Paper Title: Developing a Social Complexity Framework for Immersive Task Training

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ABSTRACT

Predictive behavior modeling poses several difficult challenges. Human behavior modeling using rational choice theory, negotiation protocols, and other socio-economic models have been somewhat successful in prediction of events on a city-wide or state-wide level (or a combination of levels) although tactical level simulations often do not consider this level of complex human interplay. Often seemingly small or insignificant tactical level events have lead to socio-political situations that shape the course of wars, influence political and policy changes, create areas of hostile incubation, and affect economic and social climates. We propose an immersive tactical level simulation framework that provides a novel method of modeling social complexity in which virtual agents perceive events and share their interpretations of events. The framework uses an open source technology design with an emphasis on generating extensible agent interaction models and realistic representations of agent's actions, gestures, communications, and responses in a virtual training environment. The organizational dynamics generated by the modeling approach produce a highly variable set of possible outcomes to the training scenario. Combined with specific learning objectives, this high degree of variability within a learning environment poses new challenges to the trainee, namely the need to be aware of how to operate in highly dynamic environments. We propose a model for simulating aspects of social complexity using an agent-based immersive training system and describe how these techniques can be applied to the development of cross-cultural competence, situational awareness, and crowd behavior analysis.

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CHALLENGES IN MODELING HUMAN DYNAMICS

Modeling individual and group level human behavior is a daunting task, for no other reason than human beings exhibit a high degree of individual and group variability. We can make general statements about social and cultural norms, biases, and historically likely responses to events, but ultimately specific social responses can best be estimated and not determined.
Theorists have applied models to describe human behavior using a variety of techniques that attempt to model interactions, cognitive theories, negotiations, socio-culture norms, and many other human dimensions. One type of human interaction modeling, *social complexity modeling*, attempts to introduce formal structured approaches (e.g.: game theory, evolutionary programming, neural networks (Barth, 2001)) to explain complex human interaction. Social complexity modeling methods have been accepted as a means to support strategic, economic, socio-geopolitical level analysis and decision making, with an emphasis on large-scale state and country wide analysis (Carroll, 2006). Although this emphasis on state wide analysis of human interaction is vital to understanding potential operational and strategic outcomes, recent operations in Iraq and Afghanistan have demonstrated that tactical decisions can have far reaching implications, and can often influence higher level outcomes. Also real-world problems tend to be ill-structured and goals are often not well defined. Decisions tend to occur in a dynamic environment without complete or accurate information (Gyllensporre, 2003). This means the soldier must acquire and employ a new set of social and cognitive skills which include cross-cultural proficiency, understanding small group and crowd behavior, verbal and non-verbal communication, and comfort in ambiguous and dynamic environments.

Enhancing competency in these areas requires significant emphasis on cultural and language studies and small group level situational awareness for collective, decentralized decision making. A training approach that provides accurate and realistic tactical level fidelity while applying complexity modeling holds great promise for satisfying much of the cognitive, cross-cultural training need at the tactical level.

Game or virtual environment (VE) systems are well suited as tools for achieving competency in tactical level leadership and decision making training objectives due to several features available in such systems:
1) Realistic perceptual cues (visual, auditory, haptic) and environments: The user is aware of critical information, sensitivities, perceptions, communications, and reasoning for decisions that are otherwise not represented in other presentation media. Social cues (e.g.: methods of communication, interaction, protocol) can also be displayed through the design of virtual agents (avatars). Agents can speak, use gestures, and exhibit most human behaviors (Greenwald, 2002).
2) *Affective state modeling*: Realistic emotion-inducing events can be generated to provide a more realistic training experience. Inducing emotional state change can aid in understanding how well the trainee works under pressure and can also help the trainee learn to operate effectively in arousing conditions (Reilly, 2001).
3) *Collaborative scenarios*: Tactical level scenarios can benefit from more than one participant working in collaboration within the scenario. Collaboration in virtual environments has been shown to be important in the overall sense-making process in the virtual world where participants can share knowledge and piece together events. This virtual world sense-making can translate to better sense-making in the real world (D'Eredita, 2007).
4) *Realistic human interaction using virtual agents*: Virtual humans can display diversity in their perceptions, interactions, individual cognitive and affective responses, belief systems, transmission and acceptance of knowledge, and communication. These

individual variables allow virtual communities to mimic the variability of behavior found in real-world communities (Helmert, 2007).

Immersive training tools, although valuable for familiarization and task training, are often not designed to create social complexity and simulate group dynamics. Semi-automated forces systems such as the open source OneSAF system can handle combat systems from the level of individual troops, up to brigade, although not much has been done to integrate

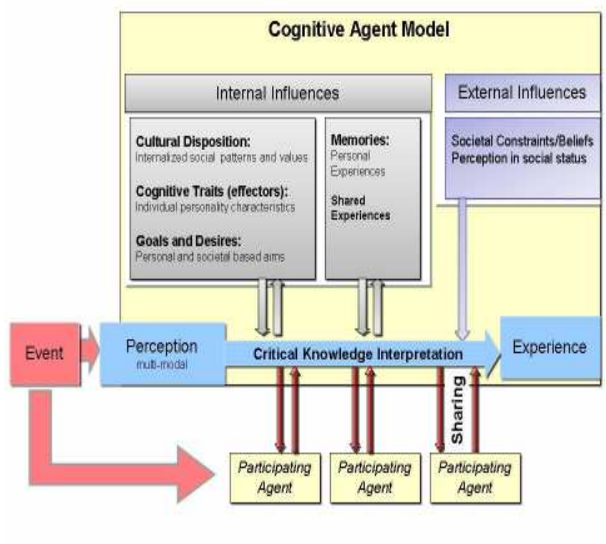

Figure 1: Cognitive Agent Model

social modeling at the immersive level. Soar Technology proposed a general purpose model of human cultural behavior based on the Cultural Cognitive Architecture (Taylor, Quist, Furtwangler, & Knudsen, 2007) designed to capture and express both psychological and cultural constraints, although elaborate socially evolving behaviors have not been incorporated.

The focus of our efforts is to generate realistic cultural and social complexity within immersive tactical training environments. The virtual tactical level training simulators will be populated with virtual humans (agents) whose design emphasizes realistic human behaviors, learning, and complex interactions. These agents will witness events and communicate information, beliefs, feelings, and overall situational awareness with other agents and immersed participants. As information spreads within the social structure, opinions, emotions, and expressions change the dynamics of the environment and ultimately influence the outcome of the training scenario. The outcome of training in these socially complex environments, specifically with the incorporation of realism (culture, physical states, emotion induced scenarios, collaboration) found in tactical VEs, provides a high-fidelity social realism not available in today's non-dynamic training exercises.

Methodology

In our approach, we develop immersive tactical level training environments with a new type of virtual agent that perceives events, interprets these events, and communicates with other agents and the immersed trainee on what the virtual agent believes has happened. Communicating agents can share information and piece together events, or learn new information from other witnessing agents. Agents can also create inaccurate information in order to hide, or hinder the spread of information. These features force the trainees to make better decisions on how to interact within complex social environments and adapt to complex social dynamics. The human trainee directly influences the agent's perception of the subject by the choices and actions that are made in the synthetic space. These experiences can be passed through the social network through agent-to-agent communication via language and/or gestures. The integrity of the knowledge passed is prone to both internal bias (belief, perceptual knowledge) and external bias (intentional and unintentional misinformation). These *socially evolving agents* have the ability to simulate language processing (speech acts, verbal cues), perception (listening or localizing for audio and visual awareness of surroundings), physical representation (culturally specific gestures, facial expressions), and actions (culturally specific responses).

The Socially Evolving Agent Model

Our approach begins with the development of the virtual agent, an agent whose primary function is to witness and share his experiences within the simulated environment. The agent possesses the following attributes: 1) an input (perception) state, which analyzes incoming data from the environment either through a sensory mode (e.g.: visual or auditory) or through communication with other agents; 2) internal (personality characteristics, memories, goals) and external influencing factors (societal pressures and constraints) that shape the acceptance of knowledge; 3) a memory model that encodes and stores discrete pieces of knowledge; 4) a filtering mechanism that allows the agent to interpret knowledge either through internal beliefs, previous knowledge, or collaborative agreement; and 5) a means to communicate knowledge in a natural manner (verbal communication, gestures) (Cummings & Leonard, 2008).

The Experience

An agent's means of encapsulating understanding of events within the simulation occurs in a model called the *experience*. The experience is defined as a relationship between specific occurrences and the meanings associated with those events. The experience is derived as $E = (0 - i)\sum Ii\ (Ei \mid Ai)$ where E is the receiving agents' interpretation of his experience plus the combined interpretations Ei of other agents' experience Ai. The belief about the experience is derived from several sources, although we model the interpretation as coming from two primary sources: the receiving agent's personal experience and the influencing statements from other agents. Figure 2 illustrates the experience as concentric circles where information at its center is

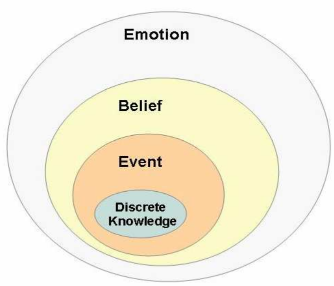

Figure 2: The Experience

discrete and non-interpretive. As the circles extend outward, data become more abstract and open to interpretation and meaning. Each of the concentric circles is explained below as they relate to the building of the experience.

Discrete Knowledge Layer

Events which occur in the synthetic environment (e.g.: weapon fire, conversations) begin as a piece of discrete knowledge. Discrete knowledge is stored as an array of variables defined as $K = (Ii, Ai, Ri, C, D)$ where I is the instigator of the event, Action A, Receiver R, the Communicator C and the Responder D Integrity i, or the level of awareness of this piece of knowledge, is a normalized value describing the degree of certainty about the critical value it modifies. Using an example of weapon fire, critical knowledge within an event is stored as K = <Agent X(i_1=.3) fireWeapon(i_2=.74) at AgentY(i_3=.9)>. Note the low AgentX integrity (i_1 = .3), the culprit may have been hidden from sight.

Interpreting Event Integrity

A virtual agent's knowledge is contingent upon how much data is available to it, and sometimes agents must piece together or predict absent information in order to accurately assess an event. Our inquiry lead to the investigation of Bayesian networks as a predictive tool for the agent. Bayesian networks allow one to calculate the conditional probabilities of the nodes (likelihood of possible interpretations) in the network given that the values of some of the nodes have been observed. It provides us a natural way to model probabilistic relationships among a set of variables of interests. Because of its probabilistic nature, a Bayesian belief network is very useful for encoding uncertain knowledge. Once the network has been defined, we can make inferences from it, no matter if it is diagnostic (from effects to causes), causal (from causes to effects), or mixed. We can then make decisions or recommendations based on the results of our inference. Bayesian causal inference modeling will be used to describe presumptions made by the agent when information is missing. In other words, we will use the causal probability model to help the agent fill in missing pieces for his missing information. Conditional probability, written as P (A|B, C), tells us the probability of the event A given the events B and C. A joint probability such as P (A, B) indicates the probability of both event A and B. The product rule of probability states a joint probability can be separated into the product of a prior probability and a conditional probability. Bayes' rule expresses this as

$$\text{Posterior} = \frac{\text{Likelihood} * \text{prior}}{\text{Marginal likelihood}}$$

$$P(R{=}r) \text{ or, in symbols, } \frac{P(R{=}r \mid e) = P(e \mid R{=}r)}{P(e)}$$

where P(R=r|e) is the probability that random variable R has value r given evidence e. The denominator is a normalizing constant that makes certain the denominator adds up to 1; it can be computed by adding up the numerator over all possible values of R. Bayesian inference calculates a numerical estimate of the degree of belief in the hypothesis after evidence has been observed. Inference usually relies on degrees of belief, or subjective probabilities, in the induction process and does not claim to provide an objective conclusion. Nonetheless, some Bayesian statisticians believe probabilities can have an objective value and therefore Bayesian inference can provide an objective method of induction.

Event Layer

The event expresses discrete knowledge from the perspective of an agent where $E = SPT$; S is the event's perceived severity, T is its occurrence over time and P is the perceptual area of recognition. The perceptual area contains input from three perceptual modalities, visual, haptic, and auditory senses each with a given level of relevance and area of influence. For example, a gunshot may contain a very small visual perceptual area in order to be witnessed but due to the loudness of the gunshot, it will contain a large audio sphere of influence.

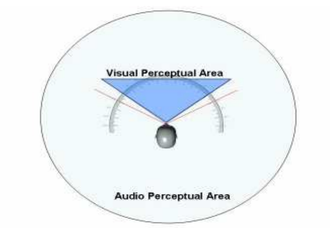

Figure 3: Perceptual Area

Belief Layer

The belief layer describes the level of acceptance of an event, and is designated as the layer that is shared with other agents. In other words, the agent is essentially describing what he believes has happened. The belief is calculated using several forms of input and is the most subjective of the layers. A belief can be determined based on a personal interpretation which may be influenced by internal states such as past memories and cultural predisposition. Figure 1 illustrates several internal and external influences that shape belief. Beliefs can also be determined based on external influences such as communication with other agents and consensus (agreements) with groups of agents. Decisions as to how a virtual agent will accept data as valid are based on models of agreement between participants. The *agreement* is a personal expression of acceptance attached to a particular belief as the basis for how information is both stored as a memory and transmitted to other virtual agents.

Belief Derived from Agreement

Agents that have experienced some event form a belief or acceptance about that event and may come to accept the experience as valid with the agreement of other agents. Although the agent may have a personal interpretation of some experience, sharing and acknowledgement of other interpretations creates both solidification and variation of belief. Agreement occurs when one or more agents communicate about an event and share their interpretations of what has happened. The agreement model $A(n) = (\alpha, \mu, \nu, \tau)$ is a function of memory recall of the event α, previous consensus of the event μ, influencing values ν (e.g.: social status, culture, memory), and *first-hand* knowledge or perception of the event τ. Believability in the proposed model is presented as *dynamic social impact theory*, which predicts that, as strength and nearness increase within a group, so will conformity. Latane and L'Herrou (1996) discuss the importance of the group and the conformance of individuals to the group's normative pressures. We use a social impact model that incorporates Wetzel and Insko's (1982) convergence research (agents are attracted to their ideal agents), and Latane homophily models (agents are attracted to like-minded agents) to determine likely candidates for communication. It is often likely that more than one agent will have an interpretation of some experience. For example, where several agents may communicate their interpretation of events, the agent uses the equation described above to determine acceptance of someone's belief. Ultimately, sharing between agents does not imply the either agent will express a true representation of what has happened. One of our areas of exploration, *Knowledge Mutation* is an attempt to mimic this variability. In our use, we separate mutation into two facets; *Unintentional Misperception*—data that is not fully available to the agent, and *Intentional Misperception*—information that is available to the agent but is intentionally modified with the intention of spreading misinformation. Intentional misrepresentation can be used as a strategy (by agent or subject) to shift or transmute knowledge as necessary (Cummings & Leonard, 2008). Knowledge mutation in our model occurs at the critical data level where, returning to our previous example, <Agent X(i_1=.3) fireWeapon(i_2=.74) at AgentY(i_3=.9)> where the instigator, action, or receiver of the event may be removed (*I am not sure who was firing at Agent* Y) or modified (*I think Agent Z was firing at Agent* Y).

Sharing the Experience through Inter Agent Communication

Agents are designed to impart their experiences in several ways including speech acts, gestures, and emotional (physical) responses that can become inputs for the receiving agent. Language transmissions are passed directly between agent communicators and are intended to 1) mimic natural responses between agents (or agent and trainee), and 2) express the communicated experience in a natural syntactical way. The developed language model and schema definition uses informing statements to convey information between agents and the immersed trainee. This type of encoding mechanism allows information to be encoded (visual and audio responses) and decoded (perception and knowledge representations) in order to represent realistic virtual agent responses and provide insertion points for researchers to extend attributes of the agent. The agent's knowledge is encoded as a communication message and passed to the receiving agent as a set of script tags. The schema contains a set of definitions for standard types of speech acts: greeting, informing, questioning, requesting, and labeling. In a positive non-verbal engagement, actions such as waving, hand-holding, or walking together may occur, where in a negative non-verbal exchange, the actions may be taunting, rock-throwing, or weapon firing. The language syntax describes both verbal (text and audio) and non-verbal (gestures, shared knowledge) exchanges.

Knowledge Notational Tags

Notational tags within the language system specify knowledge that will be retrieved from either the sender or receiver and passed as data between the conversers. In our model, data is polled directly from the language syntax (e.g.: *AgentSender <Knowledge of Event>)* and can be used to piece together compound thoughts (complex sentences) into more complete meanings for the agent. (e.g.: *I may have seen <Agent Y> talk to <Agent X> outside his faction and <I am very concerned>).* Gestures, facial cues, and other physical responses represent a source of knowledge for the receiving agent. Agent physical reactions and states are perceived by other agents as usual, unusual, suspicious, or very suspicious. Recognition of agent physical cues is described as $Ac = (P \mid F, D, t)$ where an agent will perceive any of these traits P given the response is within the physical space (field of view) F, within a specified distance D, and constrained by a time parameter t (e.g.: every 500 ms).

Agent Responses: Encoding Emotional States

Agents may express emotion (as speech acts, actions, or gestures) as a way of conveying information when communicating with other agents and training participants. The internal influence describes the agent's predisposition toward a response, modeled as cognitive states and social or cultural predispositions. The cognitive state is a personality representation where traits are assigned a normalized value describing overall aspects of behavior and a mutable factor that determines how likely the trait will be expressed. Emotion is also inherent in the design of the agent and is expressed in both internal representation (algorithmic states) and external (physical characteristics, gestures, actions in the virtual world).

Experience and Emotion

The Experience contains a set of emotional states tied to physical representations such as facial expressions, gestures, and actions. Emotional states are defined as any combination of base states (e.g. hostility, fear, anger, gregariousness, peacefulness) which can be combined to form complex aggregated states. These abstract states are expressed using fuzzy state sets, a common technique for expressing imprecise concepts and attributes. We apply a fuzzy rule set for describing transitions between the abstract states where base states contain degrees of membership within abstract states. For example, the abstract state *frustrated* contains three sets (not, somewhat, and very frustrated), and a degree of membership within each of these sets. Several abstract states may be aggregated with the notion of describing complex emotional states and behaviors. For example, within the context of inquisitiveness there are several additional traits that would help describe the emotional state such as clandestinely inquisitive or fearfully inquisitive.

Encoding Physical States

Fuzzy states are associated with physical state representations in the 3D virtual avatar where the physical representation is a procedural representation of the agent's state. We developed a tool for blending base physical states (eyes moving, angry, sad, vertical and horizontal head movement) and emotional states into a set of procedural dynamic character motions. For example the fuzzy state "nervous" (represented as somewhat, rather, and very) can be added to other abstract states (e.g. distant, playful), gestures (thumbs up, wave, etc), and/or actions (walk, talk). Figure 4 demonstrates the procedural character tool that maps encoded emotional states to physical representations. Actions and gestures, and other physical states can be generated procedurally or through a process that allows the user to modify character reactions in real-time. The image below shows an avatar that is smiling and giving a "thumbs-up" gesture. Note in the Iraqi culture, this gesture may translate as an Iraqi insult, although other cues such as facial expression would help explain the motive behind this gesture.

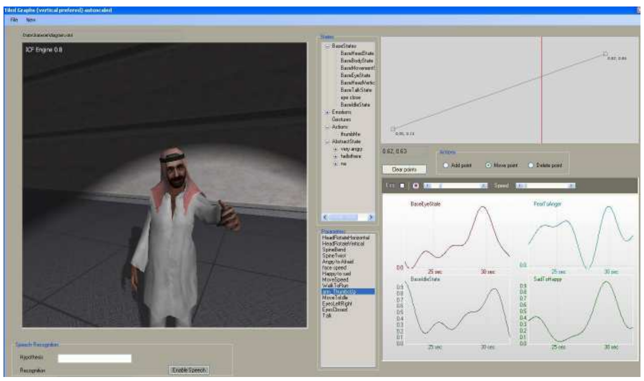

Figure 4: Procedural Character Tool

Loosely Bound Physical States

An abstract state may also contain what we describe as a loosely bound physical state, where a fully defined animation state would only appear to make sense in the context of the simulation. For example if we take the concept of inquisitive, a mildly inquisitive person may pick his head up, look around, and then continue in his current actions. On the other hand a very inquisitive individual may look intently at a target and point towards it. The loosely coupled state applies itself during the running of the simulation and blends with other procedural states.

Immersive Scenario Design

The next stage of our effort was to apply the agent model to an immersive (man-in-the-loop) 3D training framework where the user can interact and communicate with virtual agents, experience realistic environments and stressors, and engage in physical and cognitive training tasks. The immersive training framework designed for this system is based on an open source technology system (Ogre3D) that runs with a middleware framework developed to generate real-time 3D scenes and manipulate objects trivially in the scene viewer. A scenario was designed to combine specific mission objectives, cultural competency training, and an implementation of our social complexity model as a means to describe how decisions affect the social group.

Trainees were asked to locate a pre-selected character by convincing agents to point him out or lead the trainee to him. No knowledge of faction or family relationship was known and no visual information was provided to identify the culprit by face. One agent was designated as a family member (a sister of the agent in question) and was a likely best candidate for finding the missing agent. In general agents were more likely to divulge information when 1) not related to that agent, 2) emotionally predisposed to divulge information, and 3) culturally disposed to divulge information (e.g. woman speaking only to her husband, Sunni speaking to another Sunni). The agents were encoded with awareness of Arabic insensitivities and misinterpretations based on US Marine cultural sensitivity training. Agents were assigned a value that described how the cultural insensitivity influenced their overall disposition, where several additional factors weighed in to the response including relationship, faction, social standing, and overall emotional predisposition. In sum, the participant was tasked to 1) find the agent in question, 2) do so with cultural sensitivity in mind, and 3) consider the broader effects of how decisions and actions would influence finding this agent.

A three dimensional city model (Figure 5) based on Baquba, Iraq was designed with buildings, cars, market stalls, road blocks, and 50 virtual 3D agents of varying gender, emotion state, faction (Sunni or Shiaah), relationships (e.g.: brothers, friends, etc), physical traits, goals (e.g.: shopping, meeting with a friend), and awareness of cultural sensitivities. Agents were assigned similar communication syntaxes and were given time to gather information both perceptually about the environment and through communication with other agents. The syntax was limited to questions such as *How are you feeling?, What are your concerns?, Do you see anyone suspicious?, How do you feel about the factional issues here? Did you talk to anyone? And what did he ask you?, and Where are you going?* Agent conversations were given priorities based on the severity of situational events. For example, if a weapon was fired, conversations turned towards this likely topic of discussion.

Cultural competency knowledge was incorporated into the training system as computer based instruction where the participant was exposed to and tested in this competency before entering the VE. Once the trainee became familiar with the cultural awareness documents, he was provided a description of the mission objective and then was granted access to the immersive 3D environment. The participant could move freely throughout the virtual world, including entering buildings, driving one of several military and non-military vehicles, and interacting with physical objects (e.g.: carts, tents, and market stalls). The participant was allowed to greet, speak about the agent in question, use coercion tactics, and arrest any agent). A list of questions such as *Do you know <Man in Question>?, How do you know him? (Are you related?), Who else knows him? ,Can you show me where he is?* could be asked by the participant.

Figure 5: 3D Virtual Environment

Observations

The act of finding the agents in question (the primary task) gave context for observing how a simple set of actions can evolve the balance and order of the agent population. Repeatedly agents of dissimilar factions by design tended not to participate often in sharing knowledge outside of their respective groups, and if knowledge was shared it was often mutated.

A case where the training participant speaks to the wife of the agent in question while she is with her son creates a myriad of interpretations within the VE. Others question the cultural correctness of such an action (speaking to the woman in rather than her son), where still others see this conversation as an inter-factional problem (speaking with a U.S. soldier). Several operating parameters including individual social welfare, interaction with similar agents, negotiation parameters, all help to shape the experience for the agents.

As agents continue to interact and share experiences, knowledge continues to change, and agents must continuously reevaluate what they believe has happened. Where conflicting information between one or more agents must be agreed upon a *Complex Agreement* must form to make sense of the experience. The *Complex Agreement* (Figure 6) is an exchange in which two agents discuss an event with minimal overlap in perception. When there is little shared knowledge between agents about an event, we find that many competing factors influence the decision as to what may have happened. For example, partial perception, crowd consensus, ability to enroll others' past non-related experiences (memory), and random variation play a role in determining what has happened; these exchanges (complex agreements) are where we see a high degree of variation between what has happened and what is perceived.

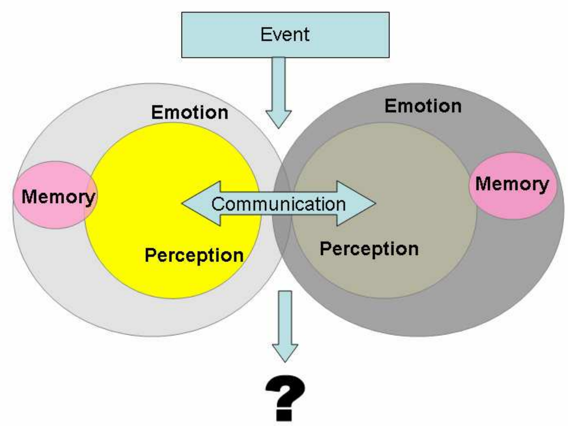

Figure 6: Complex Agreement

Conclusion

Often we are asked to piece together bits of knowledge to make sense of some event, and very often we rely on the apparent good sense of the population (consensus) to help us come to some conclusion about an event or set of circumstances. We may look to some critical level of agreement between like-minded individuals that create consensus, and to what extent validity of data (proof), cultural disposition, genetics, and other factors play in determining the consensus.

Ultimately, as information flows through the social network, what is believed to have happened may be quite different than what has actually occurred. Rather, belief can be highly variable. Our goal was not necessarily to fully understand the outcomes of complex interactions, but rather to lay the foundation for how researchers and experts in cognition, culture, social sciences, and human terrain mapping could better design scenarios which moved beyond one dimensional human complexity modeling, specifically in virtual training environments. As discussed, the nature of immersive training environments lends itself to generating rich, emotion-inducing, and perceptually realistic situations that force the trainee (and instructor) to examine alternate criteria when determining mission success. Namely, training success can be measured in more realistic ways such as 1) how well did I achieve my first order objective? (e.g.: finding the potential terrorist), and 2) how did the means I used to achieve this objective affect the social group at large?

Certainly scripted scenarios may allow us to simulate aspects of these multi-dimensional training scenarios, although this would imply the system designer would have clear notions of the impact on decisions made by the training participant. In fact, it is often the case that hard-to-predict, and rare events beyond the realm of normal expectations ("black swan effects") are the outcome. We hope to use this approach as a method to better understand how what is seen as unlikely may be more likely than we believe.

It was also our intent to examine the transmission of information between individuals within societies. The proposed system derives some of the concepts of knowledge integrity, mutation, and replication from evolutionary biologist Richard Dawkins (1989) *Memetics* model, used to describe a unit of human cultural transmission. He himself did not provide a thorough explanation of how the replication of units of information in the brain controls human behavior and ultimately culture. In our model we used the concept of the *experience* to describe this memetic unit, and apply several techniques that shape this quanta including perception, agreement, sharing with other agents, and probability techniques that estimate likelihood of acceptance. Within the experience several sub-areas (perception, communication, emotion, belief, event, and discrete knowledge) can be tailored to the design of the subject expert and instructional designer.

Future Work

We look to focus future efforts on the development of a formal set of metrics in support of the social complexity framework, and a system of encoding culture models in a standardized way. It is also proposed that a unified architecture for human behavior modeling or unified behavior architecture such as PMFserv (Silverman, 2004) be considered for integration into this framework. Lastly, we examine the integration of the framework with a Semi-Automated Forces (SAF) system such as OneSAF as a means to interoperate with existing immersive simulation systems.

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