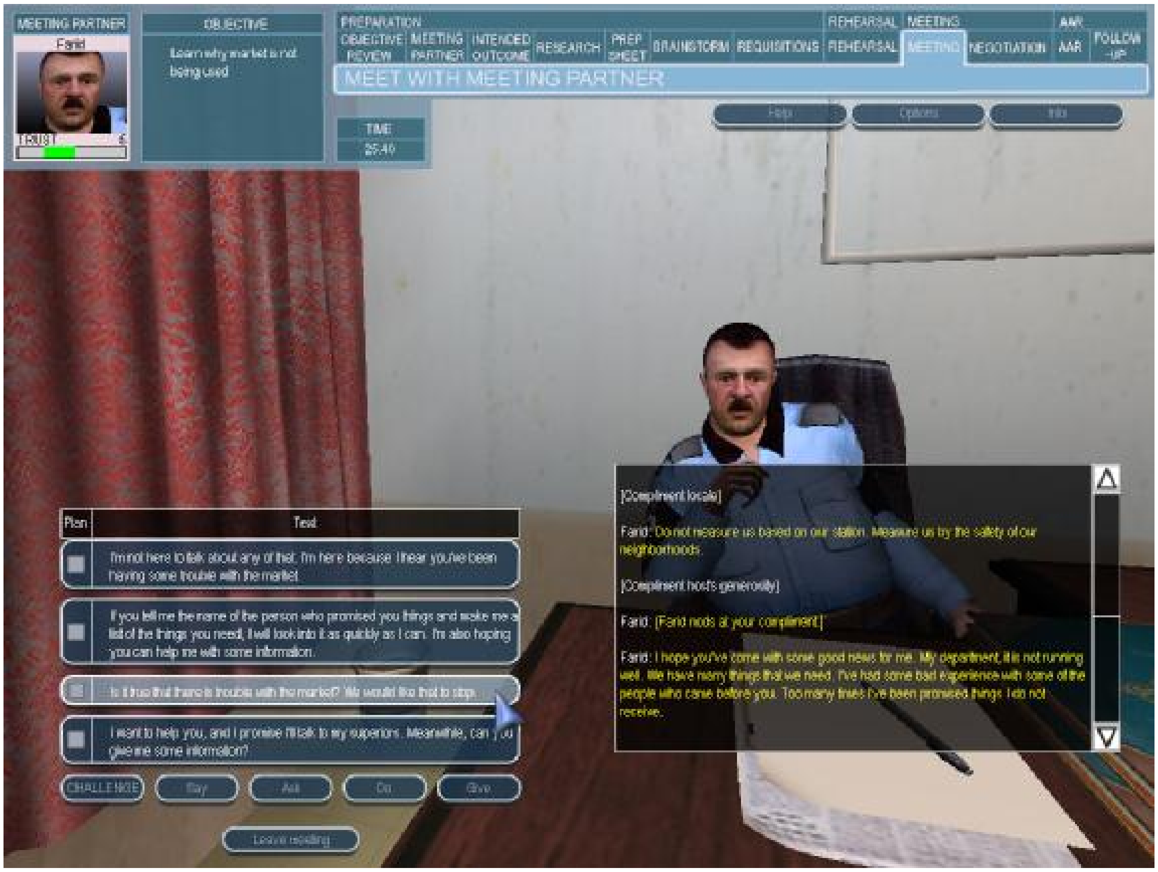

Figure 1: A screenshot from the ELECT BiLAT application which lets student practice preparing for and conducting meetings and negotiations in a cross cultural setting.

The ELECT BiLAT application (see Figure 1) gives students an opportunity to practice preparing for and conducting meetings and negotiations in a cross cultural setting. However, at present the cultural behaviors being developed for the ELECT project are specific to a single culture (Iraqi culture). The elements of Iraqi culture are not structured as a swappable module within the system but are dispersed throughout the system in both explicit and implicit ways. As a result, moving the ELECT BiLAT application to a new culture will require re-authoring much of the system rather than just the parts specific to culturally-affected behavior. By exploring the challenges involved in representing and authoring cultural behavior modules, the Culturally-Affected Behavior project has the potential to allow systems like Virtual Humans and ELECT BiLAT to be adapted to a wide variety of cultures without recreating completely new databases of behavior knowledge.

The above approach describes how cultural information might influence the behavior of a single entity. This approach will work well for modeling the influence of culture at the individual entity level and for small groups of entities, supporting users interacting with the entities in real time. However, another aspect of culturally-influenced behavior occurs at the macro-level involving behavior across large groups and populations modeled not as individual entities but as trends in behavior across interacting cultural groups. An example of culturally affected behavior at this level is the social structure of traditional tribes which varies from culture to culture. The CAB research effort focuses primarily on cultural behavior at the individual level but will also investigate these macro-level cultural behaviors as well.

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