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A Model of Emotions for Situated Agents

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ABSTRACT
Emotion is an essential element of human behavior. Particularly in stressful situations such as combat, it is at least as important as rational analysis in determining a participant's behavior. DETT (Disposition, Emotion, Trigger, Tendency) is an environmentally mediated model of emotion that captures the essential features of the widely-used OCC (Ortony, Clore, Collins) model in a computationally tractable framework that can support large numbers of combatants. We motivate and describe this architecture, and report preliminary experiments that use it in simulating combat scenarios.

Categories and Subject Descriptors
I.2.0 [**Artificial Intelligence**]: General– *cognitive simulation.*

I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence– *multiagent systems.*

J.4 **[Social and Behavioral Sciences]**: Psychology

General Terms
Algorithms, Experimentation, Theory.

Keywords
Emotion modeling, pheromones, swarm intelligence, BDI.

1. INTRODUCTION
Emotion is an essential element of human behavior. Particularly in stressful situations such as combat, it is at least as important as rational analysis in determining a participant's behavior. Recognizing this importance, a number of researchers have begun to formulate computational models of emotion. These models typically require extensive symbolic manipulation, and are not practical in domains that require real-time estimation of the behavior of large numbers of participants.

DETT (Disposition, Emotion, Trigger, Tendency) is an environmentally mediated model of emotion that captures the essential features of the widely-used OCC (Ortony, Clore, Collins) model of emotion. It does so in a computationally tractable way by using digital pheromones as the agents' main source of perceptions. It also extends current emotional models by defining a Disposition parameter that distinguishes the varying susceptibility of different agents to various emotions.

DETT is specifically designed for situated agents. It treats an agent's emotions as intimately triggered by its percepts, rather than being the result of purely internal reasoning.

In Section 3, we review previous work in computational emotions, particularly in the context of combat modeling. Section 4 describes the DETT model. Section 5 reports on some experiments with the model. Section 6 concludes.

2. PREVIOUS WORK
As a background for explaining our own work, we review the state of research in emotional modeling, and show how two existing agent-based combat models can be interpreted as supporting elements of the dominant approach.

2.1 Emotional Modeling
The study of emotion has a rich history in the psychological and physiological literature, reaching back well over a century [3] and has produced a wide range of theories, identifying emotions with outward expressions, physiological responses, distinct behaviors, or cognitive processes, among others.

Agent-based software is growing in two areas where realistic simulation of human behavior is important: agent-based modeling, and human interfaces (including gaming). This growth has led to a flurry of interest in computational models of emotion [17], each drawing on different segments of the psychological tradition.

Emotion clearly has facets related to an organism's outward expressions and physiological reactions, important for applications in human interfaces and robotics (e.g., [9, 10]). For our purposes, a cognitive perspective on emotions is more appropriate, and we draw on the OCC model [11]. The fundamental insight of this model is that emotions are "valenced reactions to events, agents or objects, with their particular nature being determined by the way in which the eliciting situation is construed." That is, the strength of a given emotion depends on the events, agents, or objects in the environment of the agent exhibiting the emotion. Their presence is mapped to a "valence," a positive or negative score, by a process called "assessment" or "appraisal."

Once an emotion exists, it impacts the subject in several ways. It focuses attention, increases the prominence of an event in memory, affects cognitive style and performance, and influences judgments [1]. In particular, according to OCC, "behavior is a response to an emotional state in conjunction with a particular initiating event." In our application, we focus on the impact of emotion on an agent's analysis and judgment, the process by which it selects its intentions from its desires.

To put this system in a broader perspective, consider the basic Belief-Desire-Intention [6, 18] data flow summarized in Figure 1. Beliefs (derived from the environment by perception) and Desires (which are constant over the time horizon of our model) feed an analysis process that produces Intentions, which in turn drive actions that change the environment. Figure 2 shows a simple enhancement of this model with the OCC model of emotion.

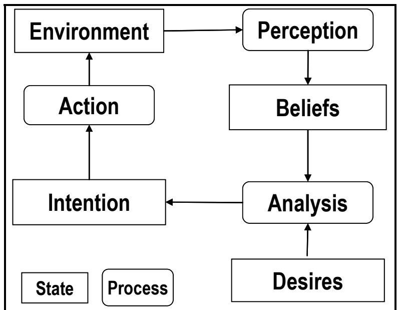

Figure 1. BDI Data Flow

Beliefs feed not only analysis, but also the appraisal process that generates emotions. These emotions in turn influence analysis and perception (the latter link shown dashed because we do not emphasize it in our current system).

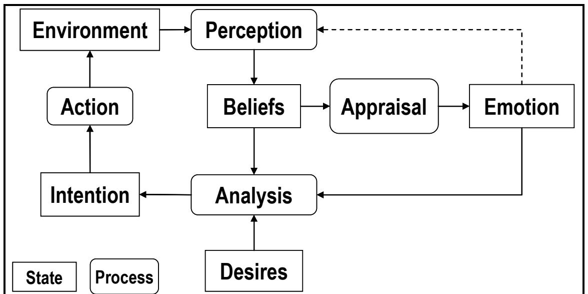

Figure 2. BDI enhanced with OCC

Gratch and Marsella [4] offer one of the more mature current computational models of agent emotion. Figure 3 sketches their model, and Table 1 summarizes the correspondence between salient elements of the two models.

2.2 Emotions in Existing Combat Models

Explicit emotional modeling is rare in existing models of combat, but two recent agent-based models have elements that can be interpreted as reflecting the structure we have derived.

Table 1. Comparison of Models

BDI + OCC (Fig. 2)	Gratch-Marsella (Fig. 3)
Environment	Environment
Perception	Causal Interpretation
Beliefs	Causal Interpretation
Appraisal	Appraisal
Emotion	Affective State
Analysis	Coping
Desires	???
Intention	Control Signals
Action	Action

EINSTein [5] represents an agent's personality as a set of six weights, each in [-1, 1], describing the agent's response to six kinds of information. Four of these describe the number of alive friendly, alive enemy, injured friendly, and injured enemy troops within the agent's sensor range. The other two weights relate to the model's use of a childhood game, "capture the flag," as a prototype of combat. Each team has a flag, and seeks to protect it from the other team while simultaneously capturing the other team's flag. The fifth and sixth weights describe how far the agent is from its own and its adversary's flag. A positive weight indicates that the agent is attracted to the entity described by the weight, while a negative weight indicates that it is repelled.

MANA [8] extends the concepts in EINSTein. Friendly and enemy flags are replaced by the waypoints being pursued by each side. MANA includes four additional components: low, medium, and high threat enemies. In addition, it defines a set of triggers (e.g., reaching a waypoint, being shot at, making contact with the enemy, being injured) that shift the agent from one personality vector to another. A default state defines the personality vector when no trigger state is active.

The notion of being attracted or repelled by friendly or adversarial forces in various states of health is an important component of what we informally think of as emotion (e.g., fear, compassion, aggression), and the use of the term "personality" in both EINSTein and MANA suggests that the system designers are thinking anthropomorphically, though they do not use "emotion" to describe the effect they are trying to achieve.

The decision systems in EINSTein and MANA are subsets of Figure 2.

Figure 4 casts EINSTein in this framework. EINSTein's personality vector guides the agent's decisions, but is itself fixed, and does not change in response to the agent's beliefs about the events, objects, or agents in its environment. Thus it is not a "valenced reaction," but a representation of the agent's desires. In this sense, EINSTein does not capture emotion.

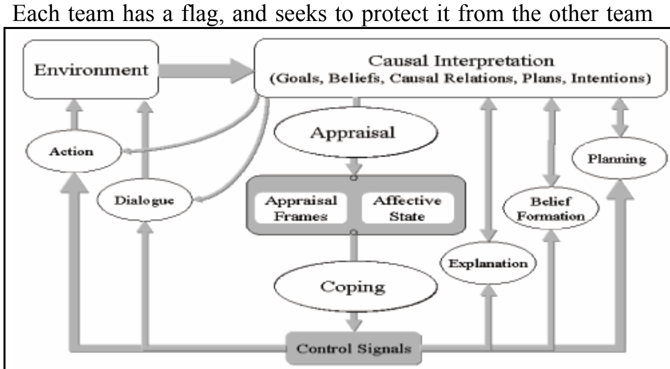

Figure 3. Gratch-Marsella Model of Cognitive-Motivational-Emotive System ([4], Figure 2)

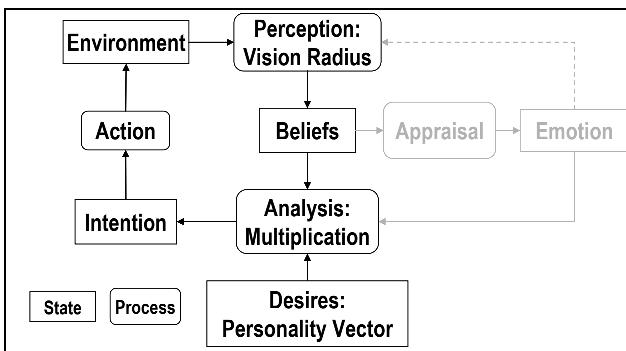

Figure 4. EINSTein as BDI + OCC

Figure 5 shows MANA. Because MANA's personality vectors depend on a trigger state, they qualify as a valenced reaction. The default personality vector that applies when no trigger state is active continues to represent the agent's desires.

In both EINSTein and MANA, analysis consists of multiplying the environmental information available to the agent by the personality vector, directly yielding a movement vector to guide the agent's subsequent actions. In both models, the perception process is represented by a vision radius within which the agent has perfect knowledge of its environment. These processes are considerably simpler than the mechanisms of symbolic AI applied in [4] for the same functions. The differences reflect the differing objectives of the systems. Gratch and Marsella are supporting a training environment with relatively few agents, and regular interaction with humans slows the pace to the point that significant computation can occur. EINSTein and MANA manipulate dozens or even hundreds of agents in non-interactive simulations of combat, and need to minimize the overall execution time to permit the execution of many instances of a scenario.

3. The DETT Emotion Model

Our work is supported by two DoD projects that require the ability to simulate large numbers of combatants very rapidly. Thus we favor agent models in the spirit of EINSTein and MANA.

3.1 Application Contexts

DETT was developed in the context of the DARPA RAID program, and is also being used to model noncombatants in another project.

The objective of RAID [7] is to anticipate enemy actions and deceptions, in order to provide real-time support to a tactical commander. We are constructing a module that reasons about the adversary's likely state and actions (thus, an Adversarial Reasoning Module, or ARM). Our particular ARM synergizes three distinct tactical reasoners: statistical reasoning for early detection of anomalous situations that might indicate risk, knowledge-based inference to reason about possible agent goals, and behavioral evolution and extrapolation, using swarms of fine-grained agents to explore possible futures of the battlespace. In this third reasoner, we evolve agents against observed reality to learn their characteristics and determine which ones are most likely to reflect future behavior. Because many of these agents must execute faster than real time, they cannot conduct complex symbolic reasoning, but use numerical computation. These agents use the DETT model.

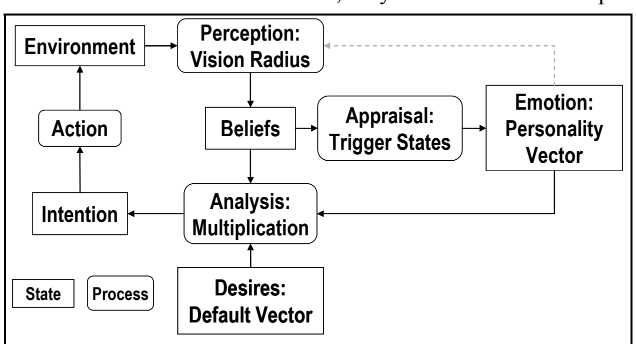

Figure 5. MANA as BDI + OCC

Table 2. Sample DETT Semantics

Disposition	Emotion	Trigger	Tendency
Cowardice	Fear	Presence of armed enemy Incoming attack	Less attention to orders Tend to move away from threat
Irritability	Anger	Presence of enemy	More likely to engage in combat Tend to move toward threat

In the other project, MAROP (Multi-Agent Representation of the Operational Environment), we are developing methods to enrich a new military modeling system (Combat XXI) by automating the reactions of non-combatants with combatants. This capability requires us to recognize that non-combatants will have a range of personality types and to incorporate these differences in their behavior.

3.2 Architecture

We need a computationally efficient way to take emotional tendencies into account in modeling combat. This reasoning takes place at two locations in Figure 2: Appraisal and Analysis. We have defined numerical methods for both of these.

3.2.1 Appraisal

MANA's use of triggered personality vectors that specify numerical weights for translating beliefs into intentions is a useful model for appraisal, but has two limitations. First, MANA defines vectors and triggers at the level of the squad, and all members of the squad share the same values. In practice, individual combatants will differ widely in their susceptibility to different emotions. A firefight that might stimulate high fear in a new soldier may have much less effect on a seasoned veteran. In order to use evolution to learn the characteristics of entities, we must parameterize this kind of difference. Second, MANA assumes that an agent in the presence of a trigger immediately adopts the associated emotion, and that when the trigger is removed, the emotion ceases immediately. Empirically, the rise of an emotion, while rapid, is not instantaneous, and the emotion will persist for a while after the trigger is removed.

To address the first concern we add a new component, Dispositions, to the model (Figure 6). There is a one-to-one

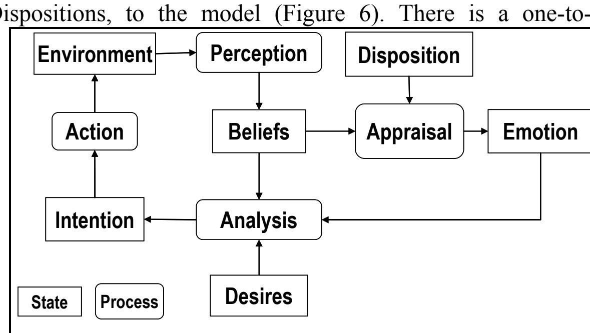

Figure 6. Incorporating Disposition in BDI + OCC

Table 3. Pheromone Flavors in RAID	
RedAlive	Emitted by a living or dead entity of the appropriate group (Red = enemy, Blue = friendly, Green = neutral)
RedCasualty	
BlueAlive	
BlueCasualty	
GreenAlive	
GreenCasualty	
WeaponsFire	Emitted by a firing weapon
KeySite	Emitted by a site of particular importance to Red
Cover	Emitted by locations that afford cover from fire
Mobility	Emitted by roads and other structures that enhance agent mobility

mapping between Emotions and Dispositions. Like Desires, Dispositions are persistent (that is, their values are constant over the time horizon of our simulations). A Disposition modulates Appraisal to determine the extent to which a given belief triggers the corresponding emotion. The emotion then modulates Analysis to impose a Tendency on the resulting intention. The main elements of this model are thus the Disposition, Emotion, Trigger (the beliefs that lead to the emotion), and Tendency (the effect on intentions) (DETT). Table 2 illustrates two Dispositions, with their associated Emotions and illustrative Triggers and Tendencies.

Our agents live in a digital pheromone infrastructure [2]. Agents sense one another's presence through labeled scalars that they deposit in the environment and that diffuse spatially and evaporate over time. The dynamics of these pheromones models (very crudely) the Perception process that maps environmental reality into agent beliefs: an agent believes what it senses in the form of pheromones in its environment. Table 3 summarizes our pheromone vocabulary in the case of RAID.

An agent's rationality is a vector of seven desires, which are values in [-1, +1]: ProtectRed (the adversary), ProtectBlue (friendly forces), ProtectGreen (civilians), ProtectKeySites, AvoidCombat, AvoidDetection, and Survive. Negative values reverse the sense suggested by the label. For example, a negative value of ProtectRed indicates a desire to harm Red. Table 2 in [13] shows which pheromones attract or repel an agent with a given desire, and how that tendency translates into action. For example, an agent with a high positive desire to ProtectRed will be attracted to RED-ALIVE, RED-CASUALTY, and MOBILITY pheromone, and will move at maximum speed.

Based on interviews with military domain experts,[1] we identified the two most crucial emotions for combat behavior as Anger (with the corresponding disposition Irritability) and Fear (whose disposition is Cowardice). Table 4 shows which pheromones trigger which emotions. Emotions are modeled as agent hormones (internal pheromones) that are augmented in the presence of the triggering environmental condition and evaporate over time.

Let $\boldsymbol{P}$ be the vector of pheromone strengths at an agent's location. The agent's Disposition is a matrix $\boldsymbol{D}$. $D[i,j] \in [0,1]$ is the relevance of the ith pheromone flavor to the jth emotion. The

[1] We are particularly grateful to COL Joseph Moore, USA (Ret), former Director, National Training Center, for helping identify the most crucial emotions to model and discussing how they would manifest themselves in behavior.

Table 4: Interactions of Pheromones and Dispositions/Emotions

	Dispositions/Emotions					
	Red Perspective		**Blue Perspective**		**Green Perspective**	
Pheromone	**Irritability /Anger**	**Cowardice /Fear**	**Irritability /Anger**	**Cowardice /Fear**	**Irritability /Anger**	**Cowardice /Fear**
RedAlive			X	X		
RedCasualty	X	X				
BlueAlive	X	X			X	X
BlueCasualty			X	X		
GreenCasualty	X	X			X	X
WeaponsFire	X	X	X	X	X	X
KeySites	X				X	

agent's jth emotion depends (nonlinearly) on the jth element of $\boldsymbol{P}^{T}\boldsymbol{D}$.

To allow emotions to vary realistically in time, agents have internal pheromones [16], or digital hormones, one for each Emotion. $\boldsymbol{P}^{T}\boldsymbol{D}$ at a given time step determines the deposit to the vector $\boldsymbol{E}$ of emotion hormones at that time step, so the longer an agent is exposed to a trigger pheromone, the higher the level of the associated emotion grows. When the relevant trigger is removed, the corresponding emotion decays exponentially. Also, the higher the disposition, the more quickly the associated emotion grows in the presence of a trigger. An agent with high irritability will grow angry faster in the presence of a triggering pheromone than an agent with low irritability.

3.2.2 *Analysis*

Analysis draws on the same pheromone vector $\boldsymbol{P}$ of beliefs as does Appraisal, and takes as input the current state of the emotion vector $\boldsymbol{E}$. In addition, it considers the values of the agent's vector of Desires or Wants $\boldsymbol{W}$. The desires we are modeling are Protect Red, Protect Blue, Protect Green, Protect Key Sites, Avoid Combat, Avoid Detection, and Survive. Each has a real value in the range [-1,1], where a negative value indicates that the agent wants the opposite state of affairs described by the desire. A movement matrix $\boldsymbol{M}$ indicates whether a given Desire tends to attract or repel the agent toward a given flavor of pheromone: $\boldsymbol{M}$[i,j] is 1 if desire j is attracted to pheromone i, -1 if it is repelled, and 0 if the pheromone is irrelevant to the desire.

absence of emotions, the agent's behavior is a function (again nonlinear) of $\boldsymbol{P}^{T}\boldsymbol{MW}$. Emotions modulate these behaviors. Elevated Anger will increase movement likelihood, weapon firing likelihood, and tendency toward an exposed posture, while elevated Fear will decrease these likelihoods. Level of a particular emotion actually models the extent to which the emotion modulates the agent's behavior. Someone who experiences high fear, but is able to continue to behave as if he were not afraid, would be modeled as having low fear. We are not trying to model emotion as experienced by an agent, only emotion that can be perceived by its impact on the agent's behavior.

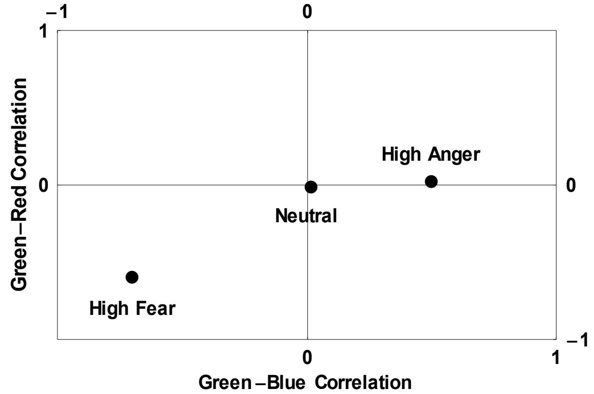

Figure 7. Effect of Emotions in MAROP (notional data)

4. EXPERIMENTAL RESULTS

We report here the initial experiments that we are conducting in the context of the two projects that are using the DETT model. At this point, our experiments are focused on demonstrating that the software mechanisms linking dispositions, pheromone-mediated beliefs, emotions, desires, and resulting intentions are working correctly.

4.1 MAROP

Our initial experiments measure the effect of the emotions of fear and anger on the spatial correlation of non-combatants with other entities of interest. All experiments are conducted on a road network modeling an urban area. In our experimental schema, Red and Blue forces follow scripted movements that carry them from opposite sides of the town to a central location where they engage in a firefight. Initially, Green agents are distributed randomly throughout the town.

MAROP uses a simplified version of DETT in which different dispositions and emotions are precompiled into an agent's attraction to or repulsion from each of four different pheromone flavors: RedAlive, BlueAlive, GreenAlive, and WeaponsFire. We define two emotions, Fear and Anger, as summarized in Table 5. (These encodings assume that the combat takes place on Red's "turf."). We can measure the resulting effect on the relative distribution of Green and each of the other classes (Red agents, Blue agents, and conflict events) by computing the spatial correlation of the associated pheromone fields. A correlation of 1 indicates that the two classes of agents tend to be in the same regions of the town, while a correlation of -1 indicates that they tend to avoid one another.

Distinct scenarios are run with Green agents coded as fearful, angry, and unemotional. Thus each experimental scenario forms a point in a three-dimensional space. Figure 7 shows a projection of this space on the plane defined by Green-Red and Green-Blue correlations, illustrating how Green agents of different emotional configuration assume different relations to the other agents in the scenario.

Table 5. Emotional Tendencies in MAROP

Pheromone	Fear	Anger
RedAlive	Repulsive	Neutral
BlueAlive	Repulsive	Attractive
GreenAlive	Attractive	Neutral
WeaponsFire	Repulsive	Attractive

4.2 RAID

RAID [13] uses our polyagent technology [12]. Each real-world entity has one agent representative, its avatar, but the avatar explores alternative possible futures by constantly sending out a swarm of ghosts whose pheromone-based self-organization then guides the avatars. Each ghost interacts with pheromones deposited by all other entities in the world, and its emotional state is driven by those interactions.

To test the effect of emotions in RAID, we arrange ten units (one avatar per unit) of each color in files, and have the Red and Green march through the Blue in formation (Figure 8). When a file reaches one extreme of the arena, it reverses its direction. The units reach their original locations after 189 time steps, and the scenario repeats. Thus the units repeatedly pass through one another, depositing pheromones that indicate their presence and sensing the pheromones deposited by the other agents. Each unit emits eight ghosts per time step, and each ghost explores the future for five time steps before dying.

Each avatar's ghosts are generated with random values of "cowardice" in [0,1]. In our full system, an evolutionary process narrows these down on the basis of comparisons between the ghosts and actual history, but this process is not operating in this experiment. Averaged over time, each avatar's ghosts have a cowardice of 0.5.

The combination of a disposition with beliefs about the environment yields emotions (Figure 6). Figure 9 (top) shows the average value of the "fear" emotion across the ghosts for Red unit #1, as a function of time. This value peaks each time the unit crosses the line of Blue units, reflecting an interaction between the ghosts' cowardice disposition and the BlueAlive pheromone that they sense in the environment.

Emotion affects the agent's analysis to determine its intentions (Figure 6). Figure 9 (bottom) shows the average level of the "avoid detection" intention across this unit's ghosts. (The use of "desire" in the legend is a typo that will be corrected in revisions to the software.) As required by Section 3, this intention increases when fear is active.

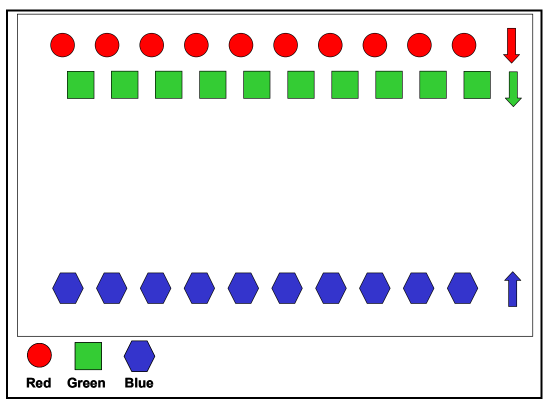

Figure 8. Experimental Configuration for RAID

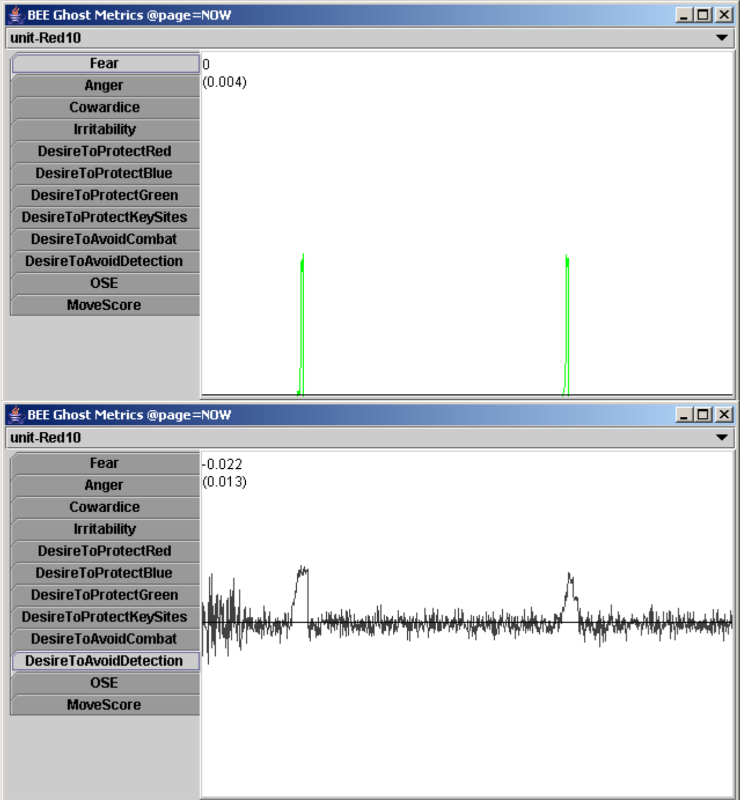

Figure 9. Fear emotion (top) and intent to avoid detection (bottom) resulting from Cowardice disposition in the presence of adversarial pheromone. X-axis is time.

The net effect is thus to modulate the agent's intrinsic desire to avoid detection on the basis of its emotional state (specifically, fear), as determined by its disposition (cowardice) and its beliefs about the environment (the presence of adversaries).

We have tested the DETT model in a series of wargames involving human players who make decisions that are played out in a battlefield simulator. The commander for each side (Red and Blue) has at his disposal a team of pucksters, human operators who set waypoints for individual units in the simulator. Each unit corresponds to a fire team. Each puckster is responsible for four to six units. The simulator moves the units, determines firing actions, and resolves the outcome of conflicts.

Our system fits the DETT model to observed behavior of units, using evolution in a faster-than-real-time simulation of the battle [13]. To test our ability to fit personalities based on behavior, one Red puckster responsible for four units is designated the "emotional" puckster. He selects two of his units to be cowardly ("chickens") and two to be irritable ("Rambos"). He does not disclose this assignment during the run. He moves each unit according to the commander's orders until the unit encounters circumstances that would trigger the emotion associated with the unit's disposition. Then he manipulates chickens as though they are fearful (avoiding combat and moving away from Blue), and moves Rambos into combat as quickly as possible.

The difference between the two disposition values (Cowardice – Irritability) of the fittest ghosts proves a better indicator of the emotional state of the corresponding entity than either value by itself. To characterize a unit's personality, we maintain a 800-second exponentially weighted moving average of the Delta Disposition, and declare the unit to be a Chicken or Rambo if this value passes a negative or positive threshold, respectively. Currently, this threshold is set at 0.25. We are exploring additional filters. For example, a rapid rate of increase enhances the likelihood of calling a Rambo; units that seek to avoid detection and avoid combat are more readily called Chicken.

In one series of experiments, we successfully identified 68% of the chickens played. The detection rate for Rambos was much lower (5%), because the brave die young and our algorithm does not have enough exposure to a brave unit's behavior to diagnose its emotional state. But we never called a Rambo a Chicken. In the one case where we called a Chicken a Rambo, logs show that in fact the unit was being played aggressively, rushing toward oncoming Blue forces.

Figure 10 shows a comparison on a separate series of experiments of our emotion detector compared with a human observer. BEE was able to detect cowards (= chickens) much earlier than the human, while missing only one chicken that the human detected.

In addition to these results on units intentionally played as emotional, BEE sometimes detects other units as cowardly or brave. Analysis of the behavior of these units shows that these characterizations were appropriate: units that flee in the face of enemy forces or weapons fire are detected as Chickens, while those that stand their ground or rush the adversary are denominated as Rambos.

We did not detect some units that were played as cowardly. Many of these non-identified cowards were red units that were far from a blue unit. This discrepancy arises from an instructive difference between our software and the emotional puckster, which illustrates the situated nature of the DETT model.

In our software, an agent's knowledge of its environment is conveyed entirely through the field of digital pheromones. If a red unit is beyond the propagation limit of the digital pheromone

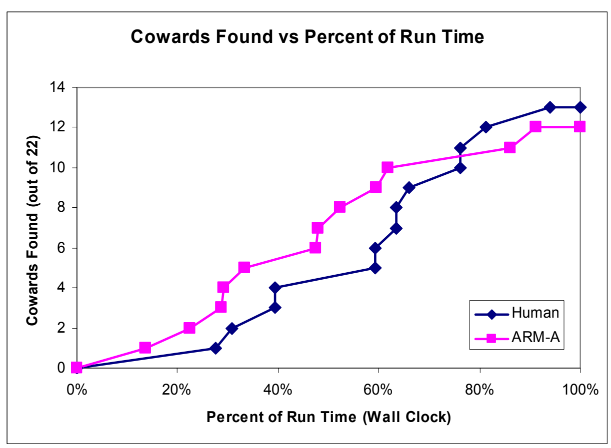

Figure 10. BEE vs. Human.—BEE can detect cowards sooner than a human observer.

representing the blue unit, the red unit does not know of the existence of the blue unit. (The propagation limit on the pheromone is analogous to a limitation on a soldier's field of vision in the real world.) Thus even if the red unit has a cowardly disposition, it will not develop fear and will not behave in a fearful way.

The puckster looks down on a map of the overall battlespace, and can see all of the units at once. Confronted with managing several units concurrently in the midst of an active battle, the puckster can easily overlook the fact that though he can see both a red unit and a blue unit, the red unit might *not* be able to see the blue unit at a given moment. He knows that a fearful red should flee from blue. He can see both the red and the blue. So he moves the red away from the blue.

In the DETT model, emotions become active only when triggered. The inconsistency between what is played and what is detected is in what the cowardly agent knows about its environment. The puckster imputes his knowledge of blue to the red unit, so from his perspective its behavior reflects fear. In the software, the red agent does not see the blue unit, and so does not sense fear or act in a fearful manner. This example makes clear that emotion is very much a situated concept. It cannot be detected by movement away from a threat, only by movement away from a threat of which the agent is aware. An emotion such as fear may well have triggers that we have not modeled, and our current approach would not detect it. The problem is circular in structure: we cannot recognize a behavior as evidence of fear unless we can associate it with a trigger, and we cannot learn that an environmental feature is a trigger unless we can detect that it causes fear. Breaking this closed loop is an interesting and challenging research question.[2]

We have embedded the DETT model in an evolutionary loop that compares simulated behavior with real-world status to estimate the emotional state of observed combatants [14]. This work shows how one agent can deduce the emotional state of other agents by observing their external behavior.

5. CONCLUSION

Emotion is a critical component of modeling the behavior of agents, particularly in stressful environments such as combat. The Gratch-Marsella model offers a sophisticated implementation of current psychological theories of emotion, but is computationally too expensive to apply to large populations of combatant agents. Some fine-grained agent-based models embed a notion of personality (EINSTein and MANA), but do not recognize the important distinctions between individual combatants.

The DETT model (Dispositions, Emotions, Triggers, Tendencies) combines the theoretical richness of the Gratch-Marsella model with the computational efficiency of EINSTein and MANA. It also extends current emotional models with the notion of disposition, accounting for differences in the emotional susceptibility of various agents by reasoning about the reaction of an internal agent characteristic to the external environment in which the agent is situated. We are using the model in two different contexts, and have demonstrated the basic computational cycle in implemented software (and in our second application, in actual wargame experiments).

The model is still an approximation. It does not implement the known effect of emotion on perception, and does not consider other possible linkages (e.g., between emotion and desire). Such simplifications are in the nature of simulation, and are justified empirically by the notion of "universality": the dynamics of a multi-agent simulation often depend more on the interactions of the agents than on the details of individual agents' reasoning [15].

6. Acknowledgements

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7. REFERENCES

[1] Brave, S. and Nass, C. Emotion in Human-Computer Interaction. In J. A. Jacko and A. Sears, Editors, *The human-computer interaction handbook: fundamentals, evolving technologies and emerging applications*, Lawrence Erlbaum Associates, Inc., Mahwah, NJ, 2003, 81-96.

[2] Brueckner, S. *Return from the Ant: Synthetic Ecosystems for Manufacturing Control*. Thesis at Humboldt University Berlin, Department of Computer Science, 2000.

[3] Darwin, C. *The expression of the emotions in man and animals*. London, John Murray, 1872.

[4] Gratch, J. and Marsella, S. A Domain-independent Framework for Modeling Emotion. *Journal of Cognitive Systems Research*, *5*, 4: 2004, 269-306.

[5] Ilachinski, A. *Artificial War: Multiagent-based Simulation of Combat*. Singapore, World Scientific, 2004.

[6] Kinny, D., Georgeff, M., and Rao, A. A Methodology and Modelling Technique for Systems of BDI Agents. In W. VandeVelde and J. W. Perram, Editors, *Agents Breaking Away. 7th European Workshop on Modelling Autonomous Agents in a Multi-Agent World (MAAMAW'96). Lecture Notes in Artificial Intelligence 1038*, Springer, Berlin, 1996, 56-71.

[7] Kott, A. Real-Time Adversarial Intelligence & Decision Making (RAID). 2004. http://dtsn.darpa.mil/ixo/programdetail.asp?progid=57.

[8] Lauren, M. K. and Stephen, R. T. Map-Aware Non-uniform Automata (MANA)—A New Zealand Approach to Scenario Modelling. *Journal of Battlefield Technology*, *5*, 1 (March): 2002, 27ff.

[9] Marinier, R. and Laird, J. Toward a Comprehensive Computational Model of Emotions and Feelings. In

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Proceedings of Sixth International Conference on Cognitive Modeling, Lawrence Earlbaum, 2004, 172-177.

[10] Murphy, R. R., Lisetti, C. L., Tardif, R., Irish, L., and Gage, A. Emotion-Based Control of Cooperating Heterogeneous Mobile Robots. *IEEE Transactions on Robotics and Automation*, *18*, 5 (October): 2002, 744-757.

[11] Ortony, A., Clore, G. L., and Collins, A. *The cognitive structure of emotions*. Cambridge, UK, Cambridge University Press, 1988.

[12] Parunak, H. V. D. and Brueckner, S. Modeling Uncertain Domains with Polyagents. In *Proceedings of International Joint Conference on Autonomous Agents and Multi-Agent Systems (AAMAS06)*, 2006.

[13] Parunak, H. V. D., Brueckner, S., Matthews, R., Sauter, J., and Brophy, S. Characterizing and Predicting Agents via Multi-Agent Evolution. Altarum Institute, Ann Arbor, MI, 2005. http://www.altarum.net/~vparunak/BEE.pdf.

[14] Parunak, H. V. D., Brueckner, S., Matthews, R., Sauter, J., and Brophy, S. Real-Time Evolutionary Agent Characterization and Prediction. In *Proceedings of International Joint Conference on Autonomous Agents and Multi-Agent Systems (AAMAS'06)*, 2006, (submitted).

[15] Parunak, H. V. D., Brueckner, S., and Savit, R. Universality in Multi-Agent Systems. In *Proceedings of Third International Joint Conference on Autonomous Agents and Multi-Agent Systems (AAMAS 2004)*, IEEE, 2004, 930-937.

[16] Parunak, H. V. D., Brueckner, S. A., Matthews, R., and Sauter, J. Pheromone Learning for Self-Organizing Agents. *IEEE SMC*, *35*, 3 (May): 2005, 316-326.

[17] Picard, R. W. *Affective Computing*. Cambridge, MA, MIT Press, 2000.

[18] Rao, A. S. and Georgeff, M. P. Modeling Rational Agents within a BDI Architecture. In *Proceedings of International Conference on Principles of Knowledge Representation and Reasoning (KR-91)*, Morgan Kaufman, 1991, 473-484.