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Modeling of Emotional Effects on Decision-Making by Game Agents

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Abstract

Game AI agents today do not reflect the affective aspects of human behavior. In particular, game agents do not reflect the effects of human emotional state on an agent's decision-making behavior. In rare instances when emotional aspects are addressed in game agent architectures, such behavior tends to be ad hoc and not informed by an underlying theory of emotion, nor validated using actual data. This paper presents a new emotional game agent architecture that is based on an underlying theory of emotion and validated by limited experiments. This architecture manifests a range of emotional effects on game agent behaviors. The overall approach is informed by both appraisal and dimensional theories of emotion. The combination of these theories as underpinnings ensures that emotionally appraised concepts in memory are reflected in the emotional state of the agent, and that such correspondence produces realistic emotional effects on the agent's decision-making behavior. The approach is validated through a series of increasingly more sophisticated experiments, in terms of scenario complexity and methods employed. The results are correlated with human data from previous cognitive science experiments. The results show that "lightweight" intelligent agents based on the new game agent architecture can exhibit realistic emotional behavior in real-time decision-making situations encountered in games across various domains.

Keywords: Agent Architectures; Game AI; Decision Making; Cognition; Emotion; Agent Behavior

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1. Introduction

Intelligent agents play an increasingly important role in game-based simulations[1,2,3] and training systems[4,5]. Agent behavior has continued to improve over the last two decades from the purely robotic to more humanlike[6,4]. In part, these advances are the result of research sponsored in human behavior representation, and presented in BRIMS conferences. An important aspect of exhibiting humanlike behavior is reflecting changes in emotional states during task performance. However, effects of emotional state on decision-making have not been sufficiently addressed in agent architectures used in game-based simulations. Fortunately, such effects are well studied in cognitive science[7], and provide a theoretical basis for creating lightweight computational models of emotionally sensitive agents[8].

The research problem addressed in this paper is the development of computational lightweight agent models that are able to reflect the influence of human emotion on decision-making in game-based simulations. An illustrative example of an agent operating a nuclear power plant game is used to demonstrate the impact of emotions on decision making. In the example, the operator (agent) needs to respond to various anomalous situations that arise during power plant operation. For instance, the operator agent, observing a sudden drop in cooling water pressure, needs to make several correct assumptions when making decisions under time pressure. Such decisions require attentional focus, accurate recall, and sound choices, which are human qualities that are susceptible to the influence of emotional state. The influence can be positive or negative. For instance, an operator in a negative emotional state is more likely to be pessimistic than an emotion-neutral operator. In this emotional state, the operator is likely to suspect a critical pipe rupture, and act accordingly. Similarly, an operator in a positive emotional state is more optimistic, and less likely to envision a worst case scenario based on the drop in cooling water pressure.

This paper is organized as follows. Section 2 discusses prior work in the areas of cognitive modeling and emotional influences on decision making. Section 3 presents an innovative approach to extending cognitive agent architectures by incorporating the effects of emotion in decision making. Section 4 presents the results and findings of experiments based on the new architecture. Section 5 discusses directions for extending the work.

2. Previous Work

2.1. Cognitive Modeling

Unified theories of cognition are designed to explain and model all known aspects of human cognition in a single system. According to the "Newell Test"[9], cognitive aspects that need to be unified include flexible, dynamic and adaptive behavior, as well as natural language processing, among others. The study of unified cognitive theories has produced several well-known architectures such as Soar, ACT-R, and CLARION. In such systems, emotion is introduced into cognitive processes through goal-based cues and biases.

The computational modeling of human decision-making as part of cognition is often an interdependent set of deliberative cognitive processes[10,8]. Kahneman and others refer to these deliberative processes as belonging to a "deliberative subsystem" of cognition, as distinct from the reactive processes of an "associative subsystem"[11,12]. The associative subsystem incorporates emotional heuristics and is described as fast, intuitive, and concurrent. By contrast, a deliberative subsystem incorporates slower, rule-based, serial cognitive processes. The two systems frequently interact and interrupt one another.

The concept of an associative memory network underlying the interaction between emotion and cognition was pioneered by Bower[13] to define and explain the relationship between emotional state and memory. Anderson's ACT and ACT-R teams developed a similar theory to formalize activation strength (i.e., importance and relevance) of linked concept "nodes" in a memory network. The activation strength formula in ACT-R represents a node's activation strength as its "base" activation (i.e., how recently and frequently the node has been activated) plus the node's strength of association with adjacent nodes. This formula does not take into account the emotional impact of a node in generating activation strength.

Bower represents human memory as a semantic network of associations. In Bower's theory, a node represents a semantic concept (or an aggregated chunk of concepts and links), and nodes are connected by directed links which themselves have semantic specifications, for instance a "causal link" (e.g., node A causes node B).

2.2. Emotional Modeling and Decision

Human emotions can cause critical interrupts in cognitive processes. Specifically, an emotional signal would cause attention to be focused on an emotion-activating stimulus. Emotional intensity causes a heightened priority to be given to relevant concepts that are attended to during an emotional episode. In a similar vein, cue utilization theory[14] states that under higher levels of emotional intensity (as with similar stressors like task urgency or difficulty), cognitive cues not central to the arousing agent or situation tend to be increasingly ignored. This "tunneling" effect can potentially lead to overlooking subtle but important details, or leave the subject open to misdirection and other forms of deliberate manipulation.

Emotion can potentially refocus attention from the task at hand, causing distraction, even though the emotional episode may be incidental / irrelevant to the task. The recorded theories of incidental emotion as distraction date back to ancient times, when people likened emotion to two horses (aka associative subsystem) drawing "the chariot of the soul," with reason or rationality (deliberative subsystem) as the charioteer. Excessive independent activity by the horses, especially the black one that represented negative emotions, could disrupt the movement of the chariot as it proceeded towards enlightenment. Emotion as an alarm signal also primes the deliberative subsystem's cognitive processes to cope with emotionally charged stimuli. In planning, the signal may cause a change of plan, or a change of goal, or a reappraisal of the stimulus and associated concepts.

Distraction, or the involuntary shifting of attention from a concept related to a task at hand can potentially play an adaptive role in decision-making. Human cognitive science studies have shown that the nature of distractors is key. If the distractor happens to be task-related, then associative creativity can result during problem solving.

Many experiments use an agent's overall emotional state to measure emotional effects on human cognition, as it provides a straightforward correlation between gestalt physiological measurements and self-reported prevailing emotional state[15]. Negative emotional state (displeasure) can lead to narrow-minded but careful decision making; positive emotional state (pleasure) can lead to broad decisions that attempt to achieve multiple goals with less attention to detail and more heuristic processing[16]. A recalled concept may be sufficiently arousing that it wrests attention from the task at hand. This ties in to the previous discussion on distraction and creative association, as emotional state-related distractors may or may not also be task-related[17].

2.3. Previous Computational Models

In current systems, attention and focus shift are frequently modeled as oversight mechanisms for sensing pattern-driven "alarms" from all levels of cognitive processing: reactive, deliberative, and even reflective. This mechanism redirects cognition to process the stimulus that invoked the alarm.

Effects on decision-making are often cast as constraints on goal and action choices[18,19,20], though there are other types of effects as well. Planning effects represent a form of coping in EMA[21], among other systems.. In EMA, appraisal and coping are interdependent in a closed loop. Furthermore, the strategy for building a plan to cope with a particular emotional stimulus is subject to change following the next round of appraisal.

Choice and decision biases are modeled by, e.g., Becker-Asano's WASABI[22]. In WASABI, the agent's overall emotional state (used throughout this paper synonymously with emotional state) constrains the set of possible next actions and goals. Other models use the concept of Relational Action Tendencies in a similar manner to constrain decisions; these tendencies are formed as a direct result of appraisals and narrow the set of next action choices. ALEC uses a fast emotional system that operates asynchronously with its cognitive system to model the Somatic Marker Hypothesis during decisions.

Emotion as a recall heuristic has been modeled in different ways. ACT-R, with its well-tested model of associative memory, has been a natural starting point for these systems. Fum and Stocco's ACT-R extension[23], for example, takes advantage of ACT-R's associative memory to reproduce the Iowa Gambling Task's results. Several models also feature emotional effects on cognitive recall and inference, particularly changes to the speed and capacity of those processes based on emotional appraisal.

It is important to note that though their designs are widely varied, existing computational models of emotional effects on decision-making tend to address one or more of the following basic components:

1. Theory of emotion supported by cognitive science
2. Memory network evaluated for emotional content
3. Humanlike cognitive process model sensitive to emotional state
4. Range of known, quantified effects of emotional state on behavior

However, no individual model offers all four components. A further gap in computational agent modeling research is that none of the systems designed to date has developed a model to underpin an open-ended set of realistic emotional effects on the decision-making behavior of humanlike agents across simulation domains. The research reported in this paper addresses these gaps by developing a computational agent architecture that is informed by cognitive science and based on computational modeling methods. Specifically, the research hypothesizes that an emotional agent architecture that correctly combines the aforementioned four principles can exhibit realistic decision-making behaviors for tasks associated with game AI or simulated operation.

In addition to the foregoing advances, game AI (i,e., agent architectures made specifically for games) is starting to embrace emotional behavior and decision-making, particularly in serious games. There are several commercial emotional game agent models which use emotional state to inform discrete action choices in finite state machines, behavior trees, and path-finding algorithms. Several experimental games also feature emotional agent models, as in Rosalind Picard's and Hyungjil Ahn's affective gaming research at the MIT Media Lab[24], and in Michael Mateas' narrative intelligence game Façade[25]. The Virtual Humans group at USC/ICT, including Gratch and Marsella's serious game work as well as that of Rizzo, Rosenbloom and others, incorporates cognitive systems such as Soar and EMA while also bringing the emotional aspects of players into games via biofeedback[21,26]. The annual Artificial Intelligence In Digital Entertainment (AIIDE) conference typically showcases new models of emotional game agents. However, one gap in game AI research is that none of the games or middleware to date has developed a cross-domain model to underpin an open-ended set of realistic emotional effects on the decision-making behavior of humanlike agents. The agent model presented in this paper is meant to address that gap.

3. New Emotional Agent Architecture and Operational Concept

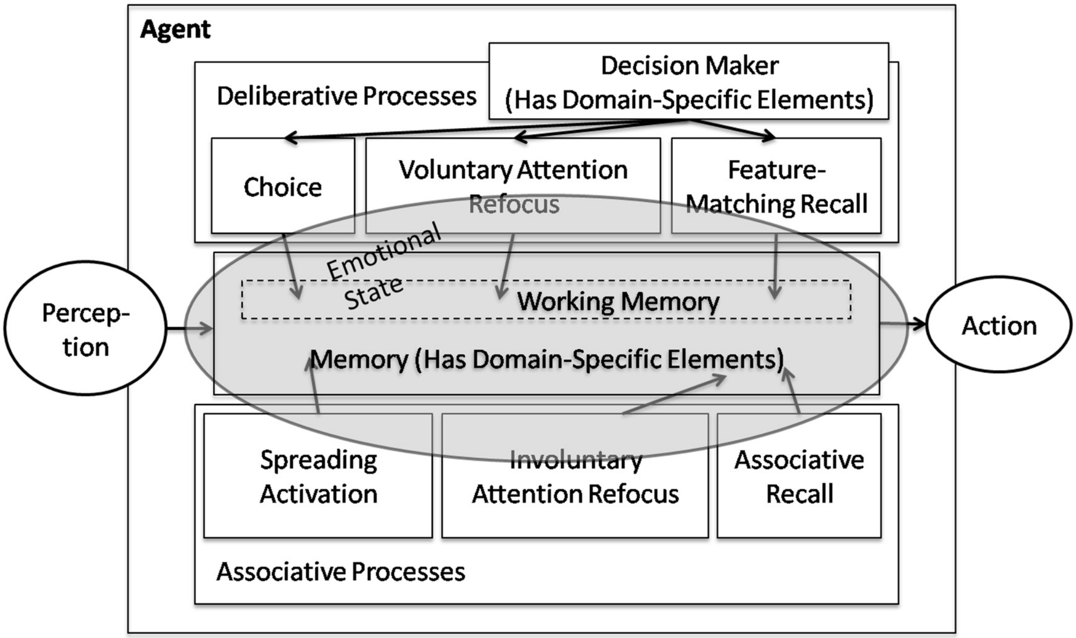

Fig. 1. Architecture Model

The new agent architecture presented in this paper and shown in Figure 1 combines several components that were gleaned from cognitive science and computational modeling literature. The specific design of each component is justified in terms of modeling principles gleaned from the previous literature.

The first component is a theory of emotion. The agent uses a hybrid dimensional and appraisal theory of emotion. From dimensional theory, we have modeled agent emotional state (core affect) as a global valence value ranging from -1.0 (negative) through 0.0 (neutral) to 1.0 (positive). Based on appraisal theory, each node in memory also has a similar emotional valence value. Flexibility is the reason for this modeling choice. Many behavioral and cognitive effects are based on the resonance between the emotional content of memory and the overall emotional state.

Another key component is a memory network that is evaluated for emotional content. The central data structure in the agent architecture is the associative-semantic network that represents long-term memory, featuring linked sets of nodes, with each node carrying emotional values (valence and arousal, among others, though only valence was used in the current round of experiments). Each node represents a single concept, and has activation strength, per the ACT-R theory of cognition, that defines how readily the node is recalled into working memory. Working memory is a dynamic, high-activation subset of the long-term memory network, accessible by the agent's deliberative processes such as decision-making. The single highest-activation node in working memory is the focus of attention, meaning that it will be acted upon in the next step of the deliberative processes. An arbitrarily complex node network allows richnessin the model. The links can be associative (undirected, with a numerical strength) or semantic (directed, with a semantic tag such as "causes" or "negates"). The divergent nature of the links allows the network to model a humanlike dual system of associative (unconscious) and searchable / deliberative (conscious) memory. A humanlike cognitive process model sensitive to emotional state acts upon the memory network. In particular, the agent uses an associative/deliberative dual process model as outlined by Stanovich and West[27].

Associative processes run in parallel over memory, continuously. Specifically, the association maintenance process strengthens or weakens the associative links between nodes, depending on how often and how recently the nodes appear together in working memory. Spreading activation maintains the activation strength of linked nodes, again dependent upon the appearance of the node or nodes in working memory. Associative recall selects the highest-activation strength nodes for working memory (so that these nodes can be accessed by deliberative processes), and involuntary attention refocus selects the highest activation strength node in working memory to be used in the next deliberative step. Deliberative processes run one step at a time on the nodes in working memory, and represent components of the conscious decision-making procedure. Processes include choice, which uses a simple utility function (probability * cost) to choose among available options. Feature-matching recall finds a desired node (or its closest match) in working memory. Voluntary attention refocus shifts attention focus to another node in working memory (not necessarily the node with highest activation strength).

Together, the dual subsystems provide humanlike realism to the agent's process model. Unconscious and conscious work together or in conflict, and all processes are suffused by and susceptible to multiple emotional effects. A final component is a range of known, quantified effects of emotional state on behavior. There are only three direct emotional state-dependent mechanisms (as increasing the number of hard-coded parameters would meanmore unforeseen interactions and corrective hacks), whose combinations lead to effects on decision-making behavior. The first mechanism is emotional state-dependent activation strength adjustment. Memory nodes with emotional rating closest to the agent's emotional state gain proportional activation strength, and vice versa. This leads to increased recall and attention focused on such nodes. The second effect is emotional state-dependent attention flexibility; the chance of involuntary attention refocus to a new stimulus is directly proportional to emotional state. The third direct effect is emotional state-dependent success probabilities. The agent's predicted probability of an outcome (of an action or an event) is directly proportional to how closely the current emotional state matches the emotional rating of the node associated with that outcome. The predicted probability is then used by the choice utility function.

One behavior that is indirectly dependent on emotional state is optimism / pessimism (e.g., in a negative emotional state, a negative event seems more likely, and is also more likely to be recalled). Another is distraction, where a deliberative task can be interrupted by attention refocus to a node with higher activation strength (particularly nodes whose strength has been increased by emotional state congruence). Similar to distraction is creative solution finding, where the distractor is actually task-relevant. Lastly, emotional state-congruent recall can arise such that emotional state-congruent nodes are activated above a threshold where they are recalled involuntarily into working memory.

4. Experiments and Results

The experimental methods employed in this research were a combination of computational modeling and statistical hypothesis testing. Results were evaluated by t-tests, correlating data from existing human experiments against data from agent models reflecting human emotional state. Two calibration experiments were done prior to a validation experiment involving a nuclear power plant operator agent. These experiments are described next.

To calibrate the system against human data, we modeled Dreisbach's 2006 experiment on emotional state and distractibility featuring the “AX Continuous Performance Task,”[28] and Phillips et al’s 2002 human experiment on emotional state-dependent planning using the “Tower of London” test[15]. The agent model is sufficiently robust to support other experiments from cognitive science that show direct effects of emotional state on decision-making; the two calibration experiments present the most quantifiable results over a range of effects.

In the AX task, the agent virtually presses one button when the letter X appeared as the second of two sequential letters, and a different button when any other letter appears in place of X. The agent was primed to expect X most of the time that the letter A appeared immediately beforehand. The AX experiment illustrated that greater flexibility (in positive emotional state) may lead to correct but unexpected solutions, depending on the task-relevance of the new node in focus. Although the agent was primed to expect X after A, in cases where X did not appear the agent pressed the correct button more often when in a positive emotional state. The t-test correlation between agent and human results was ~90%. This experiment shows the benefit of emotion-based attention flexibility on rapid decision-making when the agent is in a positive emotional state.

The Tower of London experiment involved restacking of disks one at a time into a target stack pattern. The experiment was designed to show that involuntary recall of emotionally powerful nodes could distract the agent more often in either a positive or negative emotional state (as opposed to neutral state). Moreover, the experiment showed that one effect of distraction on the decision-making process was that fewer options were presented during choice, leading to decreased performance by the agent in non-neutral emotional state. Performance was measured by the number of extra moves needed by the agent to solve the problem. The t-test correlation between agent and human results was ~90% for this experiment as well.

The two calibration experiments were followed by the Nuclear Power Plant experiment. The Nuclear Power Plant problem domain was used to further validate the calibration results on a far more complex problem space with real-world impact and implications. Human operator errors, based on emotional state, are well-known in nuclear power plant operation. Such errors encompass several issues in addition to emotional state (e.g., vigilance, cognitive overload). Keeping the agent’s perceptual ability and working memory size constant is key to controlling these issues. Emotional state was the sole independent variable in the experiment.

The test scenario dealt with a water pipe rupture, modeled after a known potential power plant crisis that required sound time-stressed decision making and judgment. The scenario is as follows. During a routine system check, water pressure begins dropping rapidly, thereby increasing coolant temperature and threatening a meltdown. In this scenario, the agent needs to realize first that the water pressure is low, then conclude that a pipe rupture may have occurred based only on the numerical readouts, and then isolate and repair the ruptured pipe by using the bypass valve and emergency sealant spray. The agent may instead assume that there is a non-pipe rupture related emergency that can only be stopped by shutting down the reactor. The pipe rupture fix, if there is a pipe rupture, is the less costly option, but a rupture is less probable than circumstances requiring a full shutdown. Moreover, fixing a pipe rupture that does not exist would still require a shutdown, and thus would cost the sum of pipe fix + shutdown. Therefore, a strictly utility function-based “by the book” emotion-neutral operator would resort to the shutdown unless the pipe rupture seemed to be more likely, which is the “pessimistic” case corresponding to negative emotional state.

The agent was also subject to distraction in the form of irrelevant stimuli. Some distractions could potentially lead to inaction and even meltdown of the plant. On the other hand, relevant stimuli (low water pressure or pipe rupture) could potentially lead to a better solution, as expected.

The agent was run ~20,000 times on the testing scenario (100 times each at emotional state ranging from -1.0 to 1.0, with an increment of 0.01). An ablated "emotion-neutral" version of the agent was also run 100 times. The distinguishing features of the emotion-neutral version were: a constant neutral emotional state of 0.0, and immunity to any emotional effects.

The emotional agent was able to detect and resolve the pipe rupture scenario more often and more readily in a somewhat negative emotional state. Any negative emotional state stronger than -0.5 caused more meltdowns due to over-focus on irrelevant details. As emotional state tended towards neutral and positive, shutdowns occurred more frequently, outpacing pipe fixes. This effect is partially due to the negative pipe rupture node having less activation strength in positive emotional states. Shutdowns also outstrip meltdowns (which represent pernicious distraction) in more positive emotional states. This is because positive emotional state will more easily allow water pressure or pipe rupture (as distractions) to involuntarily become the focus of attention. However, in positive emotional states the likelihood of pipe rupture rarely increases sufficiently for the agent to initiate a pipe fix. Consequently, there are more shutdowns. The emotion-neutral system's performance was always the same (shutdown), because it was never subject to emotional state effects (e.g., outcome likelihood variation, activation strength modification, or flexibility). Collectively, these results confirm that emotional state is an important consideration in decision-making scenarios in time-stressed real-world problems.

5. Future Work

This paper has presented a novel agent architecture that incorporates emotional effects in agent decision making. The model and architecture are framed in game AI with the intent of making game AI agents more humanlike. Several experiments were run to calibrate and then validate the agent model. To present a richer decision-making process integrated more tightly with emotional state, the implemented experiments can be enhanced. Particularly, the Nuclear Power Plant experiment can be upgraded to include multiple and sequential states and actions in memory, maintained in an interaction matrix. The decision-maker would then have several hypotheses to choose from to determine the cause of low water pressure. Also, the decision-maker would use fault-model analysis based on emotionally dependent probabilities to make its decisions, instead of a strict utility function.

The revised experiments can provide an opportunity to generate feedback changes to emotional state. Thus, in the AX experiment, these changes would be based on the appearance of an emotionally charged letter and/or bigram. The new Tower of London experiment would include alteration of emotional state based on repeated moves and positions. Emotional state may also change based on the agent getting closer to or further from the solution based on heuristic assessment. In the nuclear power plant experiment, the emotional state would change depending on the criticality of readings as well as the success or failure of actions taken. Dynamic emotional state is the first step towards a more dynamic system, culminating in experiential and emotional learning, and in case-based reasoning. These advances are expected to improve the behavior of agents in games, making them appear more credible and thereby making gameplay more realistic.

References

1. Madni, A.M. "Game-based Simulation for Cross-Cultural Decision Making Training," *Human Factors and Ergonomics in Manufacturing & Service Industries Journal*, 2011.

2. Madni, A.M., and Madni, C.C. "Intelligent Agents as Synthetic Role Players in Scenario-Based Training," *Journal of Integrated Design and Process Science*, Vol. 12, No. 1, March 2008, pp. 41-56.

3. Madni, A.M., Moini, A., and Madni, C. "Cross-Cultural Decision Making Training Using Behavioral Game Theoretic Framework" in *Advances in Cross-Cultural Decision Making*, Schmorrow, D. and Nichelson, D. (Eds.), CRC Press, 2010.

4. Madni, A., Madni, C., Garcia, S. "Cognitive Model-enabled Simulation-based Training of AOC Operators," *Proceedings of AIAA Infotech@Aerospace*, Hyatt Regency, Crystal City. Arlington, VA, September 26-29, 2005.

5. Madni, A.M. and Madni, C.C., Garcia, S.K. "Cognitive Model-enabled Simulation-based Training of Aerospace Operations Center Operators," *Proceedings of the 11th International Conference on Human-Computer Interaction*, Las Vegas, NV, July 22-27, 2005.

6. Madni, A. Madni, C., Garcia, S. Sorensen H.B. "Intelligent Agents for Individual and Team Training Applications," *Proceedings of AIAA Infotech@Aerospace*, Hyatt Regency, Crystal City. Arlington, VA, September 26-29, 2005.

7. Madni, A.M., Sage, A. and Madni, C.C. "Infusion of Cognitive Engineering into Systems Engineering Processes and Practices," *Proceedings of the 2005 IEEE International Conference on Systems, Man, and Cybernetics*, October 10-12, 2005, Hawaii.
8. Madni, A.M., Moini, A., and Madni, C.C. "Cognitecture™: Cognition-Based Interactive Architecture for Next Generation Intelligent Agents," Intelligent Systems Technology, Inc. Phase II Final Technical Report, ISTI-FTR-567-8/06, Contract #W31P4Q-04-C-R222, August 10, 2006.
9. J. R. Anderson and C. Lebiere, "The Newell Test for a theory of cognition.," *The Behavioral and Brain Sciences*, vol. 26, no. 5, pp. 587–601; discussion 601–48, Oct. 2003.
10. A. Sloman, "Damasio, Descartes, alarms and meta-management," *Systems, Man, and Cybernetics, 1998. 1998 IEEE*, 1998.
11. D. Kahneman and S. Frederick, *Representativeness revisited: Attribute Substitution in Intuitive Judgement*. New York, New York, USA: Princeton University Press, 2001.
12. S. A. Sloman, "The empirical case for two systems of reasoning," *Psychological Bulletin*, vol. 119, no. 1, pp. 3–22, 1996.
13. G. H. Bower, "Emotional state and memory," *American Psychologist*, vol. 36, no. 2, pp. 129–148, 1981.
14. J. Easterbrook, "The Effect of Emotion on Cue Utilization and the Organization of Behavior," *Psychological Review*, vol. 66, no. 3, pp. 183–201, 1959.
15. L. H. Phillips, L. Smith, and K. J. Gilhooly, "The effects of adult aging and induced positive and negative emotional state on planning.," *Emotion*, vol. 2, no. 3, pp. 263–272, 2002.
16. C. J. Armitage, M. Conner, and P. Norman, "Differential effects of emotional state on information processing : evidence from the theories of reasoned action and planned behaviour," *European Journal of Social Psychology*, vol. 29, no. March 1998, pp. 419–433, 1999.
17. R. L. C. Mitchell and L. H. Phillips, "The psychological, neurochemical and functional neuroanatomical mediators of the effects of positive and negative emotional state on executive functions.," *Neuropsychologia*, vol. 45, no. 4, pp. 617–29, Mar. 2007.
18. Madni, A.M., Lin, W., and Madni, C.C. "Human-agent Collaboration: Ontology and Framework for Designing Adaptive Human-agent Collaboration Architectures," *Proceedings of Twelfth Annual International Symposium of the International Council On Systems Engineering (INCOSE)*, Las Vegas, Nevada, July 28 – August 1, 2002.
19. Chu, Y. and Madni, A.M. "Knowledge-based Simulation of Tactical Adversary," *Proceedings of Second Workshop on AI and Simulation, AAAI Conference*, Seattle, August 1987.
20. Madni, A.M., Ahlers, R., and Chu, Y. "Knowledge-based Simulation: An Approach to Intelligent Opponent Modeling for Training Tactical Decisionmaking," *Proceedings of the 9th Interservice/Industry Training Systems Conference*, pp. 179-183, November 30-December 2, 1987, Washington, D.C.
21. S. C. Marsella and J. Gratch, "EMA: A process model of appraisal dynamics," *Cognitive Systems Research*, vol. 10, no. 1, pp. 70–90, Mar. 2009.
22. C. Becker-Asano and I. Wachsmuth, "Affective computing with primary and secondary emotions in a virtual human," *Autonomous Agents and Multi-Agent Systems*, vol. 20, no. 1, pp. 32–49, May 2009.
23. D. Fum and A. Stocco, "Memory, emotion, and rationality: An ACT-R interpretation for gambling task results," in *Proceedings of the Sixth International Conference on Cognitive Modeling*, pp. 106–111, 2004.
24. H.-I. Ahn, "Modeling and analysis of affective influences on human experience, prediction, decision making, and behavior," Massachusetts Institute of Technology, Cambridge, MA, 2010.
25. M. Mateas, "Expressive AI : Games and Artificial Intelligence," in *Level Up: Digital Games Research Conference1*, 2003.
26. J. Gratch, S. Marsella, and P. Petta, "Modeling the cognitive antecedents and consequences of emotion," *Cognitive Systems Research*, vol. 10, no. 1, pp. 1–5, Mar. 2009.
27. K. Stanovich and R. West, "Individual differences in reasoning: Implications for the rationality debate?"*Behavioral and brain sciences*, 23(5), 645-665, 2000.
28. G. Dreisbach, "How positive affect modulates cognitive control: the costs and benefits of reduced maintenance capability.," *Brain and cognition*, vol. 60, no. 1, pp. 11–19, Feb. 2006.