Proceedings of the 2007 IEEE/RSJ International
Conference on Intelligent Robots and Systems
San Diego, CA, USA, Oct 29 - Nov 2, 2007

Emotion-based Parameter Modulation for a Hierarchical Mobile Robot Planning and Control Architecture

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Abstract—**Autonomous robots are presently unable to match the adaptive capabilities of even the simplest of animals. Affective processes such as emotions are highly effective facilitators of adaptive behavior in humans and animals. Thus, it can be argued that emotions can bestow robots with similar adaptive advantages. In particular, artificial emotions can improve a robot's performance by modulating actions, prioritizing goals and providing reinforcements for learning. A hierarchical robot architecture that incorporates reactive and deliberative emotions has been developed to test this hypothesis. Reactive emotions arise from predictions of emotion-eliciting events from short-term sensor data and internal representations. Deliberative emotions are modeled as learned associations between environmental states and previous emotion-eliciting events. Emotions interact with multiple architectural levels by modulating parameters controlling the robot's degree of bias towards various competing drives, such as goal-seeking, safety and exploration. The model has been implemented on a simulated mobile robot for a navigation task.**

I. Introduction

HISTORICALLY, emotions and cognition were regarded as separate entities competing for control over the human brain. Emotions resided in the primitive sections of the brain, safely partitioned from our high-level planning and reasoning systems. This view has been challenged in recent years. Emotions are now regarded as integral to many brain functions that were once considered purely cognitive, such as problem-solving, learning, memory and perception [1]. Some researchers argue that emotions are a necessary prerequisite for intelligence [2], [3].

Since emotions play such an important role in the behavior of biological organisms, the idea of applying artificial emotions to robots deserves serious consideration. As we define them, artificial emotions are not superficial external responses intended to mimic human emotions. Rather, they are software mechanisms inspired by theories of biological emotions that enable a robot to adapt to certain situations that arise as it performs its duties.

It is hypothesized the adaptive advantages bestowed by artificial emotions should enable a robot to outperform emotionless robots in situations for which no appropriate hard-coded behaviors have been implemented. The objectives of this research are to develop a planning and control architecture for an autonomous mobile robot that incorporates artificial emotions, and to compare it with an equivalent emotionless architecture in order to test this hypothesis.

This work was supported by the N.Z. Tertiary Education Commission under a Top Achiever Doctoral Scholarship.

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II. Related Work

There are two important roles for emotions in robots [4]:

- *Social interaction* – Simulated emotions can enable robots to behave in a socially appropriate manner when interacting with humans.
- *Adaptation* – Artificial emotions are a source of adaptive behavior that can potentially improve a robot's general performance.

The robotics community has focused largely on the social aspects of emotions (e.g. [1], [5], [6], [7], [8], [9], [10]). In this domain, a robot's emotions are clearly observable in the form of facial expressions, body language and/or tone of voice. Research tends to focus on the appearance of robotic emotions [6], the subjective evaluations of humans who interact with the robots [7], [9], and the influences of human emotions on robotic learning [10].

The second domain has received less attention, as it poses considerable difficulties. Emotional responses in this domain are highly context-dependant. While a robot's overall performance can be measured in quantitative terms such as speed and number of collisions, one cannot easily verify an emotion's contribution to performance. It is also difficult to prove that any performance improvements provided by emotions cannot be achieved by an equivalent non-emotional system.

Many robots that purportedly utilize artificial emotions as a general source of adaptive behavior are nevertheless applied in a social context, interacting with humans [11], [12] or other robots [13], [16], [17]. The most common emotional function is action/behavior selection [11], [13], [14], [16], [17]. In the majority of examples, the underlying control architecture is purely reactive and/or behavior-based [11], [14], [15], [16], so the interactions between emotions and deliberative planning have received little attention.

In contrast to these approaches, we utilize emotions to improve the adaptive capabilities of a single robot in a non-social context. We represent emotions not as discrete logic states, but as continuous modulations of the robot's parameters. Our model is applied to a hierarchical architecture that incorporates reactive control, deliberative planning and exploration capabilities.

III. Model Description

A. Elicitation

Biological emotions contain both innate and learned components [18], and they interact with cognitive processes at multiple architectural levels [19]. In order to emulate some of the rich and varied interactions of real emotions, our elicitation model incorporates both hard-coded and learned associations, and receives inputs from both reactive and deliberative architectural layers.

Five basic emotions are modeled: fear, anger, surprise, happiness and sadness. These emotions are not intended to be exact representations of human emotions with the same names, but rather labels for certain categories of elicitation/response patterns. In this simple categorization, certain other human emotions can be regarded as synonymous with these emotions (e.g. frustration = anger, curiosity = surprise).

Each basic emotion is linked to a different category of emotion-eliciting events:

- *Fear* – The robot becomes damaged.
- *Anger* – Progress towards a goal is obstructed.
- *Surprise* – Perceived reality contradicts the robot's predictions.
- *Happiness* – The robot achieves its goal.
- *Sadness* – The robot is unable to achieve its goal.

Reactive emotions utilize measurements derived from short-term sensor data (e.g. obstacle proximities), to estimate the probability that an emotion-eliciting event will occur. Deliberative emotions utilize learned associations between environmental states (e.g. map locations) and emotion-eliciting events that have occurred in the past.

B. Response

Emotions and cognition are closely entwined and mutually dependent, but few researchers would argue that all cognitive functions are influenced by emotions [20]. Also, although many functions can benefit from the adaptive advantages provided by emotions, they do not necessarily require emotions to perform at a basic level.

Consequently, our mobile robot incorporates emotions into every level of its control architecture, but it is not driven solely by emotions. Even in the absence of an emotional influence, it is generally able to achieve its goals. Rather, our model implements emotions as second-order adaptations to certain situations and environments. This approach is more in line with human and animal physiology than purely emotion-driven methods. It also eliminates the need to construct a separate emotionless architecture for comparative purposes, simplifying the analysis.

Perception, learning, planning and control capabilities are provided by the robot's hybrid reactive-deliberative architecture. This architecture does not represent competing drives as discrete behaviors. Rather, multiple drives are integrated into each control layer, allowing the robot to favor one response without completely disregarding another.

Inspired by Dörner [21] and Fellous [22], we model emotions as modulations of the robot's planning and control parameters. These parameters smoothly change the degree of bias towards certain drives without explicitly controlling the robot's behaviors. The drive associated with each emotion is a reaction to its emotion-eliciting event:

- *Fear* – Avoid danger, reducing the importance of the robot's current goal.
- *Anger* – Achieve the current goal, even at the expense of secondary considerations.
- *Surprise* – Explore the environment.
- *Happiness* – Provide positive reinforcement to behaviors that led to success.
- *Sadness* – Provide negative reinforcement to behaviors that led to failure.

The robot can operate successfully with its parameters set to constant values. However, values that provide optimal performance during normal operation may occasionally result in dangerous behaviors, or failure to complete a goal. Adaptive parameter modulation solves this problem by selecting parameter values that are appropriate to a given situation.

IV. Model Implementation

The model is implemented on a simulated version of MARVIN (Mobile Autonomous Robotic Vehicle for Indoor Navigation), a custom-built mobile robot intended for security and public relations applications [23]. The robot is equipped with a two-wheeled differential drive system supported by casters at the front and rear. Exteroception is provided by of a ring of infrared and ultrasonic distance measuring sensors. The simulation environment and robot architecture are implemented using a combination of MATLAB and C code.

The robot's task is to navigate to user-specified locations within an initially-unknown, dynamic indoor environment. In this context, the robot's primary goal is to navigate from one point to another. To achieve this goal, it must balance a number of learning and survival-related subtasks, including obstacle avoidance and exploration of its environment.

In the emotion model implemented for this task, anger and fear interact with reactive and deliberative processes, whereas surprise and happiness are only active on the deliberative level. For simplicity, sadness is modeled as a negative state of happiness.

A. Reactive Emotions

The reactive controller employs an obstacle avoidance approach based loosely on the vector field histogram algorithm [24]. A target direction is selected that minimizes deviation from the goal direction and maximizes distance to obstacles. The robot is roughly circular, so for simplicity it is represented as a point object, and each obstacle is enlarged by a radius r_o. The obstacle aversion drive thus becomes increasingly dominant as r_o increases.

Following the selection of a target direction, the reactive controller selects a velocity couplet (v,ω) that moves the robot in the intended direction at an appropriate speed. Based on the dynamic window approach [25], velocity selection is performed within a discrete rectangular space bounded by the minimum and maximum linear and angular velocities achievable given the robot's current velocities, acceleration constraints and global limits.

Our implementation of reactive fear limits the robot's speed in crowded environments. The reactive fear intensity value e_F increases when there is a high probability of collision with an obstacle. Computationally, it is a function of the robot's current linear velocity magnitude v and measured obstacle distances $d(\theta)$ for angles θ:

$$e_F = \begin{cases} \kappa_1 . v \dfrac{\sum_{\theta=-\pi}^{\pi} \left(1 - \dfrac{|\theta|}{\pi}\right)\left(1 - \dfrac{d(\theta)}{d_{\max}}\right)}{\sum_{\theta=-\pi}^{\pi} \left(1 - \dfrac{|\theta|}{\pi}\right)} + \beta_1 & \text{if not collision} \\ 1 & \text{otherwise} \end{cases} \quad (1)$$

K_1 and β_1 are normalization constants.

The global linear velocity limit v_L is modulated by the robot's fear response, decreasing linearly as its e_F increases. This results in slower, more "cautious" behaviors when the robot passes through cluttered environments where collisions are more likely to occur.

Reactive anger controls the robot's obstacle aversion. The reactive anger intensity value e_A increases when its progress becomes obstructed (e.g. by local minima). Detection of an obstructed state involves a summation the robot's linear velocity vectors $\mathbf{v}(t)$ over time t:

$$e_A = \begin{cases} \kappa_2 \left(1 - \dfrac{\left|\sum_{t=0}^{T} \mathbf{v}(t)\right|}{\sum_{t=0}^{T} \left|\mathbf{v}(t)\right|}\right) + \beta_2 & \text{if } \sum_{t=0}^{T} \left|\mathbf{v}(t)\right| > 0 \\ 1 & \text{otherwise} \end{cases} \quad (2)$$

The primary response of reactive anger is to modulate the obstacle radius r_o, reducing r_o linearly as e_A increases. During normal operation, the robot behaves in a manner that could be described as "fearful", giving obstacles a wide berth. However, if the robot's progress is obstructed, e.g. by a narrow doorway, it becomes "angry", temporarily reducing its obstacle aversion in order overcome the obstruction.

B. *Deliberative Emotions*

Planning and exploration are facilitated by a dynamically-updated occupancy grid map [26]. Each node's occupancy probability p_o is updated in real time based on its proximity to measured obstacles and sensor coverage vectors. Paths to goal locations are planned using a modified A* algorithm [27]. Our implementation differs from standard path planning algorithms in that the cost c of traversing a node is probabilistic and subject to localized emotional modulations:

$$c = p_o + \left(W_1 E_F + W_2 \left(1 - E_S\right) - W_3 E_H\right)\left(1 - E_A\right) \quad (3)$$

Deliberative fear E_F increases the cost of nodes in proximity to a collision, reducing the probability that the robot will subsequently plan a path through them. Surprise E_S reduces cost, compelling the robot to explore areas where its sensor data does not match its internal map data. Positive values of happiness E_H reduce cost, increasing the probability that the robot will plan a path that has resulted in previous success, whereas negative values (representing sadness) have the reverse effect. Emotional biases are suppressed by deliberative anger E_A, allowing the robot to escape from obstructed states resulting from these modulations. Planning weights W_1, W_2 and W_3 control the degree of influence that each emotion has over path planning.

Deliberative fear controls the robot's aversion to "dangerous" locations. If a collision sensor is triggered, the deliberative fear intensities E_F of nodes close to the point of collision increase at a rate dependant on growth factor G and their distance d_c from the point of collision, otherwise they decay at rate D:

$$E_F \leftarrow \begin{cases} E_F + \dfrac{G}{{d_c}^2 + 1}\left(1 - E_F\right) & \text{if collision} \\ \left(1 - D\right)E_F & \text{otherwise} \end{cases} \quad (4)$$

Deliberative anger closes the feedback loop, modulating other emotions in order to prevent obstructed states. If a planned path traverses a node whose cost c exceeds a threshold T_A, deliberative anger intensities E_A grow throughout the entire map. When another deliberative emotion E_O grows, the corresponding E_A value decays at a rate dependant on E_O:

$$E_A \leftarrow \begin{cases} E_A + G\left(1 - E_A\right) & \text{if } c > T_A \\ \left(1 - D.E_O\right)E_A & \text{else if } \Delta \mathrm{E_O} > 0 \end{cases} \quad (5)$$

Surprise controls the balance between exploration and exploitation, or future reward and immediate gratification. Surprise intensity E_S is linked to the level of disagreement Δp_o between the robot's sensor data and its internal map. Computationally, if Δp_o of a node exceeds threshold T_S, E_S will grow, otherwise it will decay:

$$E_S \leftarrow \begin{cases} E_S + \dfrac{G\left(\Delta p_o - T_S\right)}{1 - T_S}\left(1 - E_S\right) & \text{if } \Delta p_o > T_S \\ \left(1 - \dfrac{D\left(1 - \Delta p_o\right)}{T_S}\right)E_S & \text{otherwise} \end{cases} \quad (6)$$

Happiness and sadness are analogous to positive and negative rewards in reinforcement learning. Upon completion (or timeout) of a navigation instruction, the happiness intensities E_H of nodes close to those traversed by the robot grow or decay depending on the instruction's degree of success s:

$$E_H \leftarrow \begin{cases} E_H + G(s - E_H) & \text{if } s > E_H \\ E_H + D(s - E_H) & \text{otherwise} \end{cases} \tag{7}$$

V. Results

The reactive and deliberative emotions described in Section IV have each been independently tested in simulated environments designed to reveal their performance contributions. In each experiment, capabilities that are not directly relevant to the functions of the emotion being tested are disabled. Results from several of these experiments are presented here as examples.

A. Reactive Anger

To demonstrate of the utility of reactive anger, we utilize a simulated environment in which the robot's anger response is encouraged (Figs. 1-2). The robot begins the experiment completely surrounded by obstacles whose initial positions are represented by the light grey areas on the map. In order to reach its goal, it must push the obstacles out of the way, and then navigate through a series of corridors. Deliberative path planning is disabled for this experiment, so the robot must rely entirely on its reactive controller. No hard-coded behaviors have been implemented specifically to cope with moveable obstacles. Instead, the robot must suppress its obstacle aversion response by reducing r_o. The moveable obstacles are considered "safe", so only collisions that occur after the robot has escaped from the enclosing obstacles are recorded.

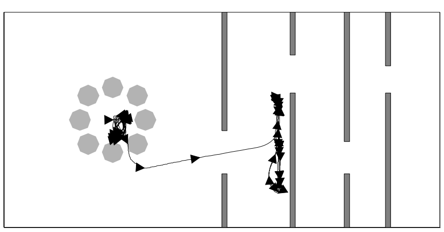

Fig. 1. Path followed by the robot with reactive anger deactivated.

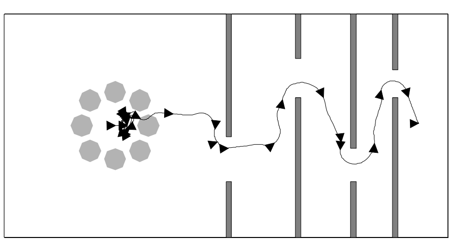

Fig. 2. Path followed by the robot with reactive anger activated.

When r_o is set to a constant value that is sufficiently low to allow the robot to escape from confinement by the moveable obstacles, the robot frequently becomes obstructed by doorway corners and thus fails to reach the goal (Fig. 1). When r_o is modulated correctly by reactive anger (Fig. 2), the robot initially avoids contact with the obstacles, but the resulting repetitive motion is soon recognized as an obstructed state. This causes e_A to quickly increase to the point of saturation, so r_o reduces to its minimum value, allowing the robot to push the obstacles out of the way. Once free of the obstacles, e_A rapidly decays, increasing the robot's obstacle aversion to a safer level, allowing it to navigate through the doorways.

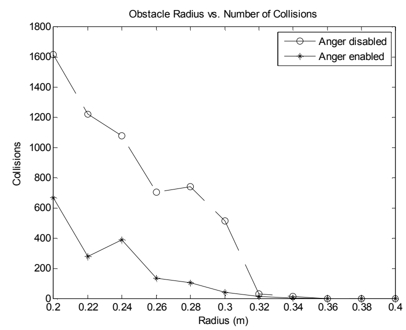

Fig. 3. Graph of the average number of collisions for each r_o value.

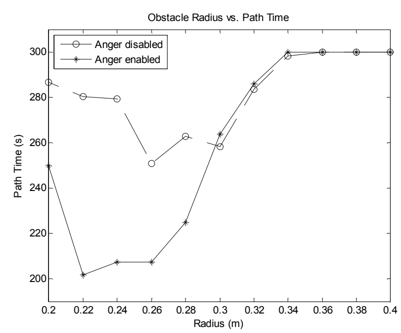

Fig. 4. Graph of the average path time for each r_o value.

Results for a selection of constant/minimum r_o values are presented in Figs. 3-4. When reactive anger is enabled, r_o is modulated between the values shown ($r_{o(min)}$) and a static maximum of $r_{o(max)}$ = 0.4 m, with the actual value of r_o at any given time dependant on e_A. In both conditions (with and without anger enabled) the average collision count reduces until $r_{o(min)}$ approaches the robot's radius (0.35 m). However, the collision count with reactive anger enabled is consistently lower than with anger disabled. Path times are initially high as a result of the robot becoming obstructed by doorways, followed by a trough over an optimal range of r_o values, and then a rapid increase as the robot fails to escape from the enclosing obstacles. The trough is more pronounced when anger is enabled, yielding considerably lower path times over an optimal range of 0.22-0.26 m. Properly tuned, reactive anger significantly improves the robot's performance during this experiment, but the resulting collision count and path times are nevertheless fairly high. This is largely due to the extreme demands that the experiment imposes on the robot.

B. Deliberative Fear and Anger

Deliberative fear is demonstrated in a simulated environment containing mapped static obstacles as well as unmapped dynamic obstacles that are moving too quickly for the robot to avoid (Figs. 5-6). The obstacles travel within the light grey areas of the map. A collision is inevitable if the robot passes within one of these areas, but the robot is given no prior knowledge of them. The robot is instructed to travel from the top left corner of the map to the top right corner, then return to its original position.

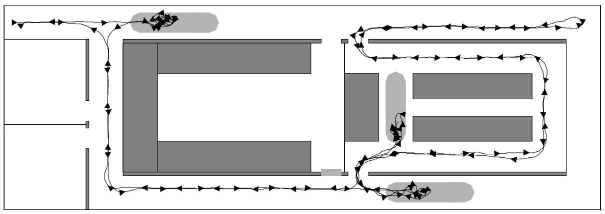

Fig. 5. Path followed by the robot with deliberative fear deactivated.

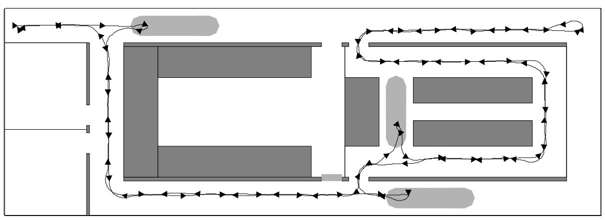

Fig. 6. Path followed by the robot with deliberative fear activated.

With deliberative fear disabled (Fig. 5), the robot travels along what appears to be the shortest path until it collides with the first dynamic obstacle. Due to the speed of the obstacle, no single node is occupied at all times. This means the dynamic mapping algorithm is very slow to increase the occupancy probabilities of nodes within the grey area, even though they are among the most dangerous areas on the map. Eventually the occupancy probabilities increase to the point where the robot plans a path elsewhere, but in the meantime a significant number of collisions have occurred. The same behavior pattern occurs as the robot enters the other two “danger zones”. Thus, the robot does eventually complete its task, but only after sustaining an unacceptable number of collisions. When deliberative fear is enabled (Fig. 6), E_F increases in nodes surrounding the point of collision. This results in a strong negative bias to their cost, causing the robot to immediately plan a path elsewhere. Thus, the robot only sustains a small number of collisions each time it encounters a dynamic obstacle. The overall task is therefore completed more quickly and safely.

Deliberative fear is undoubtedly beneficial to performance in the example presented. However, there are situations where the robot can become “trapped” by fear. For example, if the robot sustains a collision in a doorway that is the only exit from a room, it will subsequently avoid the doorway in the same manner as it avoids a wall.

This problem is addressed by utilizing deliberative anger to suppress emotions such as fear when they obstruct the robot’s progress towards a goal. To demonstrate the utility of deliberative anger, we modify the environment from the previous experiment to simulate an additional collision when the robot first enters the lower doorway (Figs. 7-8). With deliberative fear sufficiently activated (Fig. 7), this effectively traps the robot within the eastern section of the map until the E_F values of nodes in the doorway decay to the point where the robot can escape. This takes a long time and often results in additional collisions as the robot attempts to travel through other areas that are more dangerous than the doorway. However, when deliberative anger is activated (Fig. 8), the robot detects an obstructed state as soon is it attempts to plan a path through a node with a high cost (indicating that the best path available is inadequate). This causes the robot to suppress its other emotions, relying on unbiased occupancy probabilities for its next planned path.

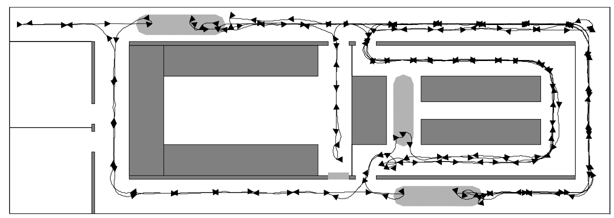

Fig. 7. Path followed by the robot with deliberative anger deactivated.

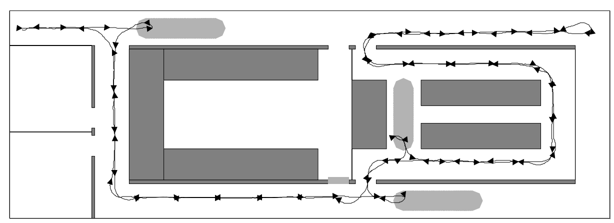

Fig. 8. Path followed by the robot with deliberative anger activated.

The overall performance of the robot during these experiments is summarized in Figs. 9-10. The weight W_I controls the intensity of the robot’s deliberative fear responses, so the total path time (Fig. 9) and number of collisions (Fig. 10) are recorded for a range of W_I values. If $W_I = 0$, fear (and therefore anger) are completely disabled. Under normal conditions (no fear trap), collision frequency and path times consistently improve until $W_I = 0.8$. In the fear trap environment, with deliberative anger disabled, the robot’s behavior follows the same trend until around $W_I = 0.4$, at which point the fear trap comes into effect, and thereafter its performance increasingly suffers. At $W_I > 0.9$ the robot often becomes permanently obstructed, unable to complete its task before it times out. When deliberative anger is enabled, it does not significantly affect performance until W_I exceeds its activation threshold $T_A = 0.6$. Thereafter, performance improves, approaching the level achieved in the absence of a fear trap. These results show that deliberative fear can significantly improve the robot's performance in certain situations, and deliberative anger can compensate for some of its adverse effects.

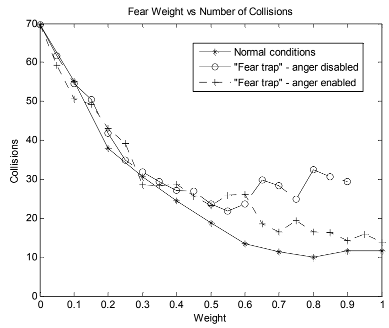

Fig. 9. Graph of the average number of collisions for each W_1 value.

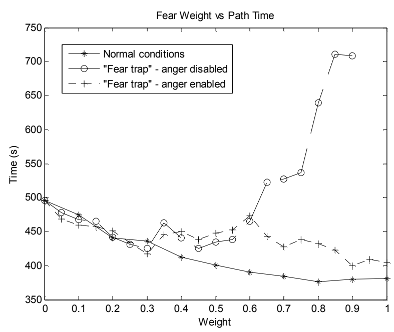

Fig. 10. Graph of the average path time for each W_1 value.

VI. Conclusion

The presented results support our hypothesis that artificial emotions can improve a robot's adaptive performance. These experiments were conducted in constrained environments designed to encourage specific behaviors, facilitating the quantitative analysis of each emotion's individual contribution to performance. Further studies will investigate any emotional synergies and emergent behaviors that arise from combinations of emotions under less constrained conditions.

Our model benefits from the proven reliability of a hierarchical reactive/deliberative architecture as well as the adaptive advantages associated with emotions. By modeling emotions as parameter modulations, we have demonstrated an effective adaptation mechanism for mobile robot planning and control.

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