A Heuristic Strategy for Cognitive State-based Feedback Control to Accelerate Human Learning

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Project Objective

- Autonomous systems are used to help humans attain new skills [1]. Existing systems use human performance feedback to predict decision making behavior [2].
- Cognitive factors are integral to designing effective human machine interaction [3]. Current intelligent tutoring systems utilize strategies to meet individual student needs, e.g., improving self-confidence [4]
- The same strategies are applicable to learning ***outside of the classroom***.

Goal: **Propose and validate a heuristic strategy that calibrates self-confidence to skill using strategic automation assistance allocation**

Experimental Setup and Methodology

User Study: Participants practice landing quadrotor in training module in 20 trials

Heuristic Strategy Design: **Manual** mode M_1 or **shared control** M_2 mode is assigned to trials based on the heuristic strategy (**Table 1**) or benchmark strategy (**Table 2**).

Figure 1: Experimental Platform

Heuristic strategy designed to calibrate self-confidence to skill.

- M_2 - user assisted by static control law u_a augmenting user input u_h. Quadrotor input $u(n) = 0.9u_h(n) + 0.1u_a(n)$.

Table 1. Heuristic strategy using performance metrics and self-confidence cognitive feedback

Green denotes calibrated self-confidence

Over-confidence

Under-confidence

	Performance Change			
	Decrease	Constant Low	Constant High	Increase
$SC \downarrow$	$2\ M_2$	$2\ M_2$	$2\ M_1$	$2\ M_1$
$SC \uparrow$	$2\ M_2$	$1\ M_1 \rightarrow 2\ M_2$	M_1	$2\ M_1$

Table 2. Benchmark strategy using performance metrics

Low Performance	High Performance
$2\ M_2$	$2\ M_1$

- Participants randomly placed into two groups. Group 1 used heuristic strategy while group 2 used benchmark.
- 40 participants completed the user study (17 male, 22 female). Participants ages ranged between 18-57 years (mean = 24 years). Each participant was compensated at a rate of $20/hr.

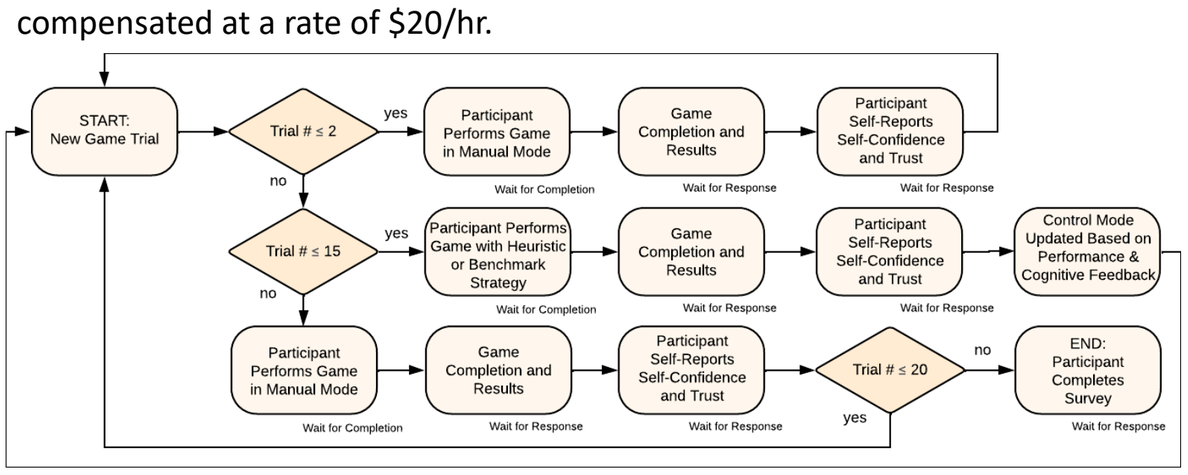
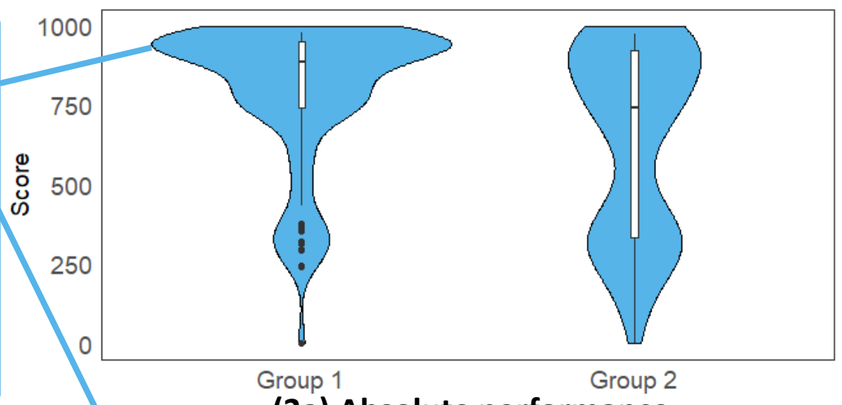


Figure 2: Flowchart of sequence of events for 20 trials

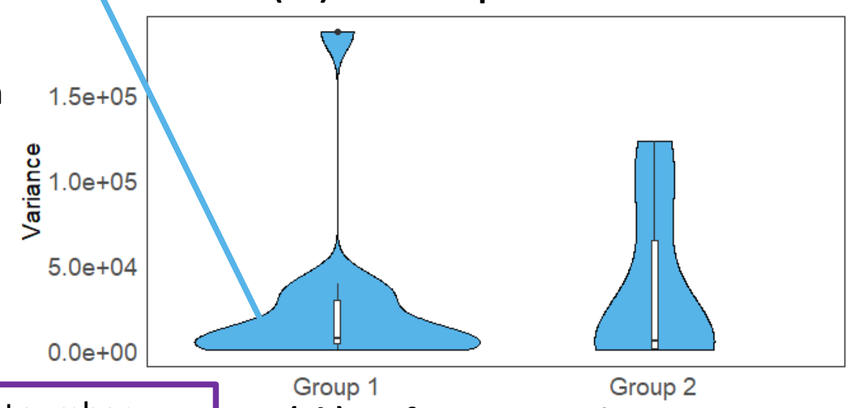
Results

Group 1 participants ***achieve higher scores more consistently*** than those in group 2



(3a) Absolute performance

Figure 3: Violin plots for performance comparison between groups. Violin plot thickness visualizes the probability density of numerical data for each variable.



(3b) Performance variance

Safe landings outnumber unsuccessful landings ***earlier*** for group 1

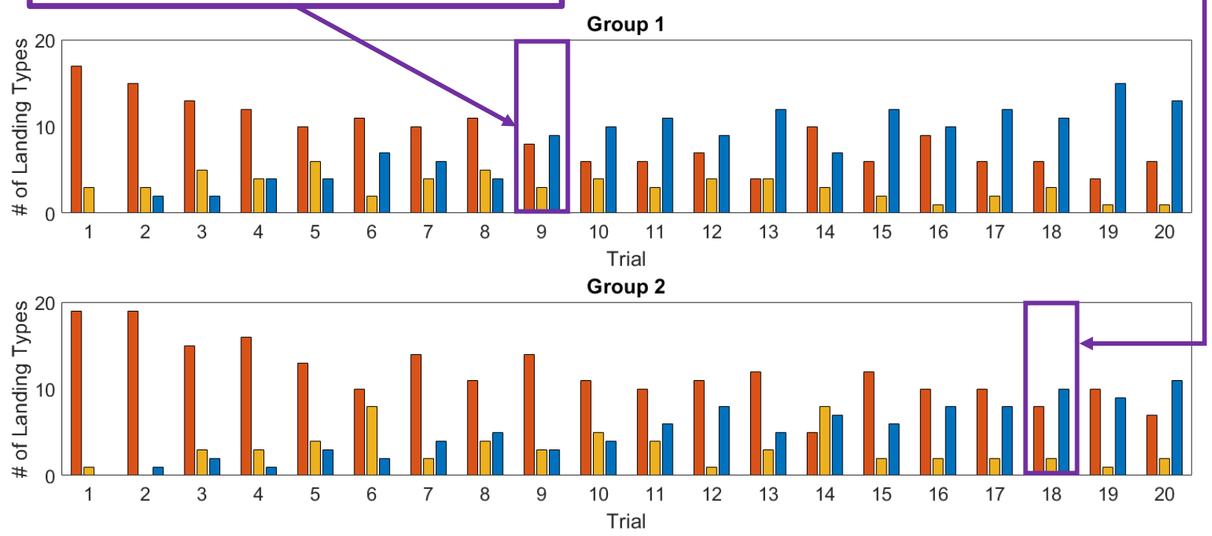


Figure 4: Bar plot showing unsuccessful, unsafe, and safe landings over 20 trials

Table 3: Self-confidence regression p-values & significance
Note: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

Regressor	Group 1		Group 2	
Intercept	0.750		0.387	
Trial k	0.349		0.900	
Previous self-confidence SC_{k-1}	$< 2e-16$	***	$< 2e-16$	***
Shared Control mode M_2	0.008	**	0.465	
RMS	0.075		0.045	*
Safe Landing	$1.210e-05$	***	0.001	**
Unsafe Landing	$2.690e-04$	***	$7.750e-05$	***
Score S_k	0.011	*	0.144	
Landing x position x_k	0.205		0.313	
Landing y position y_k	0.512		$6.140e-05$	***
Landing velocity v_k	0.059		0.331	
Landing attitude θ_k	0.402		0.337	
Landing time t_k	0.036	*	0.383	
Multiple R^2	0.8479		0.8497	
Adjusted R^2	0.8429		0.8448	

Group 1 participants focused on advanced metrics like t_k and v_k to ***achieve higher scores***.

Group 2 participants focused on ***flying the quadrotor to landing pad, <u>not</u> safe landings***. y_k and RMS more significant

Conclusions and Future Work

- Participants using heuristic strategy for self-confidence calibration demonstrated accelerated learning compared to benchmark group.
- Future work will identify differences in how novices and experts transition through learning stages and developing a probabilistic dynamic model of human cognitive states to predict self-confidence

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Experiment video

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