# Sloth and Slow Loris Inspired Behavioral Controller for a Robotic Agent

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***Abstract*—We explore the ethologically guided design of a robotic controller, inspired by sloth and slow loris behavior. These animals manage their energy expenditure efficiently under resource constrained environments through a combination of thermoregulatory and behavioral strategies. This has potential implications for the design of energy efficient mobile robots (or Slowbots) for long-term applications such as Precision Agriculture and Surveillance. In this paper, we compare two different behavioral coordination strategies, namely, Action Selection and Behavioral Fusion and evaluate their performances to determine the relative merits of each coordination strategy on the design of the Slowbot and its energy consumption.**

## I. Introduction

Sloths and slow lorises are some of the few mammals that have carved out an exclusively arboreal niche. McFarland has advocated the concept of an agent's ecological niche which mandates that for a successful robotic implementation the agent must find its place in the environment, i.e, its niche [1]. Ethological modeling methods can encode the agent-environment relationship allowing the agent to identify its place in the ecosystem [2]. Ethologically guided/constrained design is one of the approaches for specifying and designing robotic behaviors; the others being situated activity-based design and experimentally-driven design [3]. This paper explores the ethologically-guided design of a robotic controller, inspired by sloth and slow loris ethology. Owing to the slow metabolic rates of these mammals, they continue to thrive on the limited resources on trees for most of their life, without actively searching for food [4]. Pauli et al. in [5] characterize the three-toed sloth's arboreal niche as highly energy constrained. As stated in their work, "the reduced energy expenditure [in sloths] is the result of thermoregulatory and behavioral strategies rather than a proportionate reduction in BMR [Basal Metabolic Rate]". Hence, it is our contention that the ethologically-inspired design of robots, will allow these machines to persist for prolonged periods of time (and accomplish meaningful tasks) in an environment characterized by resource constraints, much like the sloths and slow lorises. As highlighted by in [6] and [7], such robots or Slowbots can carry out routine and meaningful tasks (for instance, pest removal from crops) with minimal or no human intervention while sustaining themselves in their environment for extended periods of time by efficiently utilizing their energy. This paper focuses on three specific behaviors that are potentially useful for designing such agents along with a comparison of different coordination mechanisms to identify their relative merits in the Slowbot design. The choice of coordination mechanism is an important step in designing the Slowbot architecture and hence is a crucial precursor to the overall design process. The quantitative results obtained from this preliminary analysis can serve as a guide in designing a complete Slowbot architecture encompassing all relevant behaviors.

## II. Related Work

Prior research has considered energy-efficient path planning under resource constraints. Mei et al. in [8] discuss energy-efficient path planning for robots operating under limited energy. Their method attempts to maximize the total coverage area by minimizing repeated coverage in structured and random environments. They extend the methodology to multiple agents in [9] as a means of increasing the coverage area when each individual agent operates under resource constraints. They discuss the number of agents to be deployed to accomplish a given task under time and energy constraints. Similarly, Strimel et al. [10] discuss the robot coverage problem and introduce a new sweeping path planning algorithm as a means of achieving best coverage in a small area given limited fuel. There has also been research considering the use of solar powered robots and efficient path planning for them as a means of best utilizing the limited input solar energy. Plonski et al. in [11] discuss the construction of a solar map on which effective path planning approaches can be applied to achieve energy-efficient task completion [12].

Significant research has been conducted in behavioral and bio-inspired robotics as well. For example, within our lab Arkin et al. [2] have designed a behavioral controller inspired by praying mantis ethology. The implemented behaviors included prey acquisition, predator avoidance, mating and chantlitaxia with three internal variables, namely, hunger, fear and sex-drive. In another implementation, Arkin et al. explored the design of a behavioral controller for human-robot interaction for Sony's AIBO, inspired by dog ethology [13]. Other implementations also explored the realm of multi-robot systems inspired by hunting wolf packs [14] or a navigation algorithm inspired by primates [15]. This paper also incorporates attachment behavior as implemented in [16], inspired by Bowlby's theory of attachment [17]. The overall process of transforming ethological models to a working robotic system is shown in Figure 1 [3]. We focus on the first four steps, namely: Description of the ethograms derived from ethological literature of sloths and slow lorises (in consultation with Dr. Jonathan Pauli, from the University of Wisconsin), the description of the model extracted from these ethograms followed by importing the model to a robot and running robotic experiments in simulation. We implement three behaviors from the ethogram and compare the performances of different coordination mechanisms for these behaviors.

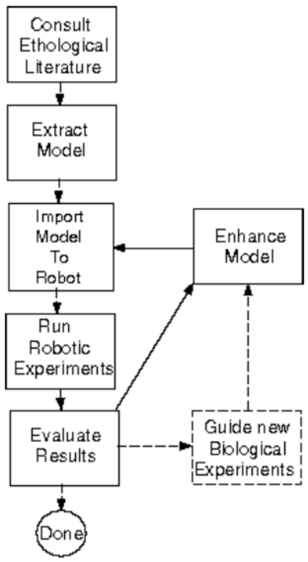



Figure 1: **Ethologically guided/constrained design for robotic systems** [3]

## III. Sloth and Slow Loris Ethograms

Based on existing ethological studies, ethograms highlighting the various behaviors of sloths and slow lorises can be drawn and behaviors relevant to the design of a robotic controller can be identified. Research described in [18], [19] and [20] serves as a resource for sloth behaviors among several others regarding sloth ethology. For slow lorises, a primary reference regarding behaviors includes the work of Nekaris [21] and Wiens [22]. [23] also summarizes various slow loris behaviors compiled from different sources in the literature. There is significant overlap between the behavioral ethograms of the sloth and slow loris with one of the primary differences being the presence of social behaviors in slow lorises. However, these social behaviors are not applicable in the context of the design of a single agent for our purposes concurrently, in the context of precision agriculture and surveillance operations. Hence, a unified ethogram highlighting the behaviors used for our research among the others is shown in Figure 2.

We now discuss the three highlighted behaviors and their implementation. Each behavior has an associated stimulus and motivational/internal variable requirements [3]. The output of each behavior consists of a response vector with an associated vector magnitude $V_{magnitude}$ and direction, $V_{direction}$. Each behavior also has an associated gain denoted as G.

| |
|---|
| Ingestive (Food and liquids) |
| Shelter-seeking |
| Comfort-seeking |
| Agonistic (Associated with conflict) |
| Eliminative (Excretion, urination) |
| Epimeletic (Care and attention giving) |
| Sexual |
| Behavioral sleep |
| Vocalization |
| Awake-fixating |
| Awake-exploring |
| Awake-alert |
| Miscellaneous |

Figure 2: **Slow Mammal Ethogram.** The implemented behaviors are shown highlighted

### A. *Ingestive or Charging Behavior*

For the Charging behavior, the associated stimulus is the presence of a food source (sunlight or a charging station). The motivational variable is the level of internal energy (like hunger) that drives the agent to move towards the food source. A detailed description of computing internal energy for an autonomous land agent by modeling the energy consumption pathway is described in [24] and we use a simplified version to compute the internal energy of the agent. The response vector magnitude (1a) and direction (1b) can be given as follows:

$$\begin{cases} V_{min} & E \leq E_{min} \\ \frac{(V_{max}-V_{min})}{(E_{max}-E_{min})} * (E - E_{max}) + V_{max} & E_{min} < E < E_{max} \\ V_{max} & otherwise \end{cases} \tag{1a}$$

$$V_{direction} = towards\ perceived\ charging\ area \tag{1b}$$

The vector magnitude in (1a) is a function of internal energy E. This function maps the vector magnitude to a value that is bounded by a minimum ($V_{min} = 0.0$) and maximum ($V_{max} = 5.0$). The gain G associated with this behavior is set to 1.0.

### B. *Comfort Seeking or Attachment Behavior*

The Attachment behavior is implemented as described in [16], by modeling a comfort function that influences the behavior of an agent in the presence of an attachment object. The area around the attachment object is divided into a safe zone and comfort zone (fig. 3):

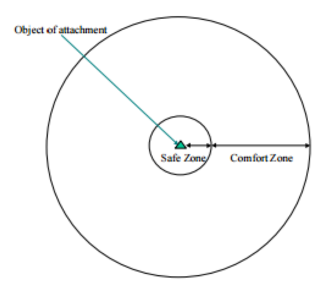



Figure 3: **The safe and comfort zones of the robot around the object of attachment** [16]

The agent behavior in each of these zones is dependent of the Attachment Intensity which is the magnitude of the attachment vector, denoted here as $V_{magnitude}$:

$$V_{magnitude} = \alpha * N * D * \phi(C) \quad (2a)$$

$$V_{direction} = towards\ object\ of\ attachment \quad (2b)$$

where $\alpha$ is the attachment bonding quality between the robot and attachment object (preset to 1.0), N is the maximum intensity level for normal attachment (preset to 4.0), D is the proximity factor which is a function of distance between the agent and the attachment object and lastly, $\phi$(C) is the comfort component which is a function of the comfort level of the agent. These functions are described in detail in [16]. The gain G associated with the Attachment behavior, as in [16], is set to 1.0. As described in their results, reducing comfort level also reduces mean distance maintained over time from the object of attachment. The direction of the attachment vector is towards the attachment object.

### C. Awake-Exploring or Wandering Behavior

This behavior causes the agent to randomly explore its environment. The gain G associated with this behavior is fixed to a value (set to 5.0) and a random direction is generated after p time steps, where p denotes persistence.

$$V_{magnitude} = fixed\ to\ unit\ vector \quad (3a)$$

$$V_{direction} = random\ direction\ change\ every\ p\ time\ steps \quad (3b)$$

The behavior as implemented in [16] combines wandering and attachment behaviors via Behavioral Fusion. This causes the agent's exploration to be influenced by its comfort level and attachment intensity.

## IV. Behavioral Controller Design

We discuss two different coordination mechanisms for the behaviors described in the previous section.

### A. Action Selection Arbitration

In this arbitration mechanism, the behavior is chosen corresponding to the highest scaled response vector magnitude, $G * V_{magnitude}$. For example, if the scaled response vector for the Charging behavior has the highest magnitude, then the Charging behavior is selected and the corresponding response vector $< V_{magnitude}, V_{direction} >$ (Eq 1a, 1b) is sent as output for execution (fig. 4). In the figures, $\phi$ denotes $V_{direction}$.

This form of arbitration often leads to behavioral dithering where there is rapid fluctuation between the behaviors chosen, due to equal $V_{magnitude}$ of multiple behaviors which creates a conflict during the max selection. To overcome dithering, hysteresis or a short-term memory (STM) of past behavior is often employed. The implementation of STM in obstacle avoidance behavior is described in [13]. Here, we explore the implementation of two types of hysteresis. In the first method, the agent executes the chosen behavior for a given number of time steps independent of the other behaviors. This helps

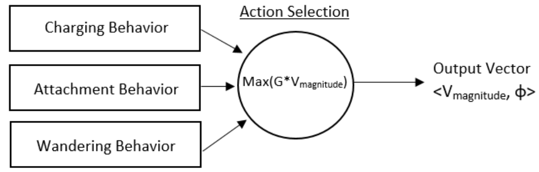



Figure 4: **Action Selection Coordination Strategy.** Selects the behavior with the highest scaled component vector magnitude and outputs the corresponding response vector for execution. $\phi$ corresponds to $V_{direction}$

overcome dithering and is a form of STM implementation. In the second approach, the agent executes the chosen behavior until completion of some trigger. For instance, if the agent chooses the Charging behavior, the agent will not choose another behavior until it has reached and completed charging at the food source. This also helps overcome dithering but is a much stronger form of hysteresis.

### B. Behavioral Fusion

In this coordination mechanism, a combination of the various behaviors is generated as output. As opposed to selecting a single behavior, the output generated is a weighted sum of the response vectors of the different behaviors, each weighted by their corresponding gains (G) (fig. 5).

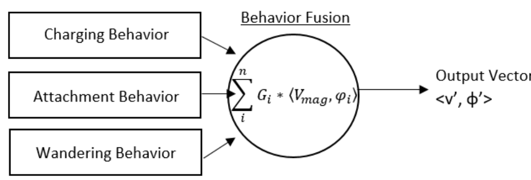



Figure 5: **Behavioral Fusion Coordination Strategy.** Outputs the vector sum of the individual response vectors weighted by the corresponding gains

This form of coordination mechanism is free from behavioral dithering since it is a combination of the different behaviors. The output is thus influenced by each of the individual behaviors, in varying degrees based on their corresponding gains.

## V. Experiment

We compare the performance of the various coordination mechanisms discussed above: Action Selection without hysteresis, with Strong Hysteresis, Weak Hysteresis and lastly, Behavioral Fusion.

### A. Simulation Environment

To test the different strategies, we created a simple environment for the agent that consists of an obstacle-free area with a point of attachment (or nest) at the origin. The radius of the safe zone and comfort zone is initialized to 5.0 units. The sunlit zone or charging station is indicated by a wall at the top of the area (similar to a forest canopy) and is outside the comfort zone of the agent. This requires the agent to traverse its environment and navigate to the top of the area to charge its energy. The agent is represented by a white box as shown in figure 6.

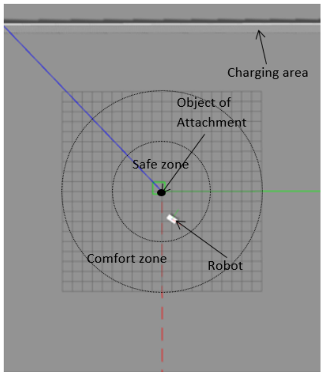



Figure 6: **Simulation Environment in Gazebo.** Agent is represented by the white box. The charging area is indicated by the wall outside of the comfort zone

### *B. Dependent Variables*

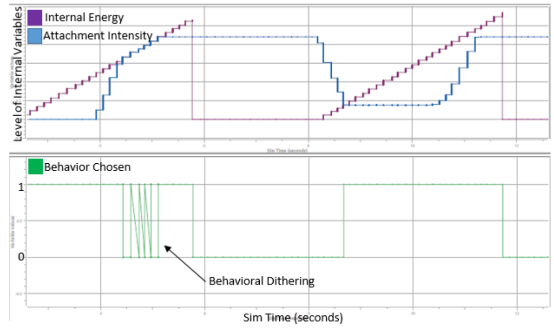
The agent does not perform any specific task except exploring its environment and moving to the charging station based on its internal variables. The primary experimental goal is to compare the different coordination mechanisms based on various metrics. The energy consumption metric is the average total energy consumed over the entire run. The total run time for each coordination strategy is fixed to 3 minutes of simulation time (simulation runs at a significantly higher speed than an actual robot would). The average distance from the attachment object indicates how far the agent strayed from the attachment object. Finally, we measure the average times spent and area explored within the safe, comfort and outside of comfort zones. We compare the different strategies based on these metrics and plot the real-time variation in internal variables of comfort and hunger as well.

### *C. Experiment details*

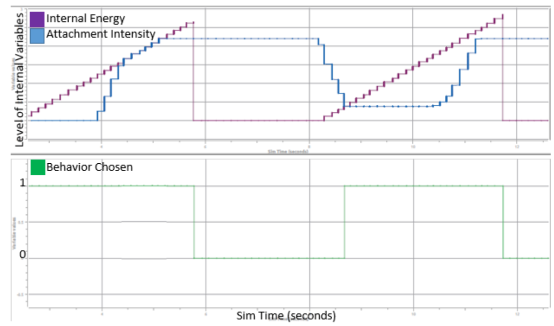
The comfort level is varied from -1 (maximum discomfort) to 1 (maximum comfort) in steps of 0.25 for each coordination strategy. All other internal variables are initialized to zero. The agent starts at the origin. There are no power constraints imposed on the agent since our goal is to measure and compare overall energy consumption across the different arbitration mechanisms.

## VI. Results

The results from each of the experimental runs are shown. Figure 7 shows the variation of internal variables for a small portion of the run for Action Selection: purple plot indicates internal energy and blue indicates attachment intensity. Green plot indicates the switching between the two active behaviors: Charging (indicated by 1) and Attachment (indicated by 0). As shown in Figure 7, the chosen behavior is dependent on the highest internal variable. Figure 7a, shows how the simple Action Selection mechanism results in behavioral dithering since the levels of attachment intensity and internal energy become equal and increase concurrently causing a fast switching between the two behaviors. This is eliminated by the introduction of hysteresis, shown in Figure 7b.




(a) Behavioral dithering shown by the arrow



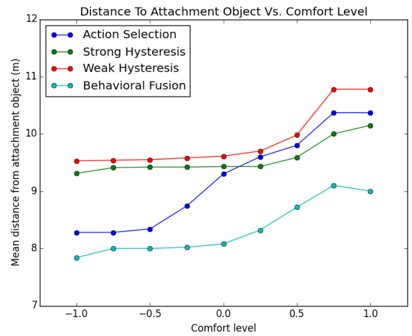

(b) Behavioral dithering eliminated using hysteresis

Figure 7: **Variation of Internal Variables vs. Time for Partial Run**

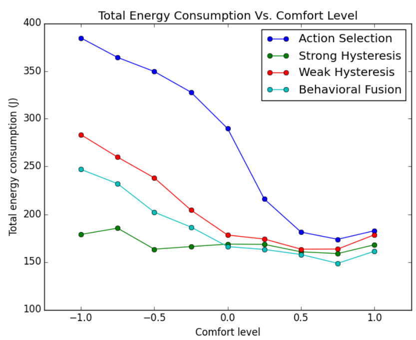
The average distance from the attachment object for various comfort levels is shown in Figure 8a. As the comfort level increases, the average distance from the attachment object increases for all the different arbitration strategies. This is in accordance with the results described in [16]. As the comfort level increases, the attachment intensity reduces and mean distance of the agent from the attachment object increases.

The total average energy consumption over the entire run for the different behavioral strategies is shown in Figure 8b for various comfort levels. For three out of the four strategies: Action Selection, Action Selection with Weak Hysteresis and Behavioral Fusion, the total energy consumption decreases as comfort level increases. In the experimental environment, the food source is located outside the comfort zone. A higher comfort level reduces the attachment intensity allowing the agent to navigate towards the food source with only reduced attachment towards the attachment object. However, Action Selection with Strong Hysteresis does not exhibit this trend since even the slightest increase in internal energy within the comfort zone where attachment intensity is 0 (As per the implementation in [16]), selects the Charging behavior. While this results in overall low energy consumption, it is not desirable. The overall energy consumption is also low for Behavioral Fusion, when compared to the remaining two strategies. In contrast to Action Selection, the output of Behavioral Fusion is influenced by all the three behaviors in varying degrees depending on the internal variables and the respective gains.

The percentage of time spent within and outside the comfort and safe zones is shown in Figure 9. For two out of the three




(a) Average distance of agent from attachment object for various comfort levels




(b) Average total energy consumption for various comfort levels

Figure 8: **Plots showing average distance to attachment object and average total energy consumption**

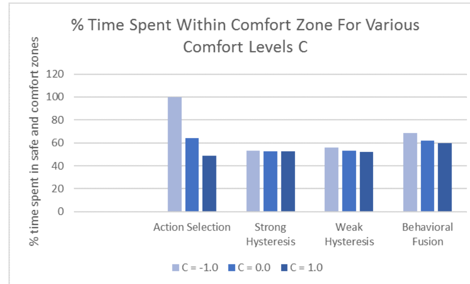



Figure 9: **% Time spent in comfort zone and safe zones.** Each bar represents the total % time spent within comfort and safe zones combined, for various arbitration strategies and 3 different comfort levels (-1.0, 0.0, and 1.0)

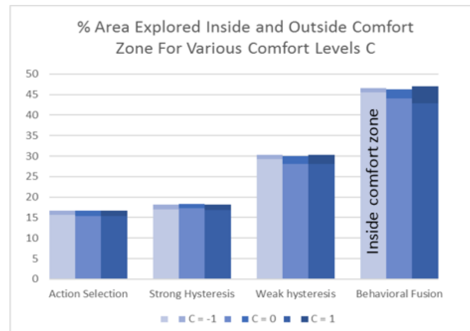



Figure 10: **% Area explored inside and outside the comfort zones:** Each vertical stacked bar represents % area covered inside (lower section) and outside (upper section) of the comfort zone for 3 different comfort levels (-1.0, 0.0 and 1.0) for the various arbitration strategies

arbitration strategies: Action Selection, Action Selection with Weak Hysteresis and Behavioral Fusion, the time spent within the comfort and safe zones decreases as comfort levels increase due to the reduced attachment intensity. For Action Selection with Strong Hysteresis, the percent time spent in safe and comfort zones is relatively equal for various comfort levels due to the frequent switching between Charging and Attachment behaviors regardless of comfort level. Additionally, the percentage of time spent within the safe and comfort zones is higher on an average for the various comfort levels for Action Selection and Behavioral Fusion. However, the percentage time spent within the various zones is not proportional to the amount of area the agent explores since some of the coordination strategies could cause the agent to spend considerably more time within small areas near the attachment point rather than covering the whole area. Hence, we additionally measure the percentage area explored by the agent for each coordination strategy.

The percentage area explored within and outside the comfort zones is shown in Fig 10. The area explored outside the comfort zone increases as comfort level increases allowing the agent to explore further away from the attachment point. It is highest for Behavioral Fusion since the output is a weighted summation of individual behaviors rather than selection of a single behavior. In contrast, Action Selection covers the least area since behavioral dithering limits the exploration of the agent.

## VII. Discussion

The results highlight various aspects of the different coordination mechanisms.

**Energy consumption**: For the three behaviors discussed, Action Selection with Strong Hysteresis results in lower overall energy consumption. However, this strategy causes the agent to move towards the food source for the slightest increase in energy consumption as described in the previous section. This may not be the most efficient strategy given that the agent can continue to explore its environment for a longer duration before having to move towards the charging area. Behavioral fusion also results in an overall low energy consumption.

**Percent time in comfort zone**: Action Selection arbitration mechanism resulted in the highest amount of time spent within the comfort zones. However, Action Selection is prone to behavioral dithering. Among the other three strategies, the time spent within comfort zones was highest for Behavioral Fusion.

**Percent area covered**: The agent explored the largest area with the Behavioral Fusion arbitration strategy. Action Selection resulted in the least coverage despite increased time spent within comfort zone perhaps due to behavioral dithering that limited the agent's exploration.

**Overall**: For the three behaviors discussed, Behavioral Fusion combines low total energy consumption with increased time spent within the comfort zones and increased area coverage. If the design choice employs Action Selection instead, then Weak Hysteresis would be the preferred option for eliminating behavioral dithering as it has advantages over Strong Hysteresis in terms of percent time spent within comfort zones and percent area covered.

The behaviors discussed here are potentially useful with respect to specific applications: Precision Agriculture or Surveillance where environmental persistence and efficient energy management is crucial. It is also desirable to explore within the comfort zone and areas beyond in the absence of threats.

Tying these observations to our original sloth-inspired design, Behavioral Fusion aligns with the behavioral patterns of Sloths and Slow Lorises better than the other coordination strategies. Sloths rarely leave their trees for fear of predation and they do so only for excretion [25]. The Ingestive behavior of sloths also highlights the notion of comfort. Sloths exhibit increased attachment to a single tree for extended periods of time and do not actively explore unless its current tree is depleted of fresh leaves [26]. Given that Sloths and Slow Lorises are exemplary models of energy conservation in nature, spending increased periods of time within their shelter, Behavioral Fusion appropriately combines low energy consumption with increased time spent in comfort zones to capture this notion. The Sloth and Slow Loris inspired design allows development of long-term autonomous robotic models that are energy efficient, thus persistent in their environment while exploring within their safety zones.

Future work aims at including additional behaviors such as obstacle avoidance, resting behaviors and incorporating 3D navigation which may be relevant to the design. Further, including a notion of stimulus strength of a food source may be beneficial for the agent to evaluate its food source and the extent of its on influence on the agent behavior.

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