DRAFT TECHNICAL REPORT:
<u>More Realistic Human Behavior Models for Agents in Virtual Worlds: Emotion, Stress, and Value Ontologies</u>

By

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<u>ABSTRACT</u>

This paper focuses on challenges to improving the behavioral realism of computer generated agents and attempts to reflect the state of the art in human behavior modeling with particular attention to value ontologies, emotion, and stress in game-theoretic settings. The goal is to help those interested in constructing more realistic software agents for use in simulations, in virtual reality environments, and in training and performance aiding settings such as on the web or in embedded applications. This paper pursues this goal by providing a framework for better integrating the theories and models contained in the diverse human behavior modeling literatures, such as those that straddle physiological, cognitive and emotive processes; individual differences; emergent group and crowd behavior; and (punctuated) equilibria in social settings. The framework is based on widely available ontologies of world values and how these and physiological factors might be construed emotively into subjective expected utilities to guide the reactions and deliberations of agents. For example what makes one set of opponent groups differ from another? This framework serves as an extension of Markov decision processes appropriate for iterative play in game-theoretic settings, with particular emphasis on agent capabilities for redefining drama and for finding meta-games to counter the human player. This article presents the derivation of the framework and some initial results and lessons learned about integrating behavioral models into interactive dramas and meta-games that stimulate (systemic) thought and training doctrine.

1) <u>INTRODUCTION</u>

A common concern amongst agent developers is to increase the realism of the agents' behavior and cognition. This is not an idle fancy, but a serious objective that directly affects the bottom line of commercial concerns, mission achievement in non-commercial organizations, and the safety and health of individuals who need to transfer skill sets from virtual to real worlds. Agent-oriented products with a better cognitive fit and that are more emotively natural tend to sell better, like Namaguchi or Catz and Dogz [6]. This lesson applies to embedded agents as well as stand-alone products. People are known to anthropomorphize technologic items like cars, slot machines, computers, ATM machines, etc. A strategy is beginning to emerge of beating the competition by including greater degrees of personality, human modes of interactivity (voice synthesis for car navigation systems), and emotivity in personas <u>embedded</u> ubiquitously (lip-synched and facially accurate expressions): e.g., see [7-9].

Similarly, in training, wargaming, and mission rehearsal systems there is a growing realization that greater cognitive subtlety and behavioral sensitivity in the agents leads to both (1) a greater ability to explore alternative strategies and tactics when playing against them and (2) higher levels of skill attainment for the human trainees: e.g., see [10-12]. For this to happen, the tactics, performance, and behavior of agents must change as one alters an array of behavioral and cognitive variables. As a few examples, one would like agent behavior to realistically change as a function of: the culture they come from (vital for mission rehearsal against forces from different countries); their level of fatigue and stress over time and in different stiuations; and/or the group effectivity in, say, the loss of an opposing force's leader?

Closely related to the topic of emulating human behavior is that of "believability" of agents. The basic premise is that characters should appear to be alive, to think broadly , to react emotionally and with personality to appropriate circumstances. There is a growing graphics and animated agent literature on the believability topic (e.g., see [6-19, 55-58]), and much of this work focuses on using great personality to mask the lack of deeper reasoning ability. However, in this paper we are less interested in the kinesthetics, media and broadly appealing personalities,, than we are in the planning, judging, and choosing types of behavior -- the reacting and deliberating that goes on "under the hood". In that regard, though we restrict our focus on behavior dynamics to the macro-level, and avoid neuro-anatomy, bio-chemical interactions, or molecular cognitive sub-processes. Finally, and perhaps most importantly many developers are in computatural fields and are unaware of the scattered behavioral literatures and of valid models for deeper behavior. Our research involves developing an integrative framework for emulating human behavior in order to make use of published behavioral results to construct agent models. We are not attempting basic research on how humans think but on how well exsisting models might work in agent settings. That is, the framework presented here is intended for experiments on how to integrate and best exploit published behavioral models,so as to improve the realism of agent behaviors.

In particular, the research described here focuses upon the growing ability to create agents that can recognize and shift play to meta-games and not get locked into brittle, narrow rules of play. The ability to do this is increasing due to the convergence and maturation of a number of lines of research in human behavior mo deling [27-46], in agent animation and expressive capabilities [6-19], and in computational sciences in general and for electronic theater and simulators in particular [20-26, 48-49, 55-63]. Our goal is to benefit from and to further that integration with the framework presented here, and to focus it upon the task of developing agents embedded in interactive dramas intended for teaching humans to be better systems thinkers. We use the term interactive drama to refer to a game that a human player engages in for the purpose of discovering insights about the portion of the world captured in that drama. This term is intended in part to convey the notion that game theory is too brittle and restrictive to cover the types of situations we have in mind: e.g., see [1-5, 64, 65]. In particular, we wish the human to learn how to change the game, discover how to redefine situations, and successfully detect and shift play to meta-games – that is the essence of systems thinking. We seek to do this by creating interactive dramas containing microworlds populated with emotive, yet bounded-rational agents that understand the meta-games and that attempt to utilize them on unsuspecting human players. By discovering those meta-games, and uncovering the plot and actor motivations, the human players increase their ability to think systemically, to learn the value of doctrine and principles.

To support this effort, there are a number of specific agent research issues which arise such as, among others, building and deploying agents that can:

- Acquire and maintain knowledge of the environment, of other agents actions (human or synthetic), and of their own experiences, successes and failures.
- Create tactical plans and carry them out in a believable manner covering both reactive and deliberative behaviors in the presence of other players.
- React appropriately to stress, fatigue, and anxiety and reflect their integrative impact on judgment and performance. For example, how can these factors (and emotive reactions) be modeled in a principled way to reflect agent interactions, behavior emergence, and punctuated equilibria in individuals, groups, and populations?
- Construe emotional reactions and mood as stimuli to personal behavior and choice. To this end we are concerned with agents that possess ontologies of values (e.g., motivations, ideology, and value systems) so those who would deploy a multi-agent system can "turn the dial" and wind up with different types of synthetic agents to play against (e.g., in a combat game this might imply fundamentalist suicidal bombers vs. clandestine anarchistic snipers vs. charismatic guerilla leaders).
- Cope with multi-stage activities (e.g.,campaigns), strategic plans, and survival and decide when to make tactical sacrifices (or not) for the betterment of larger contexts (meta-games). To this end, the agents must have a way to navigate the large, hierarchical Markov chain that any interactive drama must encompass if it is to include meta-games and complexity. How can appropriate, formal approaches such as Markov decision processing and dynamic programming be suitably adapted to include the bounded rationality processes (stress, emotion, etc.) that realistic agents must encompass?

The factors mentioned above can lead to individual differences between agents. For example, some characters will be stressed and fatigued due to their situation while others won't, and agents can have different emotions and moods depending on the events around them. Or as another example, we present ways to model agents of differing cultural and ideological background. What makes an IRA bomber different from an HAMAS bomber? And how can we capture and represent their world value differences. Despite these 'individual difference' foci, our research is not on personality per se, and we will often assume that all individuals from a given group adopt the same characteristics. One could use much of the apparatus we establish here to conduct such research, but that is beyond the current thrust.

A major concern of this research, however, is the validity of the value system ontologies and behavioral models we derive from the literature and try to integrate within our framework. We are concerned with validity from several perspectives including the data-groundedness of the models and ontologies we extract from the literature, the coherence of the agents' choices relative to theoretic predictions, and the correspondence of behavioral emergence and collectives with actual dynamics observed in the real world. We will address these validity concerns at key points throughout this article.

1.1) Definition of (Multi-)Agent Sytems

An intelligent agent is defined here as a software program that can sense and effect its environment, and use some degree of freedom in making lower level decisions that help it plan and carry out its higher level goals. Such an agent will be adaptive as needed to accomplish its intentions. Often, an intelligent agent either uses a "mental states" concept or else one is attributed to it. This makes agents an interesting architecture for modeling human-like behavior and artificial lifeforms.

The agents described in this paper are also able to (1) participate in a multi-stage, hierarchical, n-player game in which each agent observes and interacts with some limited subset of the n-1 other agents (human or artificial) via one or more communication modalities, (2) forms beliefs about those other agents' action strategies (a_{mn} in A) and stores them in a history vector (h), and (3) uses those beliefs to predict nearby agent play in the current timeframe and by that guides its own actions in maximizing its utility (u) within this iteration of the game, $G = (A_{mn}, U_n, C_n)$. This 3-step loop is depicted at the bottom of Figure 1.

Von Neuman-Morgnstern game theory dictates that if each agent is attempting to maximize his utility under iterative play, then a Nash Equilibrium solution of the game's payoff matrix is likely, though not guaranteed, to be uncovered [1]. The exceptions are that some games are cyclic and the agents can wind up never converging, while other games have multiple NE and its not clear a priori as to which of them the agents will settle on. In the latter case, it is worth reminding the reader that maximizing under local, iterative steps will not lead to NE that are strict optima or pareto efficient. In fact in the Prisoner's Dilemma game, the axioms of rationality dictate that players should settle on the coop-coop strategy, yet the NE lies at the reduced utility point of defect-defect.

In the games this article investigates, the players assign utility and perceived probability values dynamically as the game unfolds and in response to stress and emotional construals of the situation. Stress constrains the agents so they may not have the time to drive toward the utility maximum in any given step. Emotional construals on the other hand can redefine where the NE occur in the payoff table or they can redefine the entire game. That is, an emotive agent can recognize a meta-game and shift the play to a higher level of systemic interaction: e.g., see [3-4, 45-58, 64-65]. An example might be a terrorist who martyrs himself rather than be caught, and by that catalyzes his cause.

1.2) Meta-Games and Interactive Dramas

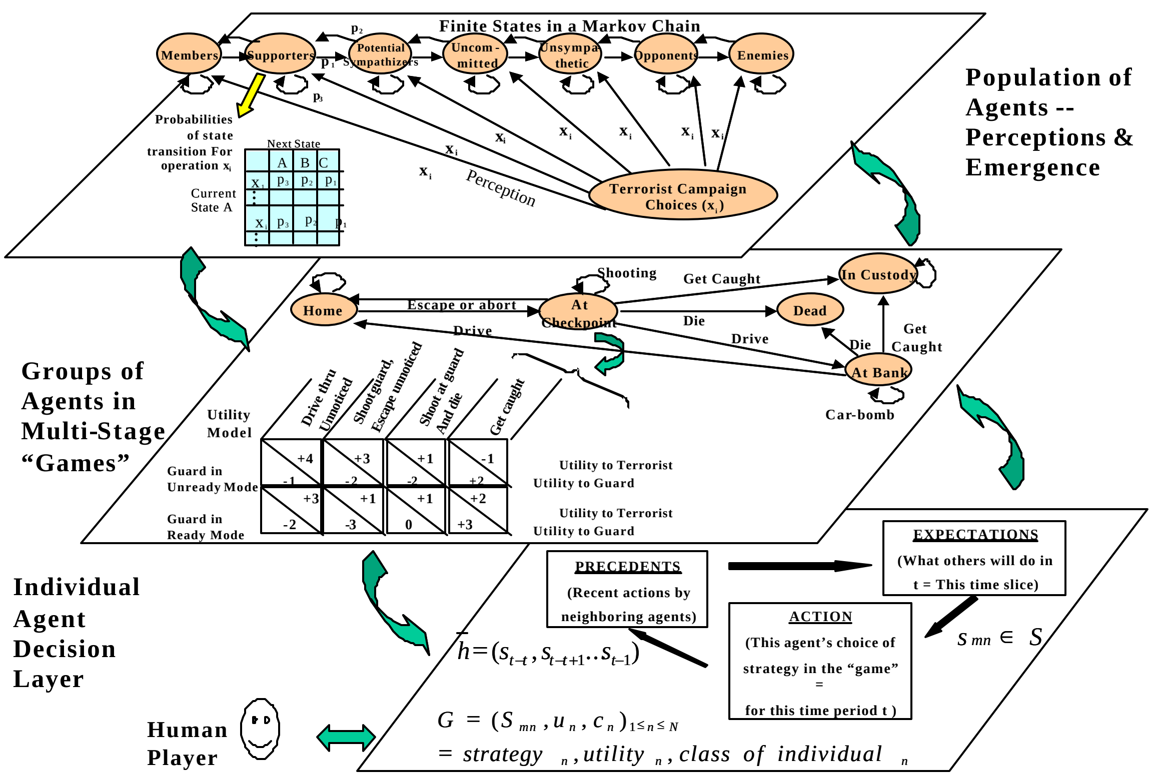
In general, this research focuses on games that have multiple stages, each of which may involve expansion to part of a higher level, or decomposition to a lower level, game. This nested hierarchy of games leads to the ability to include meta-games or games behind the obvious game unfolding on the screen. The overall game is less rigid as a result, and it can be represented as a hierarchical Markov chain of nodes, or as one very large chain that is not always fully traversed if portions of the game are omitted by the human or agent players. As in the classical definition we assume a Markov chain is a graph of nodes that are states and edges or links that represent actions that lead to new states. Also, there are transition probabilities, and the notion that, for any specific level of a hierarchy, any given state is only conditional on immediately previous states.

While a hierarchical Markov chain will describe the major states (minor states may exist for every change in each variable and we only capture significant changes in the chain) that can be reached by the human players and the agent lifeforms, it does not indicate whether a given agent will ever seek to visit a sub-game of the chain. That is, a Markov chain does not describe what causes an agent to choose a given action. So beyond Markov chains of the major possible states of the world, there must be an onotology of agent values and a cognitive apparatus for the agent to isolate the utility of each action it takes. We refer to all of this as the interactive drama opera – the microworld of the simulation, the hierarchical Markov chain, and all the behavior that might be chosen by the various agent lifeforms that populate the microworld.

As an example, consider a scenario in a microworld consisting of a poor population living in one half of a land and a wealthy population in the other half. A guerilla group has sprung up in the poor area. An example shred of the overall Markov chain for this world is in the middle of Figure 1. This represents one mission of a larger campaign that is addressed by the upper layer of Figure 1. In the larger campaign, the guerilla group seeks to overthrow the established authority by conducting a number of missions to shift (meta-game) popular opinion of their supporters in their favor and to instill fear in the population of their enemy. The particular mission expanded in the middle of Figure 1 covers the possibilities of one or more terrorists leaving their home base to travel through a checkpoint to deliver a car bomb at a bank and escape after detonating it to return safely home (and to continue the campaign). Along the way there are games to be played at each node, and depending on the node outcomes a terrorist also may wind up in jail or dead. It is not of course clear from this level of inspection whether the terrorists find some of those alternatives to have significant utility or not. Given their value ontologies and emotional construals they derive about their values, one of them very well might think that getting caught after shooting a guard at the checkpoint or committing suicide is still a media coup and has substantial utility for catalyzing popular support.

The idea of such a "drama" is that one human player will exist to direct the policies and behavior of the defenders. This player actually experiences and interacts with the world in the effort to prevent, mitigate, or otherwise manage potential bombing incidents, crowd protest scenes, and other peacekeeping activities. One can be efficient in any single incident, and in fact in all of the early ones, by show of force to squelch conflagrations, yet lose the game as the opposing populace grows more sympathetic of the guerillas, provides greater funding for its missions, and joins its ranks to increase the scale of the conflict. By design, there is a macro-game behind all the micro-games that one only discovers after playing for a while. That is, the population feedback effect and emergence of heightened violence if the human player and defenders are abusive and do not provide fair ways to redress legitimate grievances in the local incidents. This is the same effect one sees in police forces that draw political disfavor and lawsuits from racial profiling, from overly-aggressive protester treatment, and from mis-handling demonstrations. Win the battle, lose the war. Think reductionistically, and fail to recognize systemic dramas.

Figure 1 – Overview of a Hierarchical, Multi-Stage, n-Player Game That Agents Engage In and That Illustrates the Nature of Research on Human Behavior Dynamics



So this scenario raises the prospect of researching the integration of (1) low level contributants to human behavior from a number of stressors, fatigue factors, and emotion, (2) decision-making at the individual level, (3) behavior emergence and social interactions of crowds, and (4) potential media impacts on the population. This simple scenario requires one to model terrorists, defenders, civilians, crowd dynamics, population opinion evolution, and so on. Implementing such a game would involve a lot of research to understand how these all work and interact. The challenges of doing that are the reasons for this research and the focus of the Section 2 of this article. Before moving to that topic, we comment briefly on the state of the art in human behavior modeling in video games, interactive simulations, and virtual worlds.

2) Human Behavior Modeling for Virtual Agents

A large number of challenges exist for human behavior modeling to increase the realism of agents in simulations, videogames, and virtual worlds. This section begins with a broad overview of those challenges, and then includes some specific issues at the frontier of attempting to investigate these challenges more thoroughly.

2.1) Challenges for Increasing The Realism of Human Behavior Modeles

One of my students recently asked: why conduct this research when there are already so many computer games that simulate characters interacting in ways described in the introduction? Games like Maxis' The Sims, Microsoft's Age of Empires, Microprose's Civilization, and lesser known competitors straddle many of the topics, including models of fatigue and hunger, stress, conflict, emotion, crowds, tactical skirmish and strategic campaign planning, computerized drama, and politics and diplomacy. Why not just go to these companies, buy a license to their source code, integrate the relevant parts, and be done with it? After all, the Marine Corps has done something like this with Doom, turning it into a training simulator for hand to hand combat.

There are several reasons that this is not feasible, and these reasons constitute ongoing challenges for the research community, and for constructing an integrative framework, including:

1) **Game Makers Omit Reasoning and Mathematical Foundations** -- The coding of the software by game-makers and military wargame modelers is usually created in the simplest manner and in response to a market or project deadline. Historically there has been little capability for deliberative reasoning by these agents and one doesn't encounter theoretically rigorous constructs that can be counted on to perform according to mathematical theory. Due to these constraints, perhaps the most popular construct for game creation and other simulations is the finite state machine (FSM) approach. FSMs offer the rudiments needed to implement Markov chains and MDPs, and to organize agents into iterative meta game-playing participants within a multi-stage, hierarchical network. However, the vast majority of FSM systems implemented to date are programmed from the bottom up, with little agent reasoning and without the concept of a larger theory to validate them against. Using the FSM approach, character animators have created virtual lifeforms (e.g., fish, plants, talking heads, full body characters, semi-automated forces, and groups) that are self-animating, physically realistic, and geometrically and kinesthetically accurate when motoring about their virtual settings: e.g., see [13-14]. There has even been significant development of architectures for self-animating characters that react appropriately to a small range of emotive and environmental stimuli such as fright and flight, flocking, or lip- and facial-movement-synching to utterances or stimuli: e.g., [15-16]. These tend to be reactive systems with no significant cognitive processing. The interactive computer gaming industry has recognized all these shortfalls and many game environments now publish interfaces for developers and power users to another more intelligent and realistic behaviors for the various characters in these on-line games and dramas. As a result, recently there are a few early efforts to tie-in a deliberative, or deeper decision and cognitive functioning and: more intriguing emotive and motivational processes: e.g., see [17-19], [75-76], In short this is an exciting time in the interactive game community and they are now looking for help to advance their behavioral approaches.

2) Artificial Intelligence has Focused on Higher Level Functioning – The goal of artificial intelligence researchers is to give agents a goal- or intention-seeking behavior combined with the abilities to create and use knowledge about a domain, to communicate with and form beliefs about what other agents know, and to use their knowledge and beliefs to plan out decisions and actions needed to reach their intentions. Researchers in this Belief, Desires s, Intention (BDI) agent community have created a wide array of methods, often formal and grounded logics, for agent reasoning [20], inter-agent communications [21], and autonomous planning and learning [22, 23]. These agents have ways to sense their environment and procedures to effect it. However, as Laird & Van Lent [75] point out the researchers typically examine very narrow capabilities quite deeply (e.g., natural languages, or navigation or planing) and rarely worry about integrative architectures. Further their agents often are un-embodied and thus can free up extensive computing cycles for the reasoning, planning, learning, orbelief processing that they are implementing.. Its not clear that artificial life characters can free up such cycles and maintain realistic lower level performance parameters. Worse still, many game creators, training world authors, and military simu lation developers do not want their agents to be BDI-based or planners and learners. Instead, they want their agents to perform the same each time the game is replayed so they can maximize control and replication of training situations [24] and/or the need for consumers to buy new games. On many levels this would appear to run counter to the philosophy of creating agents that are more realistic. A more appropriate solution is to give the developers the ability to rollback the knowledge the agents have learned when they need to replicate an earlier training level, but to allow for BDI agent planning, and learning to occur as trainees become more competent (or after payment is received for the next level of play).

3) **Lack of First Principles in Current Systems** -- Most of the games and artificial lifeforms out there are artistically and stylistically impressive (very impressive), but not entirely faithful to real human behavior. Usually, the game makers hire a psychologist to verify the behaviors seem plausible, but they rarely get down to actual fine-grained details and rarely implement models based on first principles (e.g., reflexes, reaction times, effects of stress, fatigue and adrenalin effects, judgment rates, etc.). While there are some important exceptions such as SOAR [23] or ACT-R [25], in general, both the game/graphics animators, and the researchers in the AI and BDI communities tend to view their models and methods as performing tasks that humans can do, but doing them differently than humans would. Deep Blue does not play chess like a human would. So, care must be taken when trying to use the BDI and AI approaches to enhance the behavioral and cognitive fidelity of synthetic characters. It is easy to use these techniques to create capabilities that no human possesses, or ever could possess. An artificial agent will perform a task the same each time regardless of fatigue, stress, exposure to biochemicals, and so on. For example, the Merman in [17] swims from a shark and reasons equally well regardless of how long the chase continues or how close the shark gets. Likewise the teambots of [19] can traverse the length of the playing field at full speed without tiring, and repeatedly turn around and return the full field at the same speed. Yet this is not realistic, and as a result current agents do not accurately mimic human opponents or collaborators. For this reason, it is important to ground agent behavior and cognition in the psychological sciences inempirical findings.

4) Behavioral and Cognitive Researchers Ignore Implementation – There are well over a million pages of peer-reviewed, published studies that can serve as first principles on human behavior and performance as a function of demographics, personality differences, cognitive style, situational and emotive variables, task elements, group and organizational dynamics, and culture. This is a potentially rich resource for agent developers, however, almost none of this literature addresses how to interpret and translate the findings into principles and methods suitable for agent implementation [26]. Often the factors described in this literature are only roughly quantified, rather than laid out as neat dose-response or performance moderator functions (PMFs). So, informed judgement and/or further testing is required to parameratize them. Finally, it is time-consuming and perhaps beyond their abilities for lay-persons (agent builders) to determine the validity and generalizability of the findings in any given study in the behavioral sciences.

5) **Game Theory Ignores Systems Thinking and Meta-Game Dramas** – Traditional game theory is mathematically rigorous but overly simplistic. The games that are most commonly studied involve fixed, highly constrained payoff tables; intellectually hobbled opponents; and single layer of play where meta-gaming and systemic thinking is not allowed. Yet the goal of this research is to study human decision makers in complex and distributed settings, to analyze performance obstacles and judgment biases, to derive principles of design of software systems so they enhance rather than hinder systems thinking, and to develop and study new classes of agent technology that foster human abilities to shift their mindset and

increase understanding and wisdom about their situation, tasks, and environments. This research straddles a number of topics on modeling the human mindset/cognition in specific task-environments and to designing intelligent software and related workflow processes that attempt to shift and change behavior from the biased to the statistically debiased, from the individual muddler to the participative satisficer, from the narrow analytic with little organizational memory to the broad synthetic enabled with historical and contextual awareness. To that end, meta-game theory and soft game theory are of interest here, though the thrust in that field to date has focused largely on the use of interactive drama for human-to-human negotiation: e.g., see [64-65]. The goal here is to extend those ideas into the 'interactive drama' domain, into the realm of animated agent players who interact with human players and help them recognize and play at the level of meta-games.

6) **<u>Dearth of Interchange Standards</u>** – Even if all these other challenges were eliminated, we can't take existing games or AI systems and easily replace their "made up" characters with ones we'd like to interact with. We can't turn the dial to the opponents we choose and the scenarios that interest us, only those some artists have rendered. So one can't readily extend existing systems for interesting additions, research variables, and behavioral studies. There are no interchange standards used in these communities. This would be like going to a hardware store where every maker of screws and nails followed their own whim and there were no standard sizes of things. What you're able to buy probably won't plug into to the other things you buy elsewhere. And even if some bits of diverse game-maker or AI code look good, one can't readily take from A and merge with B. Given the rich diversity of what's offered from the various communities that overlap the virtual agent field, some argue that interchange standards are needed immediately in order to help this field to mature. At the simplest, such standards might cover API specifications for plug and play modules. Far more complex standards might be for the exchange of knowledge and ontologies that the agents use and/or for the exchange of behavior models and how to transform them into diverse implementations. It is not clear what exactly is needed.

<u>7) Model Validity Issues</u> – A folkism goes "all models are broken, some are useful." No model will ever capture all the nuances of human emotion and the range of stress effects and how they effect judgment and choice. That does not mean it cannot be useful. Games are useful if they entertain, distract, and engage our attention. That does not mean we believe they are real. However, if 'usefulness' involves training and transferring some insights about the real world, then it's important to try and evaluate the models and the human behaviors they produce. One issue is that there is no way to run existing game worlds against real past campaigns that aren't the stylized versions the game folks have pre-set into the codes. In fact, most game worlds are nothing more than actual preset campaigns. Likewise, there are the validity issues raised by the AI/BDI models of agent reasoning that usually don't replicate human-like reasoning, yet are able to perform human-like tasks. Similarly, many of the first principle models from the behavioral literature have been derived within a given setting, yet simulations may deploy them within somewhat altered contexts. What is the impact of doing this? When do they succeed or fail? And what happens when one attempts to integrate numerous stress factors given that the research to date is strongest on each factor separately rather than on the integrative effects? Emotion modeling is an example of another new frontier modelers are rushing into, yet to date it is rich in theory but short on actual data. What methods of validation should be used and for what purposes are any of these models to be considered trustworthy? These are a few of the many questions one must struggle with in order to identify where an agent based model of human behavior dynamics is useful or not.

<u>2.2) Role of Emotion and Value Ontologies in Agent Behavior</u>

For the most part, the principal contribution of our research to the human behavior modeling field lies in our efforts to provide an integrative framework that enables one to recognize the availability and test the relevance to interactive dramas of the contributions from several diverse behavioral fields . However, in the area of emotive computing we make several other contributions including: (1) extending the emotion construal implementations, which are inherently reactive, into new forms of deliberative reasoning beyond what has already been done in works such as [49, 56]; (2) providing a unification of classical decision theory with emotion construal theories via subjective expected utility models, a unification formalism which has advantages for both fields; and (3) going beyond current emotion model implementations, such as [48, 58] which focus on emotion processing for broadly appealing personality in interactive drama, to provide mechanisms for deriving both the emotion-eliciting relations and the utility values from widely available ontologies of values (e.g., ideological standards, need hierarchies, and preferences about the world). This third contribution is to use value ontologies to create agents able to reason deeply (with the help of the utility approach of #2) about meta-games and to participate in immersive dramas that stimulate systemic thinking. Let us examine these contributions more closely.

"Emotive computing" is often taken to mean the linking of the agent state to expressive facial and body expressions, vocal intonation, humorous or quirky animation effects, and the like: e.g., see [17-18, 43-44]. However, a different focus of emotive computing lies in recent theories that indicate the central role that emotions play in human rationality. The idea that humans are rational actors whose decisions are often clouded by emotion is as old as Western thought. Until recently, cognitive scientists and artificial intelligence research concentrated primarily on the "rational" aspect of thought, reasoning that since the problem of making good decisions is so difficult in itself that to introduce emotion into the equation would make the performance of the agent even worse. Recent theories e.g. [45, 46, 52, 54], however, suggest a quite different relationship: that emotions are a vital part of the decision-making process that manage the influence of a great deal of competing motivations. According to these theories, integrating emotion models into our agents will yield not only better decision-makers, but also more realistic behavior by providing a deep model of utility. These agents will delicately balance, for example, threat elimination versus self-preservation, in much the same way it is believed that people do. It is ironic that through the ages, humankind has been taught that rationality is the product of cold logic and that emotions cloud the mind from being rational. Yet, the newest theories suggest that without adding emotional construal of events, the agents won't know the seriousness of their situation, won't know what to focus upon and what to ignore, and won't know how to balance the set of next-step alternative actions against larger concerns, as in the case of Damasio's pre-frontal cortex damaged patients who spend the entire day mired in highly logical decision analyses of banalities, even at the cost of their own self-interest and survival.

Important implementations of these ideas and theories were attempted by the Oz project [58, 59] and by the Affective Reasoner [48], both of which seek to improve the believability of characters' behavior in fictional settings with the help of the OCC model of emotion [52]. The OCC model is probably the most widely implemented of the cognitive appraisal theories [e.g., 45, 50, 52, 54] which explain the mechanisms by which events, actions, and objects in the world around us activate emotional construals. In both the Oz and Affective Reasoner projects, emotion was largely modeled as a reactive capability that helped characters to recognize situation and to reflect broad and believeable personality charateristics. Later versions of Oz include a behavior planner, but the link between emotion construals and behavioral choice is never well articulated in their published accounts [58]. On the other hand, Gratch [49] and el Nasr, Ioerger, & Yen [56], concretely extend the OCC model via the use of an event planner into a deeper deliberative reasoning mode -- depth vs. breadth of emotive reasoning. .Thus agents were now able to construe the value of plans and plan elements (events that haven't happened yet). In the current paper, we make use of deliberative ideas of several of these earlier implementations, (though we replace the formal planner with a metagame optimizer) and we extend this still further so that agents can construe the value not only of plan elements (future events), but so they also can construe the impact of objects and behavior standards both on themselves and on those they like/dislike. We go beyond this too to the area of what is probably unconscious construals of stressors such as fatigue, time pressure, and physiological pressures. This means we provide a fairly full implementation of the OCC model for reactions and deliberations of all types of events, actions, and objects.

We do this largely by adopting a mathematics of subjective expected utility based on formally derived value ontologies for events, actions, and objects in the world. This approach provides a generalizable solution to another issue with these earlier implementations, that the emotion-eliciting condition relations (and the mechanism for summing resulting emotions into utilities) had to be generated without any guidance about their source. That is, the OCC model indicates what emotions arise when events, actions, or objects in the world are construed, but not what causes those emotions or what actions an agent is likely to take as a result. There is no connection between emotion and world values, even though other theories suggest such a link [45, 54]. In contrast, value ontologies are readily available in the open literature (e.g., the ten commandments or the Koran for a moral code, military doctrine for action guidance, and need hierarchies such as Maslow for event guidance) and may readily be utilized to implement an agent of a given type in the framework we present here. We tie such ontologies in directly to the emotional processes of the agent, so that situation recognition as well as utilities for next actions are derived from emotions about ontologies and so that both reacting and deliberating (judging, planning, choosing, etc.) are effected by emotion. In this fashion, such agents are capable of surprising the human player, of detecting a meta-game, and of shifting the computerized drama to a new plane of systemic interaction.

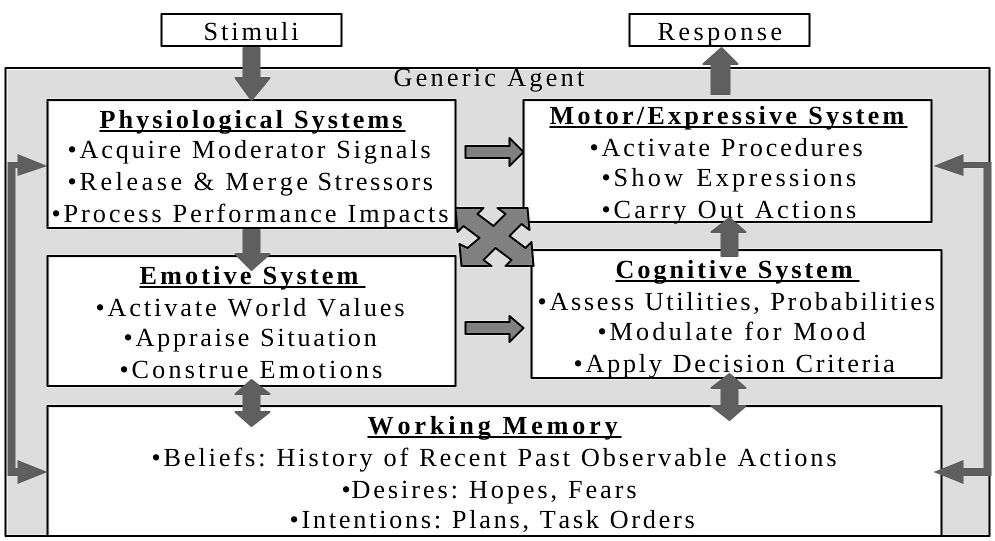
2.3 Criteria for More Behaviorally Realistic Agents

The discussion up to this point has been relatively broad ranging so it might be useful to organize it by presenting the top level of the integrative framework. In doing so the discussion will also reflect some desiderata or success criteria against which one could measure the deeper level of an integrative frame work. In particular for both the overall architecture and for each subsystem of the architecture we highlight two criteria that we believe would represent advances to agent behavioral realism if they could be satisfied . One could select other criteria but these were chosen since they reflect integration issues that were highlighted in 2.1 and that pose significant challenges for agent behavioral modeling that researchers can make inroads against.

The research described here is not to propose the best cognitive architecture or agent algorithms but to propose a reasonable framework within which the many contributions from the literature can be integrated, investigated, and extended as needed. That itself is the first criterion (A1) and to satis fy it we believe requires constructing some variant of four somewhat arbitrarily separated subsystems plus a memory that form the stimulus-response capability of an agent as shown in Figure 2. There are a large number of similar frameworks in the literature. For example, Wohl [66] uses what he refers to as the SHOR paradigm, standing for stimuli, hypothesis, options, and response. Likewise, the US Army calls these four steps acquire, assess, determine, and direct [67], and Boyd & Orr [68] call them the observe, orient, decide, and act (OODA) loop structure. A useful comparison of 60 such models may be found in Crumley & Sherman [70].

The model we depict here may be readily mapped to any of these similarly four-stepped architectures. In this model subsystems receive stimuli and formulate responses that act as stimuli and/or limits for subsequent systems. The flow of processing in a purely reactive system would be counter-clockwise starting at the "stimuli" label, however, we are also interested in a delibera tive system, one that can ponder its responses and run clockwise from the "cognitive system" to seek stimuli to support alternative response testing. A2 is thus that the system must be both interactive and deliberative. For the sake of expository convenience, however, we describe Figure 2 in a counterclockwise rotation from the "stimuli" node, after first introducing its working memory.

Figure 2 – Top Level of the Integrative Architecture for Researching Alternative Algorithms for Generic Agents



The agent model of interest to us is that of a modified Markov Decision Process (MDP). That is, the agent seeks to traverse a hierarchical and multi-stage Markov chain which is the set of nested games such as those that were introduced in earlier Figure 1. In order for the agent to be aware of this chain one would need to place it into the agent's working memory as a set of <u>intentions</u> or plans, goals, and tasks that the agent is seeking to work its way through in the current situation, and/or that the current situation poses as new task elements. More broadly, working memory should store (W1) and process (W2) beliefs, desires, and intentions – in recognition of the BDI agent model. The <u>beliefs</u> are those processed in the game theoretic sense of observing the world and of forming and remembering simple statistical models of the actions of those near us in the situation of interest as mentioned in the equation embedded at the base of Figure 1. <u>Desires</u> are not well-defined in the BDI model, so here we define them as the future-focused affective states or hope and fear as generated by the emotion system and as described more fully in Section 3.3.

Moving on to the , physiological subsystem it initially reacts to a set of stimuli that are perceived from and/or experienced in the environment. This subsystem includes all sensory apparatus, but also grouped into here are a number of physical processes that may be thought of as reservoirs that can be depleted and replenished up to a capacity. Some examples are energy, sleep, nutrients, and physical capacities. For each of these there are a large number of stressors that moderate its ability to perform up to capacity, and that in some cases send out alarms for example when pain occurs or when other thresholds are exceeded (e.g., hunger, fatigue, panic, etc.). An important criterion for such a module is (P1) that it supports study of common questions about performance moderators: e.g., the easy addition or deletion of reservoirs of interest to a given study or training world (e.g., stress from proximity to land mines), individual differences in reacting to the same stressors, and/or how to model reservoir behaviors either linearly or non-linearly such as with bio-rhythms. Another vital criterion for such a module is (P2) that it should support studying alternative mechanisms for combining the many low level stressors and performance moderator functions into a single stress level. It is the overall stress that effects each of the other subsystems, and one would like a framework that shows how to compute an integrated level and then each of the subsequent modules need capabilities to reflect how their functioning is effected – emotions about stress, judgments under stress, and stressed motor/expressive acts.

The <u>emotion subsystem</u>, largely but not exclusively in the prefrontal cortex, recieves stimuli from the sensors as adjusted and moderated by the physiological system. It includes a long term associative or connectionist memory of its values hierarchies or ontologies that are activated by the situational stimuli as well as any internally recalled stimuli. These stimuli and their impact on the value ontologies act as releasers of alternative emotional construals and intensity levels. These emotional activations in turn provide the somatic markers that serve as situation recognition and that help us to recognize a problem that needs action, potential decisions to act on, and so on. In order to support research on alternative emotional construal theories this subsystem must include (E1) an easily alterable set of activation/decay equations and parameters for a variable number of emotions. Further, since construals are based on value ontologies, this module must serve (E2) as a values ontology processor and editor. Simply by authoring alternative value ontologies, one should be able to capture the behaviors of alternative "types" of people and organizations and how differently they would assess the same events, actions, and artifacts in the world. This requires the emotion module to derive the elements of utility and payoff that the cognitive system will use to access alternative actions.

The <u>cognitive subsystem</u> is the locus of reasoning as guided by the sensory and emotive subsytem stimuli. Once it receives their assessment of the situation and its gravity, plus any weightings and emotional feelings about potential actions (next steps), the cognitive subsystem synthesizes this material into an expected utility and a best reply (or set of actions in a plan) that it then conveys to the motor subsystem. In reactive mode, the cognitive subsystem is triggered by the emotive and sensory ones, while in deliberation mode it might invoke them to seek more input and assess its significance. Either way, it is up to the cognitive subsystem to pick a decision processing mode and, using that mode, to select the actions to take next. The selection of decision processing mode is a major topic in the human behavior research literature, and a primary feature any integrative framework should include. Its goal should be (C1) to support testing of a wide range of alternative decision processing modes, from normative to descriptive, from rational to emotive- and mood-influenced, and from unstressed to panic- and crisis-directed. Also where the cognitive system supports reasoning hypothetically and retroductively to drive the other subsystems, it should include (C2) both normative and descriptive versions of these abilities. For example if it includes a normative path planner, it should also call for that module's performance and output to degrade due to stressors and/or emotive factors.

Turning now to the motor/expresive node of Figure 2, this module contains libraries of stored procedures that allow the agent to interact with the microworld and that allow it to display its motor and expressive outputs. Based on stimuli from all the other susbsystems, the motor subsystem recalls, activates, and adjusts the relevant stored procedures so it can perform the actions intended to reach the (best reply) next state. In attempting to carry out the actions the motor system (M1) should only carry out best reply actions and perform up to the limits that the physiologic system imposes, so it is vital that the stored procedures include functions that allow them to portray alternative behaviors. Also, the motor system (M2) should be able to serve as stimuli to the other systems. For example crouching for a long period might cause fatigue, pain, emotive distress, and so on.

3. Common Mathematical Framework for Behavioral Modeling

Section 2.3 introduced the top level overview of the integrative architecture (Figure 2). The objective here is to present the next layer of detail of the framework, a level at which it is meaningful to taxonomize and compare different contributions from the literature. To do so we must adopt both a common semantics and concepts as well as a mathematical and measurable basis for comparing alternative contributions. This section presents that semantics and mathematics. We turn now to a more indepth review of the mechanisms involved in the phsyiological subsystem (Section 3.1), the emotive subsystem (Section 3.2), the decision strategy or cognitive subsystem (section 3.3), and the motor/expressivity subsystem (section 3.4).

3.1) The Impact of the Physiological System on Performance and Decision Making

Here we are interested in how diverse PMFs or stressors combine together to moderate two things: (1) Given an alternative action set to choose from, what is the likelihood that the agent will do the right thing at the current game iteration? and (2) For whatever strategy is chosen, will they do it right? The former of these determines if the agent will be able to find the Best Reply (BR) in the strategy set, while the latter pertains to their Performance Effectiveness (PE) when they carry out their chosen strategy. In the next section we address how they derive their strategy set to begin with.

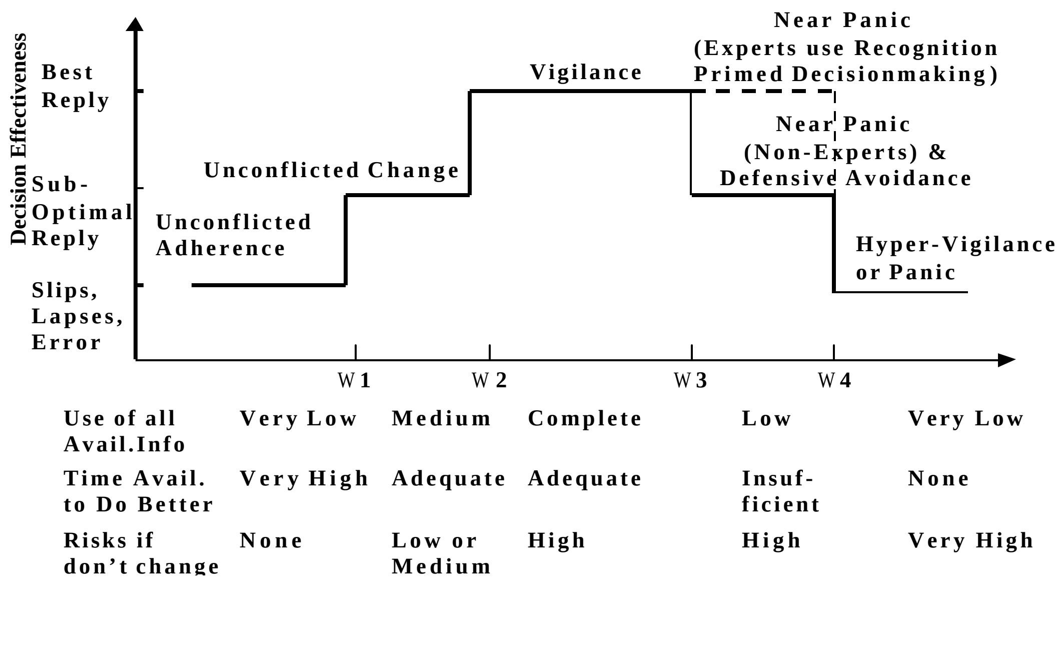
There is a voluminous literature on behavior under stress, easily numbering in the 10,000s of studies. One of the earliest studies is the classic Yerkes-Dodson "inverted u" which shows that as a stimuli or moderator is increased, performance is initially low, then rises, and then falls off again after a threshold is passed [27]. Thus some degree of presence of various stressors is better than none (e.g., performance can be better in slightly chaotic, moderately time-pressured settings). Some of the best reviews of this literature are in military meta-analyses such as, among others, the Virtual Naval Hospital which addresses the many dozens of factors effecting combat stress and the stages of stress one can evolve through [28], Driskell et al who conduct an exhaustive meta-analysis review [29], and Boff and Lincoln's data compendium which includes many classic studies and useful surveys on specific PMFs, though no overall meta-analysis [30]. In our own research, Silverman et al. have assembled nearly 500 Performance Moderator Functions from the literature and abstracted them into an anthology that includes assessments of their validity and data groundedness [3]. About 2/3rds of this collection concerns individual stressor PMFs and the remainder deals with emotive, motivational, and ideological factors that effect judgment and behavior. A finding of the Silverman anthology is that there is no validated model of how the many diverse stimuli and PMFs interact and cross-connect to effect stress and behavior. This finding is also confirmed by Hammond's insightful meta-analysis and attempt to delineate an integrative research paradigm for judgment under stress [31].

Despite this obstacle, there are a number of efforts that attempt useful integrative models[32-39]. Depending on their study or simulation requirements, their integrations differ sometimes dramatically, though each provide useful insights into the process. One of the more grounded of these examples, is Hursh [36] who reviewed 1,300 studies to develop a model of decision making in battle that focuses solely on <u>effectiveness</u> under stress. Gillis and Hursh [32] later extended this model to account for what they claim are the prime determinants of (stressed or non-stressed) performance: fatigue due to sleep deprivation/accumulation; time pressure; individual abilities such as intelligence, experience and training; and personality in the form of risk taking propensity; and the frequency and magnitude of events that are adverse/favorable and that they plot into event stress. A few concerns are that: (1) many of these factors are co-dependent, (2) they ignore the many alternate PMFs that can lead to fatigue such as exertion, noise, light flashes, smoke, etc. (see below), and (3) their formulation for personality and event stress is based on raw counts which ignores emotional construals, an item we address in the next section. However, they provide some interesting ways to integrate well-grounded models of the effect of training, intelligence, and experience. Further they address the issue of level of experience and incorporate the Recognition Primed Decisionmka ing approach of Klein [37]. They also attempted some initial studies of the validity of their model for simulated multi-day military missions (so they could assess the sleep deprivation) and they found that their factors had moderate explanatory effect at the .01 significance level.

A more theoretically inspired approach was taken by Hendy and Farrell [35] who adopt an information processing theory and model. This model focuses less on field combatant and more on equipment and screen operators including factors such as task workload (bits to process) and work rate (bits/sec). They offer an information processing (bit throughput, error rate, decision time) account that attempts to explain the effects of time pressure, task difficulty, mental capacity, fatigue, motivation, anxiety, and the like. They also model the operator's allocation of attention across subtasks and track tasks shed, interrupted or postponed. Further, they scale the model to repetitive tasks and to a network of operators. This model claims that time pressure is the primary determinant of operator workload, performance and errors, but as yet, they have little empirical results to back up their claims. Also, this account is at odds with alternative theoretically-based approaches that emphasize cognitive resource-sharing is the prime determinant of performance: e.g., see [38].

At a more macro-behavioral level, yet another approach was taken by Janis and Mann [39]. This includes a meta-analysis of the literature plus an account of many of their own numerous studies of stress and decision making under conflict. Janis-Mann provide what is probably the most widely sited taxonomy of decision strategies for coping under stress, time pressure, and risk. We interpret this taxonomy on the as the steps of the U-curve of Figure 3 and define it below. The taxonomy includes a flowchart or algorithm (they call it a decisional balance sheet) that indicates how stress, time pressure, and risk drive the decision maker from one coping strategy to another and we depict these items across the X-axis of Figure 3.

Figure 3 - The Classic Performance Moderator Function is an Inverted-U



In particular, we use the algorithm to derive the values of what we call integrated stress, or the iSTRESS variable:

iSTRESS $\leq \Omega 1$ unconflicted adherence, select $m_t = m_{t-1}$ (3.0)

$\leq \Omega 2$ unconflicted change to next S_m in MISSION set

$\leq \Omega 3$ m = 1, M whichever is Best Reply (vigilance)

$\leq \Omega 4$ near panic so, m = 1 of 1,M (if highly experienced m = BR and this turns into Recognition Primed Decisionmaking as per Klein [37]. Also, defensive avoidance occurs at this level for non experts)

$> \Omega 4$ panic, so S_m = run amok or cower on ground (hyper-vigilance)

where, according to Janis and Mann, the five coping patterns are defined:

1) *Unconflicted adherence (UA)* in which the risk information is ignored and the decisionmaker (DM) complacently decides to continue whatever he has been doing.
2) *Unconflicted change (UC)* to a new course of action, where the DM uncritically adopts whichever new course of action is most salient, obvious, or strongly recommended.
3) *Vigilance (VG)* in which the DM searches painstakingly for relevant information, assimilates it in an unbiased manner, and appraises alternatives carefully before making a choice.
4) *Defensive avoidance (DA)* in which the DM evades the conflict by procrastinating, shifting responsibility to someone else, or constructing wishful rationalizations and remaining selectively inattentive to corrective information.
5) *Hypervigilance(HY)* wherein the DM searches frantically for a way out of the dilemma and impulsively seizes upon a hastily contrived solution that seems to promise immediate relief, overlooking the full range of consequences of his choice because of emotional excitement, repetitive thinking, and cognitive constriction (manifested by reduction in immediate memory Span and simplistic ideas). In its most extreme form, hypervigilance is referred to as "panic."

All but the third of these coping patterns are regarded by Janis -Mann as "defective." The first two, while occasionally adaptive in routine or minor decisions, often lead to poor decision-making if a vital choice must be made. Similarly, the last two patterns may occasionally be adaptive but generally reduce the DM's chances of averting serious loss. The authors note, vigilance, although occasionally maladaptive if danger is imminent and a split-second response is required, generally leads to decisions of the best quality". Some authors have since refined these ideas as with Rasmussen [74] who showed that skill level performance happens in the pre-vigilant stages (subconsciously) such as with a rifleman shooting ahead of an animal fleeing away. In Rasumussen's model vigilance occurs at the rule and knowledge levels of cognitive processing. Klein [37] in turn, shows that experts work effectively in the "near panic" mode where they immediately recognize a best or near best alternative without vigilant scanning of other alternatives.

Unfortunately, Janis -Mann do not provide either (1) precise threshold values (Ω_i) that indicate when decision makers trigger a change in coping style, or (2) any insight into how to integrate the many diverse stimuli, factors, or PMFs that determine stress and time pressure or risk. For these purposes, we draw from the literature mentioned above and provide an integrative model in the remainder of this section, a model that is intended to support the use of the Janis -Mann coping styles in equations 3.

In particular, we model integrated stress or iSTRESS as a result of three prime determinants – event stress (ES), time pressure (TP), and effective fatigue (EF) -- each of which is quantitatively derived and then emotionally filtered, f(.), since a stoic will construe the same facts differently than a nervous type. The next section describes the emotional filtering. Here we examine the quantitative factors that go into these modifiers and the rationale for combining these three modifiers.

$$\text{iSTRESS}(t) = f\{ES(t), TP(t), EF(t)\} \qquad (1.0)$$

Event stress (ES) is derived as the simple sum of the number of events in recent history (τ periods back) that are either positive in terms of sub-game goals, or negative and hinder or slowdown the agent's reaching his best reply to the current node of the multi-stage Markov chain and in past nodes within the historical period. Adverse events might, as a few examples include schedule delays; intermediate state failures; realization of inaccuracy in prior information; inability to get better information; proximity to unfriendlies or opponents (particularly if they are firing in your direction) and encountering hazards and threats such as mines or gas; and loss of or isolation from peers, among others. Thus ES is potentially reflective of how confident the agent is that its next actions will be successful or not. ES can vary over the interval 0,1 with 0 being over-confident and unstressed, 0.5 is neutral, and 1.0 is totally battle stressed and cowered. How the quantity of events maps onto this scale is a matter for further empirical derivation, however, at present follow qualitative guidance from the Virtual Naval Hospital [28] and translate that into 0.5 as the starting position for a novice and 0.1 for an experienced combatant. We further assume that each event adds or subtracts 0.1 of ES, subject to the processing by the individual's construal filter. Unlike [28], however, we do not model post traumatic stress disorders, and restrict our focus to the time frame of the game only.

$$ES(t) = \sum_{\psi = t - \tau}^{t} [\text{positive-events}(\psi) - \text{adverse-events}(\psi)] \; / \; \tau \qquad (1.1)$$

$$0 <= ES(t) <= 1.0$$

This approach is relatively consistent with Gillis and Hursh [32], although they also consider frequency and not just quantity of past confidence building/depleting events, and their numerical scale uses a different range. However, they rely on the quantitative scores only and ignore the emotional construal of event stress. As already mentioned, we model this construal in the next section, where we also model risk-taking propensity, aggressiveness, and over-confidence in terms of what causes the agent to place riskier strategies in the set, S. Also, the reader will recall from equation 1 that smaller Δ tends to bias the agent toward potentially riskier strategies as the end of a stage of the game is neared.

Driskell [29] has summarized the literature on time pressure (TP), and found that a relatively simple linear equation relates the magnitude of time pressure to stress. Thus if one has a task that requires 30 seconds to do it accurately (ideal time or T_I), and there is only 20 seconds to do it in (available time or T_A), there will be a stress effect (and a performance impact that we address shortly). Hursh [36], in turn, further reviewed the literature and recommended that the magnitude of the time stress, TP, be computed as:

$$TP = T_I / (T_I + T_A) \qquad (1.2)$$
$$0 <= TP <= 1.0$$

Thus for the example here, TP = 0.6. In this manner, $0 < TP <= 1.0$, where TP approaches completely time stressed as T_A shrinks to nil, while TP stress disappears as the available time, T_A, approaches infinity. As with event stress, we believe that time stress is not just a quantitative effect, and that inexperienced and not recently trained individuals as well as others will experience an amplification effect where TP is further increased as they construe that they do not have the time to complete the task as well as they'd like to. More on this in Section 2.2.

Effective fatigue (EF) is modeled as depleting a cognitive reservoir that starts out full when the agent is rested, and that begins to refill every time the agent rests and is removed from relevant PMFs. The reservoir is depleted by a number of PMFs suggested in the literature such as sleep deprivation; exertion intervals; bruises and non-incapacitating wounds; temperature, noise, smoke, and explosive light effects; and lack of nourishment, among others. For each of these there is a fatigue tolerance (FT) and a reservoir replenishment due to removal of the moderator from the environment. For the sake of simplicity in the current version, we assume the replenishment takes 10 time periods, or $1/10^{th}$ of the PMF's effect disappears each time period after the presence of the PMF is removed. Also when they are present, we model the effect of each of the PMFs as a linear function in a similar manner to that of time pressure, such that $PMF_i / (PMF_i + FT_i)$] is the behavior of each of the I moderators which very from 0,1. As a default, FT_i is set to unity, though it could be increased to suggest greater stamina of a given type of individual. We then combine these PMFs as a normalized sum so that the overall EF grows the longer the agent is exposed to the PMFs and decays after they are removed:

$$EF(t) = EF(t-1) + \{\Sigma_{i=1,I}\, w_i[PMF_i(t)/(PMF_i(t) + FT_i)]/I\} - \{EF(t-1)/10 \text{ if } 0=\Sigma PMF_i(t)\} \qquad (1.3)$$
$$0 <= EF(t) <= 1.0$$

We do not currently differentiate the weights, although some evidence in the literature suggests that sleep deprivation is the dominant factor [12, 40]. However, in short run intervals, continuous exertion can be a serious temporary debilitator even for well-rested individuals [12, 41]. The literature on temperature, light, smoke, and noises effects is mixed particularly in the presence of adrenalin and other motivational factors. We currently model the absence of these latter PMFs such that the individual can recover from them just with the passage of time, as in the formula above. Recovering from sleep deprivation cannot happen unless the individual is actually immobile, then sleep is assumed. Recovery from exertion begins once the activity level falls below an exertion threshold. Lastly, to recover from mal-nourishment and non-incapacitating wounds, we make the simple assumption that the arrival of food and medical attention will suffice to immediately eliminate those effects. Overall, the reservoir starts off as full and its then depleted in each time interval as EF grows, and if there is no rest, recovery, and/or replenichment periods. One can alter the value of FT_i to represent the tolerance of well-trained individuals to specific PMFs, but we do not currently do so.

At present we use logic rules to combine these three factors. For example, such rules must account for facts such as a Very High value of anyone of the factors could push the agent to panic. However, panic is more likely if at least one factor is very high and another is high. Or alternatively, if one factor is very high and both of the others are moderately high, panic might also result. At the other end of the spectrum, as another example, all three factors must be very low to result in unconflicted adherence. These two rules are listed below, and similar ones exist for each of the other threshold cutoffs. At present we do not have empirical verification for these threshold levels, but this seems to work in the simulations.

Panic (ISTRESS>= Ω5)= VERY HIGH + HIGH or
VERY HIGH + MEDIUM HIGH + MEDIUM HIGH

Unconflicted Adherence (ISTRESS<= Ω1) = VERY LOW + VERY LOW + VERY LOW or ~0

3.2) **Emotion Appraisal as a Deep Model of Utility (with contributions from Michael Johns)**

In the next section we will examine how to combine multiple emotions into a utility estimate for a given state. For now we will only examine how our different emotions arise when confronted by a new state, s, of the world, or in reaction to thinking about being in that state. In general, we propose that any of a number of ξ diverse emotions could arise with intensity, I, and that this intensity would be somehow correlated to importance of one's values or value set (C) and whether those values succeed or fail for the state in question. We express this as

$$I_x(s_k) = \sum_{j \in J_x} \sum_{c \in Cijkl} [W_{ijl}(c) * f1(r_j) * f2(O,N)] \qquad (2.0)$$

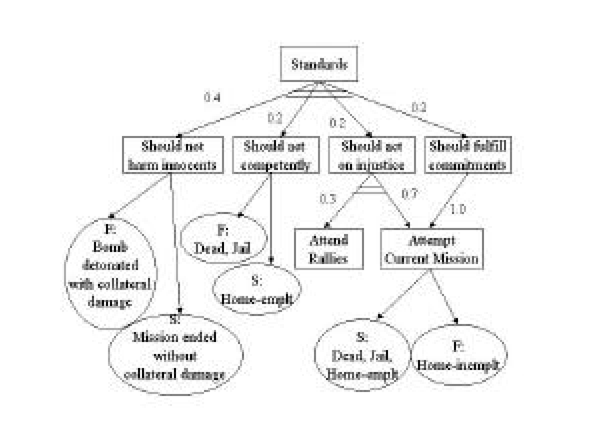
Where,

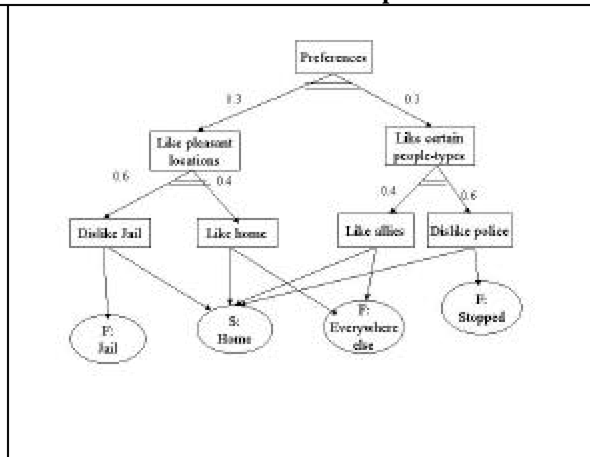
$I_\xi(s_k)$	=	Intensity of emotion, ξ, due to the kth state of the world
J_ξ	=	The set of all agents relevant to x. J_1 is the set consisting only of the self, and J_2 is the set consisting of everyone but the self, and J is the union of J_1 and J_2.
$W_{ij}(C_{ijkl})$	=	Weighted importance of the values of agent j that succeed and fail in one's ith concern set.
C_{ijkl}	=	A list of paths through the ith ontology of agent j triggered to condition l (0=success or 1=failure) by state k.
$f1(r_j)$	=	A function that captures the strength of positive and negative relationships one has with the j agents and objects that are effected or spared in state k
f2(O,N)	=	A function that captures temporal factors of the state and how it impacts one's

emotions from the past, in the present, and for the future

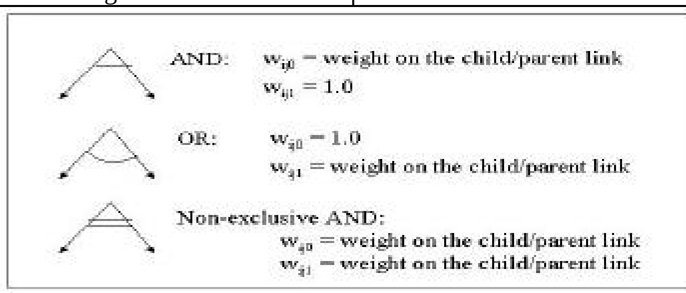
This expression captures the major dimensions of concern in any emotional construal – values, relationships, and temporal aspects. For the sake of simplicity, we assume linear additivity of multiple arousals of the same emotion from the i=1,I different sets of values that the state may precipitate. Also at this point, the terms of this equation are still vague, a fact we now attempt to correct.

Figure 4 – Value ontologies Showing Part of the Standards and Preferences of a Sample Terrorist





5a – Terrorist's Standards for Agent Behavior/Action | 5b – Terrorist's Preferences for Artifacts or Objects



There are several emotion models from the psychology literature that can help to provide greater degrees of detail for such a model, particularly a class of models known as cognitive appraisal theories. These include the models of Lazarus [5], Roseman [9], and Ortony, Clore, and Collins (OCC) [7], and take as input a set of things that the agent is concerned about and how they were effected recently, and determine which emotions result. Most of them fit into the structure of equation 4.0 but they have different strengths to bring to bear. At present we have decided to pursue the OCC model to see how it helps out.

Before elaborating on the OCC model and how it helps to further define Equation 2.0, it is worth introducing some preliminaries about concern trees. Let us suppose as in Figures 4a & b that we have a terrorist agent who has two concern trees (let |C| = 2): one for standards (i=1) about how agents should act and one for preferences about objects or artifacts in the world (i=2). Of course any such agent would have many more concern trees and each might be more richly filled in, but these will suffice for the sake of the example. And in fact, the stopping rule on filling in concern trees for any agent is the limit of what behavior is needed from them in the scenario or micro-world in question. One can see from Figure 4 that concern trees bottom out in leaf nodes that can be tested against elements (events, actions, nearby objects, etc.) of the current state, k. Further, concern trees hold an agent's previously learned values or importance weights. Each link of a concern tree is labeled with a weight, w, and the sum of child weights always sums to 1.0 for the sake of convenience. The children can be either strictly or non-exclusively conjunctive or disjunctive.

Thus far in our research we have derived the structure and weights on these trees manually as part of the process of building agents for a given micro-world, though one could in principle derive these trees via machine learning and knowledge discovery when interacting with a news event dataset about a given terrorist group. The way we use these trees in Equation 2.0 is as an evaluation function for Wi. That is, when a given state of the world causes a leaf node to fail or succeed, that leads to the wi being multiplied together up the branch of the tree from leaf node to root, and the overall Wi of that concern tree is computed. This may be expressed as:

We then multiply up the tree for each appearance, and sum them:

$$W_{ijl}(c) = \sum_{appearances(Ci)} \prod_{Ci=c}^{Ci=root} w_{ijl}(c_i, parent(c_i)) \qquad (2.1)$$

where,

ci	=	child concern or node
parent(ci)	=	parent node

As an example of Equation 2.1, consider how the use of the trees of Figure 4a&b result in the weighting on a strategy resulting in being dead. Upon the agent's death (k="dead"), one standard (i = 1) directly succeeds and one fails. He feels pride at having attempted his mission (c="attempt current mission") for two reasons: he has fulfilled his commitment to the organization, and has attempted something to correct a perceived injustice.

$$C_{1,1,k,0} = \{\text{"attempt current mission"}\}$$

$$\begin{aligned} W_{1,1,0}(\text{"attempt current mission"}) = & \sum_{appearances(c)} \prod_{ci=c}^{ci=root} \mathrm{w_{ijl}}(\text{ci, parent(c)}) \\ & [w_{1,1,0}(\text{"attempt current mission"}, \text{"fulfill commitments"}) * \\ & \mathrm{w}_{1,1,0}(\text{"fulfill commitments"}, \text{"standards"})] + \\ & [w_{1,1,0}(\text{"attempt current mission"}, \text{"act on injustice"}) * \\ & \mathrm{w}_{1,1,0}(\text{"act on injustice"}, \text{"standards"})] \\ & = [0.7 * 0.2] + [1.0 * 0.2] \\ & = 0.14 + 0.2 \\ & = 0.34 \end{aligned}$$

r_{1c} is 1.0 by definition, as the cognitive unit with one's self is always perfect.

Since we are only considering the feelings of one agent, J is the singleton set {1}.

$$\begin{aligned} I_{pride}(\text{dead}) &= \sum_{j \in J} \sum_{c \in C_{1,1,1k}} W_{1,j,0}(c) * r_{1c} \\ &= 0.34 * 1.0 \\ &= 0.34 \end{aligned}$$

However, his mission involved returning home safely, which is clearly thwarted by failing to survive. Consequently, he will feel shame at his incompetence as well:

$$C_{1,1,k,1} = \{\text{"act competentl y"}\}$$

$$W_{1,1,1}(\text{"act competentl y"}) = w_{1,1,1}(\text{"act competentl y"}, \text{"standards"})$$
$$= 0.2$$

$$I_{shame}(\text{dead}) = \sum_{j \in J} \sum_{c \in C_{1,1,k,1}} W_{2,1,1}(c) * r_{1c}$$
$$= 0.2 * 1.0$$
$$= 0.2$$

No preferences (i=2) are caused to succeed or fail by being dead. Consequently, no emotions are generated from this agent's preference ontology.

Let us turn now to the OCC model and how it expands Equations 2.0 and 2.1. Appraisal models are consistent in their reliance upon a set of agent values, but for the most part give no advice about how to determine what these values might be for a fully developed agent. So one generally needs to look to other sources for guidance. In one study, a hierarchy of values for terrorists has been elaborated in Weaver & Silverman [10]. That work shows a hierarchy of cases that differs across terrorists who come from different organizations. Further it shows how to devise hierarchies for new groups as a function of their political setting, ideology, campaign & mission aims, operational objectives, and so on. At still lower levels, values vary widely among individuals. To develop a complete model of what an agent cares about, we must probe deeper into who we are modeling. Upbringing, personal history, and individual quirks can all significantly effect what goals, standards, and preferences an agent is likely to hold. Two terrorists even from the same group will tend to have differences in their cares. However, we may not care to model such fine-gained differences. Also, several effects in clandestine terrorist cells tend to drive them to be consensual (e.g., being isolated from others and needing to belong to the cell, as well as the well known "risky shift" effect).

As mentioned previously, the OCC model divides the values of an agent into goals about events, standards for how agents should behave, and preferences for items or artifacts. These become the elements of C in equation 3.0, with goals at i=1, standards at i=2, and preferences at i=3. So we discuss these separately in what follows.

3.2.1) Goals for Events

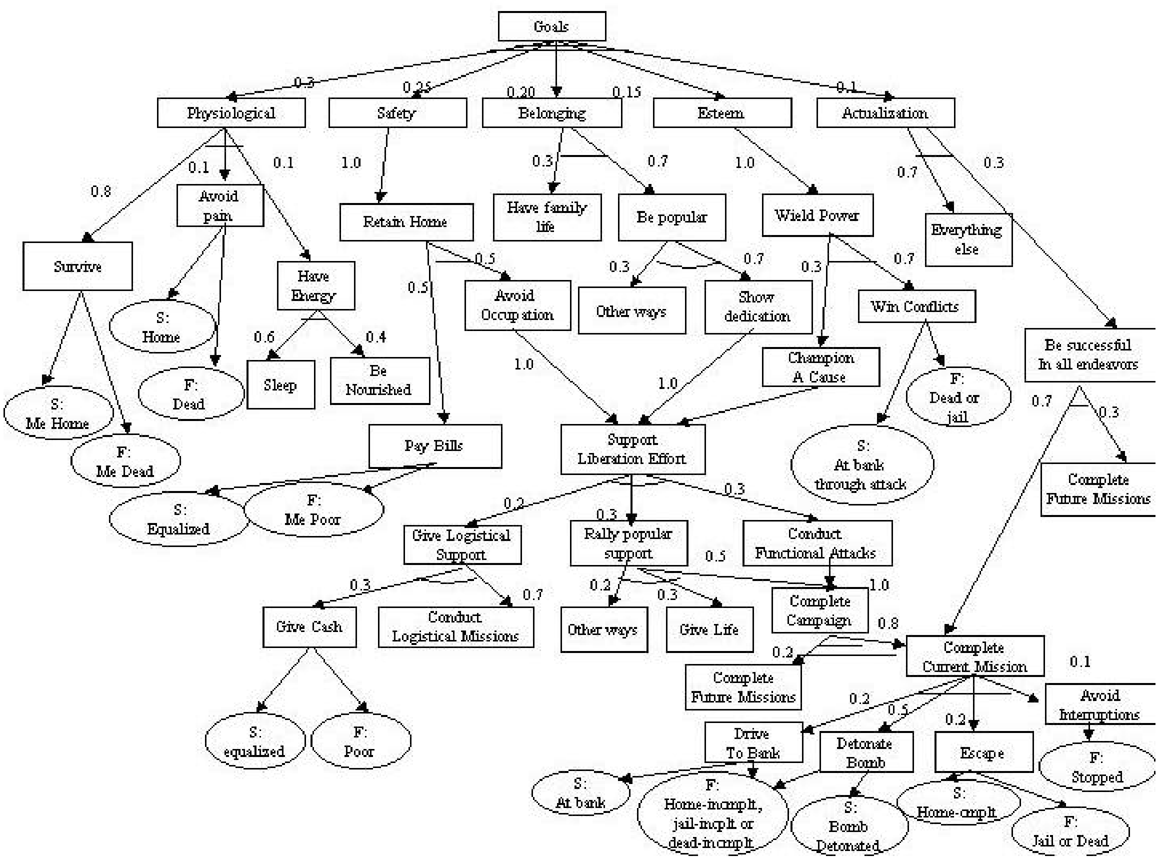
At the highest level, the work of Maslow [51] is a useful starting point in understanding what goals an individual will have, showing five basic motives from which all others are derived: 1) physiological needs; 2) safety needs; 3) social belonging; 4) personal esteem; and 5) self-actualization needs. Though we reject his seriality premise, Maslow's work has been empirically shown to be descriptive of individuals across cultures, age groups, and generations, and is consequently a rich source of high-level goals and drives.

Figure 5 shows the goal structure for an example terrorist. Maslow's needs are used as the motivating forces of all other goals, and consequently appear at the top of the hierarchy. Since this terrorist was designed as a "have not" in a financially divided society, he is primarily concerned with his more basic needs; self-actualization is relatively unimportant to one who is struggling to keep a roof over his head. Our terrorist is concerned about three aspects of his physiological well-being. Like all living things, he has a desire to preserve himself. In terms of the particular scenario being simulated, this fails when he is dead, and succeeds when he has returned home safely. Secondly, he would prefer to avoid situations that put him in pain, and finally, he wants to conserve his energy, which consists of sub-goals to stay rested and well-fed. The only safety/shelter need modeled for this terrorist is his desire to retain his home. In order to do this, he must both pay the bills and avoid situations where his land becomes militarily occupied. At the beginning of the simulation, his goal to pay the bills is already failing due to his extreme poverty, and this is one of the contributing factors in his decision to support the liberation effort in the first place. In addition, he sees the liberators as a force to defend his land from occupation. This is the first of several places in his goal ontology where it becomes important to in some way support his terrorist organization. We will return to what is involved in such an effort shortly.

This terrorist has two primary belonging needs: among his family, and among his comrades. Since we are not simulating his family life, this goal serves only to consume importance, and to remind our terrorist (and the agent author) that his social life has not collapsed entirely if he leaves the organization. To be popular among his comrades, again an untested goal is used to account the fact that visibly showing your devotion to the cause is not the only way to gain admiration despite this being the only way our simulated terrorist can do so. This terrorist believes that supporting the liberation effort will prove his dedication and thus garner him the adulation of his comrades. Esteem is considered to be primarily about power. Specifically, in this scenario, our terrorist's esteem depends on emerging as the victor in violent conflicts, and influencing his environment via participating in the efforts of his organization. In a longer-term game, this is also where rising in rank becomes important, however this is not yet accounted for. Self-actualization needs are for the most part not simulated, as such things take place primarily in an individual's free time. Therefore, an untested goal consumes the majority of the importance allocated to these needs. However, it is important to our terrorist to succeed in whatever he does, and as such the completion of his current and future missions are given additional value here.

As the primary simulated function of this terrorist, supporting his organization is an extremely important goal that serves a variety of higher level needs. In order to participate in the organization, this individual can do one of three things. The first is to lend logistical support, either by direct cash donations (which are made impossible by poverty), or by conducting missions that bring in cash or equipment. The second is to rally popular support for the organization, which can include unsimulated methods such as distributing flyers, or directly supporting the current campaign of terror that the organization has undertaken. Lastly, it is enough to rally significant amounts of support for a cause by simply becoming a martyr for it, and to give one's life for this reason is a possible goal in itself.

Figure 5 – Initial Goal Ontology for a Terrorist Agent



From the terrorist's point of view, the campaign consists of his current mission plus an abstract notion of future missions. Again these future missions serve only to consume importance, as the terrorist should not believe that his current mission is the only determinant of the success of the campaign as a whole. The current mission, then, contains each step in the process as a subgoal. In this case, that involves driving to the bank, detonating the bomb, and escaping. Our terrorist is also a perfectionist in that the slightly awry step of being stopped by the police at a checkpoint will sour the experience for him. There is, however, no reason why this goal cannot be moved elsewhere to lessen its impact on a more relaxed terrorist.

Goal-based emotions -- Goals can take one of three forms: 1) active goals, which the agent can directly plan to make happen (I want to reload my rifle); 2) interest goals, which are states of the world that the agent would like to become reality but generally has no say in (I want important missions); and 3) replenishment goals, which periodically spawn active goals based on time since last fulfillment (I do not want to starve).

In order to determine the intensities of emotions pertaining to the success or failure of goals, the OCC model uses several variables depending upon the context of the situation. Specifically, the variables used depend on whether the event is confirmed, disconfirmed, or unconfirmed, whether the event was anticipated, and whether it happened to the agent itself or someone else. Unfortunately, it is far from clear how some of these can be computed. For this reason, the system as implemented to date tracks only the importance, probability, and temporal proximity of goals. The variables pertaining to how one agent feels about another are considered relationship parameters, and will be discussed later. Degree deserved, effort expended, and degree of realization are left for future research.

Under the OCC model, unanticipated confirmed goal successes and failures for one's self generate joy and distress, where anticipated goal effects in an unconfirmed state generate ***hope and fear***. In a confirmed state, hope and fear will turn to ***satisfaction or disappointment***, respectively, and in the disconfirmed state fear and hope become ***relief*** and, for lack of a better term, ***fears-confirmed***. When evaluating how the goals of others have been effected, goal successes will generate ***happy-for or resentment,*** and goal failures will generate ***gloating or pity***, depending on whether the agent in question is liked or disliked by the agent experiencing the emotion. We explicitly define the latter as the r_L and r_D relationship parameters, respectively, which vary on a scale from 0 to 1.

3.2.2) Standards for Agent Behavior

There are innumerable sources one can turn to for material to include in standards trees. A few examples are military doctrine, ethics and morality writings, religious works, and the like. In fact, when modeling religious terrorists it is a good idea to include the principles of their religion in their standards trees. Likewise it is equally useful to include their doctrine and codes of behavior as found from published accounts. For the sake of simplicity in this writeup, we will only describe the standards as those given in earlier Figure 5a.

It should be noted that standards are not unlike interest goals in that they are passive in nature. However, since they represent how people should behave, they are triggered not only when something relevant happens to the agent, but when something relevant happens to anyone. We are affected by reading accounts of ancient warfare practices not because these still can threaten us (or anyone we care about) in any tangible way, but because they often differ so greatly from what we consider acceptable.

Standards are responsible for what the OCC model terms "attribution emotions". When responsibility for an action is attributed to one's self, ***pride or shame*** will result. When attributed to an external agent, these turn to ***admiration or reproach***. The intensities of standards-based emotions are effected by three primary factors. (1) The degree of judged praiseworthiness or blameworthiness is the first, and is implemented as the result of the intensity equation 2.1 for an effected standard.

(2) The strength of the cognitive unit, R_C, between the emoting agent and the agent performing the action determines the degree to which one will feel, for instance, shame as opposed to reproach for the blameworthy actions of another person. It is often the case that one will indeed feel a self-focused emotion about, for instance, the actions of one's country, even though that individual strictly had nothing to do with that particular action.

(3) The third intensity factor involves deviations from role-based expectations. This captures the idea that we generally do not develop intense feelings about things we expect of people. As there is not yet a system in place for managing roles and the development of beliefs about another agent's concern structures, this intensity factor is not is not yet implemented.

3.2.3) **<u>Preferences for Artifacts</u>**

Lastly, preferences track the likes and dislikes of an agent, and we earlier included a sample preference tree as Figure 4b. While typically pertaining to objects (I dislike broccoli), it is important particularly in military scenarios to note that it is entirely possible to view another agent as an object. This has the side effect of making them not subject to standards, and consequently an agent will not feel standards-based emotions about anything done to the objectified agent. This includes, for example, avoiding the shame normally felt for inflicting needless harm on another person. We explicitly model degree of being perceived as an agent as R_A and degree of being perceived as an object as R_O – both of which also vary on a scale from 0 to 1.

Emotions resulting from effects upon preferences come only in two varieties under the OCC model: liking and disliking. Preference-based emotions have only two intensity factors. The degree to which an object is considered appealing or unappealing is modeled again using the intensity function of earlier Equation 2.1. As advertisers are well aware, familiarity with an object breeds a tendency to express a preference for it, and as the second intensity factor, this amplifies the intensity of liking and dampens the intensity of disliking.

<u>3.2.4) Computing the 22 OCC Emotions</u>

The previous subsections enumerated 11 pairs of emotions due to the concern trees and relationship parameters. We are now in a position to provide the equations that generate these emotions. First let us assume that C is the set of all effected values for all agents as described above; W is the set of total weights of all values computed according to equation 2.1 r_{jl}, r_{jd}, r_{jc}, r_{jf}, r_{ja}, and r_{jo} are the liking, disliking, cognitive unit, familiarity, agent, and object relationship parameters, respectively; P is a function determining the probability of the success or failure in question occurring; and I_ξ is the emotion intensity function given previously (equation 2.1). Then we can see that Equation 2.0 takes on the following form for each of the 22 emotions:

$$I_{\text{happyfor}} = \sum_{j \in J_2} \sum_{c \in C_{1,j,0,k}} W_{1,j,0}(c) * r_{jl}$$

$$I_{\text{gloating}} = \sum_{j \in J_2} \sum_{c \in C_{1,0,0,k}} W_{1,j,0}(c) * r_{jd}$$

$$I_{\text{resentment}} = \sum_{j \in J_2} \sum_{c \in C_{1,0,1,k}} W_{1,\text{j},0}(c) * r_{jd}$$

$$I_{\text{pity}} = \sum_{j \in J_2} \sum_{c \in C_{1,0,1,\text{k}}} W_{1,\text{j},1}(c) * r_{jl}$$

$$I_{\text{hope}} = \sum_{j \in J_1} \sum_{c \in C_{1,1,0,\text{k}}} W_{1,1,0}(c) * P(c) * N$$

$$I_{\text{fear}} = \sum_{j \in J_1} \sum_{c \in C_{1,1,1,\text{k}}} W_{1,1,1}(c) * P(c) * N$$

$$I_{\text{satisfaction}} = \text{Previous } \; i_{\text{hope}} * (1 - N)$$

$$I_{\text{fearsconfirmed}} = \text{Previous } \; i_{fear} * (1 - N)$$

$$I_{\text{relief}} = \text{Previous } \; I_{\text{fear}} * (1 - N)$$

$$I_{\text{disappointment}} = \text{Previous } \; I_{\text{hope}} * (1 - N)$$

$$I_{\text{joy}} = \sum_{j \in J_1} \sum_{c \in C_{1,1,0,k}} W_{1,1,0}(c) * O * (1 - N)$$

$$I_{\text{distress}} = \sum_{j \in J} \sum_{1c \in C_{1,1,1,k}} W_{1,1,1}(c) * O * (1 - N)$$

$$I_{\text{pride}} = \sum_{j \in J} \sum_{c \in C_{2,1,0,k}} W_{2,j,0}(c) * r_{jc}$$

$$I_{\text{shame}} = \sum_{j \in J} \sum_{c \in C_{2,1,1,k}} W_{2,j,1}(c) * r_{jc}$$

$$I_{\text{admiration}} = \sum_{j \in J} \sum_{c \in C_{2,1,0,k}} W_{2,j,0}(c) * [(1 - r_{jc}) + r_{ja}] / 2$$

$$I_{\text{reproach}} = \sum_{j \in J} \sum_{c \in C_{2,1,1,k}} W_{2,j,1}(c) * [(1 - r_{jc}) + r_{ja}] / 2$$

$$I_{\text{gratification}} = \begin{cases} 0 \text{ if } \operatorname{abs}(I_{\text{pride}} - I_{\text{joy}}) > .2 \\ \max(I_{pride}, I_{\text{joy}}) \text{ otherwise} \end{cases}$$

$$I_{\text{remorse}} = \begin{cases} 0 \text{ if } \operatorname{abs}(I_{\text{shame}} - I_{\text{distress}}) > .2 \\ \max(I_{\text{shame}}, I_{\text{distress}}) \text{ otherwise} \end{cases}$$

$$I_{\text{anger}} = \begin{cases} 0 \text{ if } \operatorname{abs}(I_{\text{reproach}} - I_{\text{distress}}) > .2 \\ \max(I_{\text{reproach}}, I_{\text{distress}}) \text{ otherwise} \end{cases}$$

$$I_{\text{gratitude}} = \begin{cases} 0 \text{ if } \operatorname{abs}(I_{\text{admiration}} - I_{\text{joy}}) > .2 \\ \max(I_{\text{admiration}}, I_{\text{joy}}) \text{ otherwise} \end{cases}$$

$$I_{\text{liking}} = \sum_{j \in J} \sum_{1c \in C_{3,1,0,k}} W_{2,1,0}(c) * r_{jo} * r_{jf}$$

$$I_{\text{disliking}} = \sum_{j \in J} \sum_{1c \in C_{2,1,1,k}} W_{2,1,1}(c) * r_{jo} * r_{jf}$$

$$N = \begin{cases} 0 \text{ if the time interval in question begins after now} \\ 1 \text{ otherwise} \end{cases}$$

$$O = \begin{cases} 1 \text{ if we have previously had a} \\ \quad \text{prospect - based emotion about this goal} \\ 0 \text{ otherwise} \end{cases}$$

The way these equations work is governed by earlier equations 2.0 and 2.1 so that all trees are processed on each tick of the simulator and all instances of an emotion are generated and summed so that in total there are 22 separate values created. One of the most important functions of emotions is to regulate our behavior in social situations. As such, agents must represent not only their own values, but also those of the other agents they know. The OCC model uses four parameters involving how agents feel about one another, again dependent upon the type of emotion being generated. For each pair of agents (X, Y), the following are defined by the model: 1) the degree to which X likes Y, r_L; 2) the degree to which X dislikes Y, r_D; 3) the degree to which X has formed a cognitive unit with Y, r_C; and 4) the degree to which X is familiar with Y, r_F. Two additional parameters were added for implementation purposes, to be used in determining the intensities of agent action-based and artifact-based emotions, respectively: 1) the degree to which X views Y as an agent, r_A; 2) the degree to which X views Y as an object, R_O. In Elliott's construal frame representation of the OCC model, a field indicating that it was someone else who was affected by a particular concern's firing models relationships implicitly. While the end result is the same, it is non-obvious how the various aspects of relationships identified by OCC fit into this representation. An explicit representation allows for these effects to be isolated and coded as part of the model.

In our implementation, relationships are explicitly modeled using the liking, disliking, cognitive unit, familiarity, agent, and artifact parameters, in addition to having each agent model the values of each other agent. As it stands, each agent has a perfect model of the values of those it knows, but this could easily be changed through an editor or, more interestingly (but requiring substantially more effort) agents could determine the values of others automatically by recognizing their actions and hypothesizing motivations. Depending on the scenario it may be useful to explicitly model what various agents believe to be the value structures of other agents. It is precisely such misunderstandings that lead to significant amounts of conflict in the first place. However, if the scenario does not simulate such situations, it is also possible to grant agents perfect models of one another.

Credit/Blame assignment is another problem that is relatively well studied if nonetheless still perplexing. While the environment will likely be able to provide rudimentary answers for determining who performed certain actions, the construal process will often transform this information, generalizing or tracing back to other influences. A person performing some atrocity at gunpoint is no more to blame than the person holding the gun, though different people will assign this differently. Still others may blame the manufacturer of the gun, and others society at large. This type of transformation seems either to be worthy of a fair amount of research, though determining the science of this process is likely cutting edge psychology. One way to approximate this seems to be to represent relationships hierarchically, with multiple parents per child. An agent assigning credit for an action will then traverse up the tree searching for a particularly strong relationship. Racists rarely see the actions of individuals; they instead see the actions of someone representing a group. This seems a particularly important thing to capture particularly for crowd and population modeling, and it is a feature we hope to implement in a subsequent version.

Before concluding this section, it is worth briefly mentioning a few temporal and likelihood issues. For example, if a particular goal has been effected, a list of time intervals when the statement is believed to be true is returned along with confidence values (interpreted as probabilities) and variable bindings. Consequently, four pieces of information are conveyed to the agent: 1) whether this concern has been effected in the past or may be effected in the future, 2) how confident the agent is that this is the case, 3) who is responsible for this occurring, and 4) who was affected by this event. The structure of this information closely resembles that which is conveyed in the construal frames of Elliot [2].
The current approach to estimating the future is to generate occurrences of hope and fear at the beginning of every new action. While this approach misses all occurrences of hope/fear caused by external events, it *is* better than nothing. The probability estimation in the current implementation, however, as it assumes the mutual exclusion of sub-values: each is treated as equi-probable with these probabilities summing to 1. We return to this subject of probability estimation in the next section.

3.3) Game Theory and the Strategic Layer

The cognitive subsystem serves in our model as the point where the diverse emotions, stressors, memories, and other factors are all integrated into a decision for action (or inaction) to transition to a next state (or return to the same state) in the Markov decision process (MDP) sense. In essence, at each node of the Markov chain (and at each tick of the simulator's clock) each agent must be able to process the following information: the state name (or ID); the allowable transitions and what action might cause those state transitions (a_{nm} in A(iSTRESS)); current intentions as provided in a task list or plan and the intentions of their prior actions; expectations of what other agents are going to do in this state based on recent history and other memories/beliefs; desires for actions based on the 11 pairs of emotional scales ($I_\xi(s_k)$ where ξ = 1,22); stress-based coping level (Ω_i where i = 1,5); and a mood, μ, that we define below. Using all this information as stimuli, the agent must select a decision style, Φ, also defined below, and process the stimuli to produce a best response (BR).

Ideally, we might like the agent pursue a pure MDP process. Specifically within a hierarchical chain, MDPs model decision theoretic planning problems in which an agent must make a sequence of decisions to maximize its expected utility given uncertainty in the effects of its actions and its current state. Classically, at any moment in time, the agent is in one of a finite number of states (s=1,S) and must choose one of a finite set of actions (a=1,A) to transition to the next state. More specifically, optimizing a Markov decision process was defined in [61-64] as a dynamic programming problem that maximizes expected, discounted rewards or utilities across future periods as follows:

$$\text{Max } U^* = E\left[\sum_{t=1}^{T} \delta^t \, U(s_t, a_t)\right] \qquad (3.0)$$

where,

U^* = optimum value point (in terms of "utility")
$E[\ ]$ = expected value of the discounted future utility over iterations t=1,T
δ^t = discount factor ($0<\delta^t<1$, but in short horizon problems let $\delta^t=1$)
$U(\ )$ = reward function or utility from selecting action a_t at state s_t

Often this formulation is expanded to a "value iteration" formulation where one loops across iterations (t=1,T) and for each iteration, one then loops across all states (s=1,S) to find the BR action or set of actions that maximizes both current and future rewards so as to avoid local optima: e.g., see [62-64]. This expansion is captured by finding the maximal value of the following function after testing all possible actions, a=1,A:

$$BR_t(s,a) = U(s_t, a_t) + \delta \sum_{s_{t+1}=1}^{S} \pi(s_t, a_t, s_{t+1})\, U_{t-1}^{*}(s_{t+1}) \qquad (3.1)$$

where,

$\pi(s_t, a_t, s_{t+1})$ = the transition probability of being in state s_{t+1} immediately after taking action a_t from state s_t (This is of course a function of external perturbations of nature, equipment reliability rates, actions other agents also take, and so on.)

$U_{t-1}^{*}(s_{t+1})$ = $BR_{t-1}(s_{t+1}, \Phi(BR_{t-1}(s,a))$
where $\Phi = \text{argmax}_a$, a function that finds the maximal utile action

Thus, recursive equation (3.1) summarizes the standard computable "value iteration" formulation of the dynamic programming optimization of a Markovian decision process. Ideally, this formulation assumes that an agent can project the utility of each state of the chain of the game they are now in (and of any meta-games) and infer the maximally utile action for each of those states and work backward from the 'winning' end-game state to derive the path of maximal actions to reach that end-game. In fact, the computational complexity of doing this for games like chess is overwhelming and simplifications are introduced like δ for discounting future moves and like iteractive play. An agent using these simplifications would need to reapply equation 3.1 at each new step of a simulation to determine what new state arose as a result of his and any other agents' actions in the prior state, and to redefine the optimal path to maximize its utility through the remainder of the chain. In the end, since we are pursuing dynamic programming through iterative play, the solution policy (i.e., graph edge transition matrix) that results is itself emergent. That is, we do not and cannot know the path that an agent will take through the very large Markov chain, and can only study it a posteriori.

However, an agent using even this 'simplified' formulation would be potentially at odds with the spirit of human behavior modeling, since: (1) the algorithm is entirely silent on how U is derived and it is convention in the research community to derive U experimentally via an arbitrary reward for winning the game; (2) humans are often poor at looking even a few moves ahead ($\delta \sim 0$) and are weak with probability estimation (π = unknown); (3) people succomb to stressors (fatigue, time pressure, etc) so that they don't have the time and motivation to fully process (eq. 3.1) over and over; and (4) they often replace functions like "argmax" with any of a number of alternative stress- and/or mood-influenced decision processing styles we label here as Φ. When we add such desiderata, we realize we need to further alter the MDP to reflect human behavior more faithfully. Ideally, it might not always find global optima, it might seek NE that are local utility hills, it should settle for lesser solutions when it is fatigued and stressed, and it may discover and shift play to (emotion-based) meta-games. What further changes are needed to effect these results?

The first change is that we assume utilities for next states are released from the emotional activations. The previous section used the OCC model to help generate up to 11 pairs of emotions with intensities (I_ξ) for the current and/or next state of iterative play. In this section we now are in position to derive the utility as called for in Equation 3.1. Specifically, utility may be thought of as the simple summation of all positive and negative emotions for an action leading to a state. Since there will be 11 pairs of oppositely valenced emotions in the OCC model, we normalize the sum as follows so that utility varies between –1 and +1:

$$U(a,s) = \sum_{\xi} I_\xi(s_k)/11 \tag{3.2}$$

While one can argue against the idea of aggregation and of masking out individual emotions, this summation is consistent with the somatic marker theory. One learns a single impression or feeling about each state and about actions that might bring about or avoid those states. The utility term, in turn, is derived dynamically during each iteration from an emotional construal of the utility of each action strategy relative to that agent's importance-weighted value ontology minus the cost of carrying out that strategy. We further introduce two modifiers on the emotional construal function – the first is a discount factor, Δ, that more heavily weights game achievement the closer the agent is to the end of that stage of the game. Thus an agent might be conservative and construe survival as more important early in the game, yet be willing to make more daring maneuvers near the end point. The other modifier on utility is a multiplier, μ, that alters immediate emotional construals based on mood and/or other longer term personality factors such as risk-taking propensity, impulsivity, and the like. We will explore more details about the derivation of the mood term shortly.

As a second change, we also permit the integration here of probability of success estimations, in the sense of expected utility and decisions under risk, if the somatic system of the agent has learned them, otherwise decisions are selected according to criteria of decisions under ignorance (p is removed from the equation). This does not mean that π is non-existent. On the contrary there is always an implied or after-the-fact inferable π in a Markov chain, or at least there would be if the drama were repeated enough times. What it means though, is that from each agent's perspective, probability is a perceived probability of the expectations of what other agents will do based on working memory-stored observations (beliefs) of them from τ periods in the past. We introduce a discount factor into the probability expression that can be set to more heavily weight the past by increasing its value.

With these changes, equation 3.1 is revised into the following formulation:

$$\text{BEST REPLY } (BR_t) = \Phi_{\mu,\, iSTRESS,\, \Omega}\{U_{mn}\,(s_t\,,\, a_{mnt}\,),\, p_{mn}\} \qquad a_{mnt} \in A(iSTRESS) \tag{3.3}$$

Where,

$\Phi_{\mu,\, iSTRESS,\, \Omega}\{.\}$	=	as defined below for the alternative values of μ, iSTRESS, and Ω
p_{mn}	=	$(1 - \Delta)\, e_m + \Delta_{m\tau}\, p_{m\tau}$
	=	perceived probability
u_{mn}	=	(1-δ)x(U from equation 2.3)
Δ	=	memory coefficient (discounting the past)
τ	=	number periods to look back
e_m	=	$\begin{cases} 0 & \text{action m not situationally relevant} \\ 1.0 & \text{action m is situationally relevant} \end{cases}$
δ	=	expectation coefficient (discounting the future)
A(iSTRESS)	=	action set available after integrated stress appraisal (*see Section 2.1*)

In terms of the perceived probabilities of Equation 3.3, at present we simply pre-specify these by hand. However, one could conceive of a machine learning program that keeps track of all possible outcomes from all permissible actions at each state of the game, and that derives the probability of success and failure from this information. To date we have made no such attempt. However, it would have to consider factors such as we are now able to introduce such as, for example, an agent who has discounted the vulnerability of himself and his comrades (prior probability of being hit) will consequently lower his estimated probability of losing the battle. Or a nervous soldier will tend to overestimate his probabilities of significant failures (risk averse on the prospect of a heavy loss), etc. This brings us to the earlier discussion about time pressure (TP) and how it effects decision making. At present all actions carry an ideal time to complete estimate (T_I) and the simulation generates an available time (T_A). We earlier gave the equation for TP fro m these factors, but omitted the idea that as TP increases it directly impacts probability or P. Thus the less time we have to complete a task the less likely the task outcome will be successful.

It is useful to now turn to the discussion of the decision processing style function, $\Phi_{\mu,\ \mathrm{iSTRESS},\ \Omega}$. There is a large literature on decision style functions (e.g., among many others see [22,25,31, 37, 39, 45-47, 53, 66, 69-70]), and the discussion here is merely to indicate that there is a rich set of possibilities that one can explore within the modified MDP framework proposed here. We begin by indicating how the various components of iSTRESS (beyond just TP) and coping level (Ω) might impact upon an agent's choice of decision strategy. The rules for selecting a decision processing style are a matter for extended research, something beyond our current focus. Our goal here is only to show an illustrative set of rules that we are now working with and the idea of providing a mechanism for evaluating alternative rules that may exist in the literature such as in those references just mentioned. As do [39], we postulate that a balanced emotional construal of all values as something that happens only under vigilance at moderate stress levels. As event stress approaches very close to zero, one tends to do drop into unconflicted coping states and one does not invoke the emotional capabilities for situation recognition or for recognition primed decisionmaking [32, 46, 66]. At the other extreme, as event stress approaches some upper threshold, only the physiological concerns become significant and, once panic sets in, one tends to cower in place (if its safe) or run wildly away if not as in [39, 57-58]. Also, as do [36, 40-41], we assume that being fatigued puts one in a state of wishing the world would slow down, and hence one tends to reduce the importance of values about higher level goals (ie, those above physiology and rest), and remote objects. We thus use the following as a guide to adjust the settings of all the equations presented in this paper.

Emotional Construal of Stress Components (impact of iSTRESS in $\Phi_{\mu,\ \mathrm{iSTRESS},\ \Omega}$)

Near Zero Event Stress:	use initial task plan and don't call emotion model (no situational construal) Ignore probabilities and apply criterion of optimism (see below)
High Event Stress:	same as near panic (see below)
Fatigued (EF):	reduce all positive goal- and preference-based positive emotions (become timid). ignore probabilities and apply criterion of pessimism described below
Time Pressure (TP):	primary impact is to reduce probabilities of success for an action

Alternative Coping Strategies (impact of W on $\Phi_{\mu,\ \mathrm{iSTRESS},\ \Omega}$):

Vigilant:	see Criteria under Risk (and/or Ignorance)
Unconflicted:	same as Near Zero Event Stress (see above)
Denial:	ignore emotional construal (ignore situation). reduce probabilities of any dis-utile things down to zero (disbelief of negatives). base choice of action on minimum regret criterion
Near Panic – Expert:	same as vigilant
Near Panic – Non-Expert:	as in Equation 2.0, ignore situation and emotion, and randomly choose 1 of M actions available or base choice on minimum regret
Panic:	If feel safe at current location, then remain rooted Else, drop artifacts (e.g, weapon, tools, etc.) and run blindly away from threats

A number of theoreticians also indicate that mood alters emotional construals, so an important potential determinant of $\Phi_{\mu,\ \mathrm{iSTRESS},\ \Omega}$ is to use a mood filter or weighting function. Damasio [45] indicates that mood is derived via the same neural apparatus as emotion, but that mood is more deeply engrained and that it lasts for longer periods of time, for example, on the order of hours to days. Frijda [71] has surveyed the mood literature and found that mood studies tend to identify either 2 or many more (e.g., 10) affective states. Frijda further indicates that the consequent of mood is not always clear, but one can choose to interpret it according to various sources in the literature. For our purposes, if we wish to model only the two universal moods including positive and negative, then a reasonable reference is Iser [71]. Iser indicates that the impacts of positive vs. negative affect are to shift subjects to less risky, less costly strategies [72]. We thus can derive positive and negative mood by using the settings just mentioned for vigilance and high event stress, respectively. More formally in a game-theoretic sense, as expressed below we might use Hurwicz's criterion of optimism (that nature will be kind) and Wald's criterion of pessimism which assumes nature (and opponents) will always be malevolent: e.g., see [73]. However, at present we assume that positive mood corresponds to vigilance (according to Iser) and that negative mood corresponds to the criterion of pessimism, as per Wald.

On the other hand, if we wish to model a longer list of affective states or moods, Frijda's survey reveals alternative clusterings from diverse studies. Many of these studies mention moods such as egoism and self-interested, fatigued, anxious, nonchalant or optimistic, and angry and vengeful, among others. Some of these have already been addressed. For the mood of extreme anxiety we can assume it is the state of near-panic or panic for the non-expert and panic for experts, as modeled above, and in a similar way the fatigue mood is already represented by EF above. As shown below, one can model the rest of these moods via any of a number of classical decision- and game-theoretic rules such as found in standard textbooks on the topic: e.g., [1-2, 73].

To determine the overall utility of a given action under each mood, depending on what agent perspective we include or exclude we can make the agent greedy (self-optimizing at each iteration as in earlier Equation 2.0), collaborative, altruistic, or vengeful. For example, greed or self-interest is the standard maximin criterion of iterative play that is intended to derive Nash Equilibria for oneself. To reach the other behaviors or moods, the agent must compute the utility for the other agents and to do that assumes he has a version of their values tree. For now, as mentioned earlier, we assume all agents are omniscient if they need to make such computations, otherwise they aren't. Thus a greedy agent does not know the concern trees of any other agent, whereas an altruistic one assumes he does. In this fashion, if an agent includes his teammates in the maximin, the mood might be said to shift from greedy to collaborative, though still self-interested. One can extend this to altruistic by factoring the utility of actions from opponents' perspectives. Vengefulness, on the other hand, implies an attempt to minimize an opponents perceived utlity. Also, we include below the criteria for the cases where probabilities are not known, or where the agent might assume they aren't as called for in our stress and coping style construals discussed earlier.

Criteria Under Risk (impact of m on $\Phi_{\mu,\, iSTRESS,\, \Omega}$):

Greedy (utility maximizer):	Max E(U)	=	$P(a_i)$ U(self)
Collaborative (Pareto-local):	Max E(U)	=	$P(a_i)$ U(self + friends)
Altruistic (Pareto-global):	Max E(U)	=	$P(a_i)$ U(self + friends - opponents)
Vengeful	Min E(U)	=	$P(a_i)$ U(opponents)

Criteria Under Uncertainty (impact of m on $\Phi_{\mu,\, iSTRESS,\, \Omega}$ if probabilities unknown):

Criterion of Pessimism (maximin)	Max (Min(-U))	=	U(a_i , worst-possible-outcome)
Criterion of Optimism (maximax)	Max (Max(U))	=	U(a_i , best-possible-outcome)

3.4 Motor/ Expressivity Subsystem

At this juncture, the intended action has been selected and the various parameters for modifying expression and motor function are known. The motor/expressivity subsystem must next use it's library of stored procedures and modify them as relevant to appropriately reflect stress (iSTRESS), coping level (Ω), mood (μ), and which of the 22 emotions (I_ξ) have been activated. We review several of these adjustments in what follows.

Up to this point we have primarily examined the impact that iSTRESS has on selecting the strategies available for a decision. Its also true that iSTRESS effects how one carries out the actions of a given decision, what we call Performance Effectiveness (PE). The Janis-Mann model and its layers already helps to derive several aspects of PE including: (1) how inattention to task and slips and lapses arise such as in the low stress or unconflicted states; (2) how sensor information and input is ignored in the denial or defensive avoidance state; (3) how random action arises in the inexperienced agent in the near panic state; and (4) how task interruption and abandonment occurs in the state of panic.

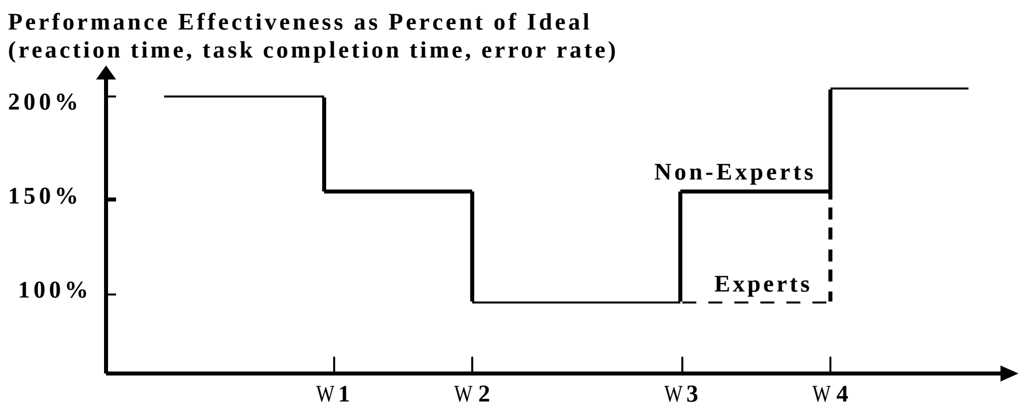
Beyond this, for whatever action is selected, PE also requires input on how to adjust the pre-, during, and post-action dimensions including reaction time, task error rate (aim, driving, etc.), and task completion time, among others. For the sake of simplicity in the early versions, each of these j=1,J dimensions of PE are assumed to be impacted by the various factors of iSTRESS in a step function approximating the inverted U of the classic Yerkes-Dodson PMF. Thus, the ideal PE level is only attained for the mid-range of iSTRESS, while too little or too much stress lead to greater reaction times, error rates, and completion times as follows:

$$PE_j(t) = PE_j(ideal) \begin{cases} 1.0 & \text{if } \Omega 2 < \text{ iSTRESS} < \Omega 3\text{(novice) or } \Omega 4\text{(expert)} \\ 1.5 & \text{if } \Omega 2 >= \text{ iSTRESS or iSTRESS} >= \Omega 3\text{(novice)} \\ 2.0 & \text{if } \Omega 1 >= \text{ iSTRESS or iSTRESS} >= \Omega 4 \end{cases} \qquad (4.0)$$

Here we try to account for novice vs. expert differences in terms of experience and training combined. One could add more layers of skill, and one could also add a differentiator for intelligence, however, for the current version we ignore these individual differences and only permit two differentiators. We manage this differentiation by setting the Ωi levels differently for novice vs. expert, so that the expert cutoffs are double or triple on the right side of the U and about half to a third on the left side.

One can plot the relationship of Equation 4 as shown in Figure 6. Here we see a U shape since we are plotting the worsening, rather than increasing performance along the vertical. Also, we preserve the steps from the Janis-Mann taxonomy, however, their meaning differs somewhat here. Specifically, the table along the base of the figure shows each of the three determinants of iSTRESS can independently drive an agent to a given level of performance effectiveness. These are qualitative indicators plotted on a seven point scale: ~0 or very low, low, medium low, medium, medium high, high, and very high.

Figure 6 - Mapping the Janis-Mann Taxonomy for Decision Effectiveness Onto Physical Performance Effectiveness



Event Stress	**~0**	**Low**	**Medium to Medium High**	**High**	**Very High**
Time Pressure	**~0**	**Low**	**Medium to Medium High**	**High**	**Very High**
Effective Fatigue	**Just Waking**	**Medium**	**Low**	**Medium High**	**Very High**

Beyond adjusting for ISTRESS and Ω level, the motor/expressivity subsystem also needs to reflect emotion and mood. Of course the primary purpose of emotion and mood in this framework are decision processing entities. Nevertheless since they are known , it is possible for the agent to reflect their status in it's embodied or graphical self. Since this is largely an animated topic, we omit discussion of it here, and point the reader to our other articles on this topic and the excellent general literature on it; e.g., see[43-44,48-49,56-58,81].

4.0) Conclusions and Next Steps

Some of the lessons learned to date are:

- The literature is helpful for improving the realism of behavior models – We have completed an indepth survey of the literature and have found a number of models that can be used as the basis of cognitive models for agent behavior. In fact the problem is less that there aren't any models, so much as the fact that there are too many and none of them are integrated. The bulk of the effort we undertook to date is to document those models, and to figure out how to integrate them into a common mathematical framework.

- Benefits and costs of modeling stress-emotion-decision processing as an integrated topic – In attempting to create an integrated model, the benefits of this approach are that it is more realistic to try and deal with the interplay. Certainly these dimensions are connected in people, and the ability to address all of them in simulations opens up a large number of possibilities for improving agent behavior and for confronting trainees with more realistic scenes. These benefits are not cost-free, and it is expensive in terms of game developers' time to try and learn all these factors, and to adapt them so they fit the scenarios of interest. Perhaps more importantly, there is no single validated theory for integrating these elements, and the result may be appealing but ungrounded.

- Role of value ontologies and how can ongological engineering help – The approach we presented in this paper relies on a common mathematical framework to integrate many disparate models and theories. However, the implementation in any given simulation will also require extensive ontological engineering to flesh out the lower levels of the value ontologies used by the emotion model to compute the utility of any given action, to assess agent preferences, and to determine when an agent wants to follow or deviate from orders and doctrine. Our current efforts are aimed at adding a set of tools for authoring, maintaining, and visualizing these ontologies.

- Using emotion models for utility and decision making as well as for expressivity – A principal contribution of this paper lies in the use of emotion to help derive utilities dynamically. Thus agents are able to compute their own feelings about events and actions. In standard decision theoretic models there is no basis for agents to compute their own utilities. Instead these are derived by subject matter experts and then mathematically manipulated by the decision functions. In the approach postulated here, the subject matter experts would interact at a stage earlier, at the stage of helping to define the value ontologies so that the agents can derive their own utility values and tradeoffs. This approach frees experts from having to infer utilites, and it places the debate more squarely on open literature accounts of value sets. One can use sources such as the Bible, the Koran, family values, and news accounts to capture and express these values.

- Importance of transforming reactive finite state machines into deliberative, Markovian players -- In order for the approach outlined here to work, one cannot simply implement it within a low level, reactive automata that is the bread and butter of so many computer generated force simulations. For example, most of the Semi-Automated Force (SAF) environments used in the military rely heavily on finite state automata for the agents to carry out their tasks. This approach works well for graphical representation of the agent reactions on the screen, and even for supporting the integration of physiological layer models such as fatigue, hunger, etc. which might slow or alter the agent's abilities in performing the current task. In these systems, however, it is difficult for the agent to be deliberative, to reprogram his orders or tasks, to interrupt what it is doing and to decide on a new course of action. In theory we have presented the framework that will support reactive agents who are also capable of deliberation. In reality, this requires significant coding effort and we are now exploring such issues. That framework is rather abstract, and it is sometimes difficult for people to see how it helps them when it comes time to implement the agent characters. In the future we hope to develop several case studies to highlight how the framework may be used.

- Creating Games that cause players to focus on systemic thinking -- As complexity grows, organizations shift from top down command and control to decentralized management – to rely on co-evolving, self-adaptive sub-groups and individuals. Such is often the case with peacekeeping in the asymmetric conflict era. These approaches typify the fact that many of today's leading enterprises run the risk of a system continually caught in local optima. No one is in a position to conduct the parallel hill climbing needed to find the global maximum for the overall enterprise. No one is focusing on the systems approach. We believe that the use of hierarchical chains and of human behavior models permits games that involve the player in learning how to think about the larger system, not just the immediate here and now. We plan to test that thesis by saeeing if we can use the framework presented here to implement games such as the terrorism scenario from the introduction.

One immediate focus of our efforts will be on crowd modeling. Crowd behaviors are frequently modeled with non-linear dynamical equations (e.g., see [77, 78]). This works effectively for handling the movement of individuals in a group as they try to channel through a narrow opening, as they flock together (.e.g, birds in a V-formation), and so on. It is a useful way to permit the state machines to navigate the spatial area and avoid each other as they do so. One could also use this approach to introduce panic and cases where the state machines do not avoid each other, and they wind up colliding and hurting one another.

However, this approach ignores the root causes of crowd behavior—the semantics. What causes young males to leave their homes and arrive at a protest site? What value ontologies lead them to choose between violence and non-violence? What events at a protest might cause them to shift their behavior from non-violent to violent protest such as rock throwing or rampaging and looting? Developing the ontologies and markov chains that might lead to such behaviors is an example of the type of implementation we hope to begin to develop as a follow on to the framework development documented in this paper.

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