Embodying Human-Like Modes of Balance Control Through Human-In-the-Loop Dyadic Learning

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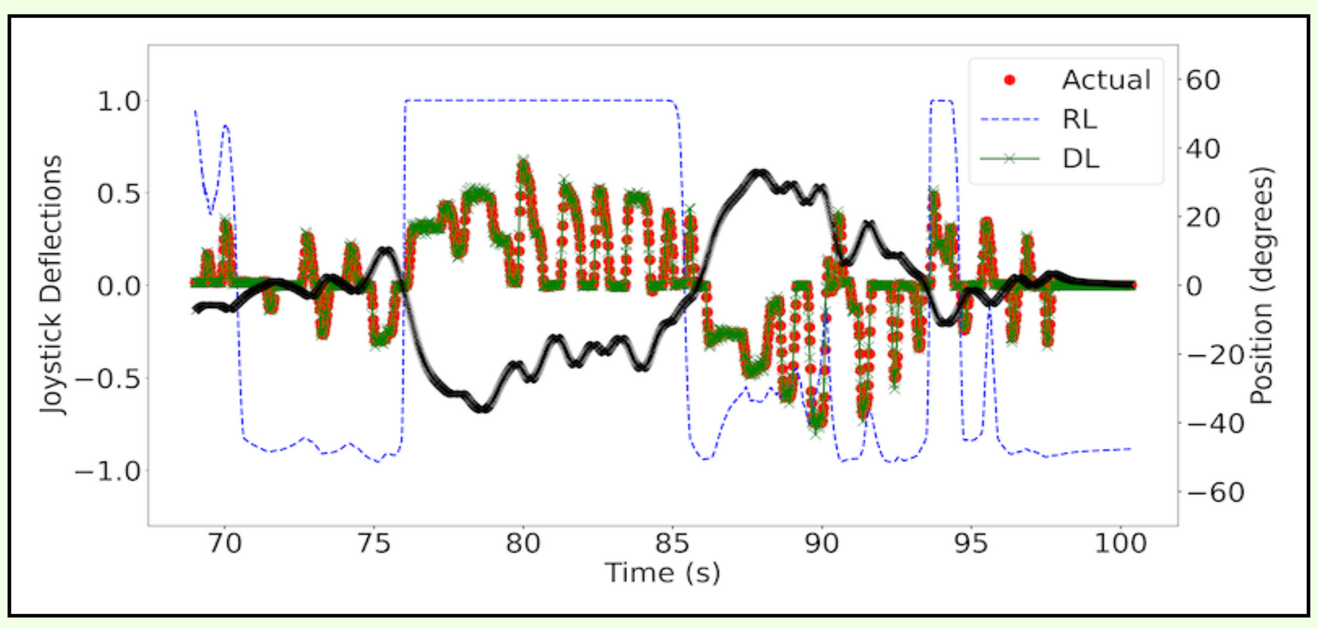
Introduction

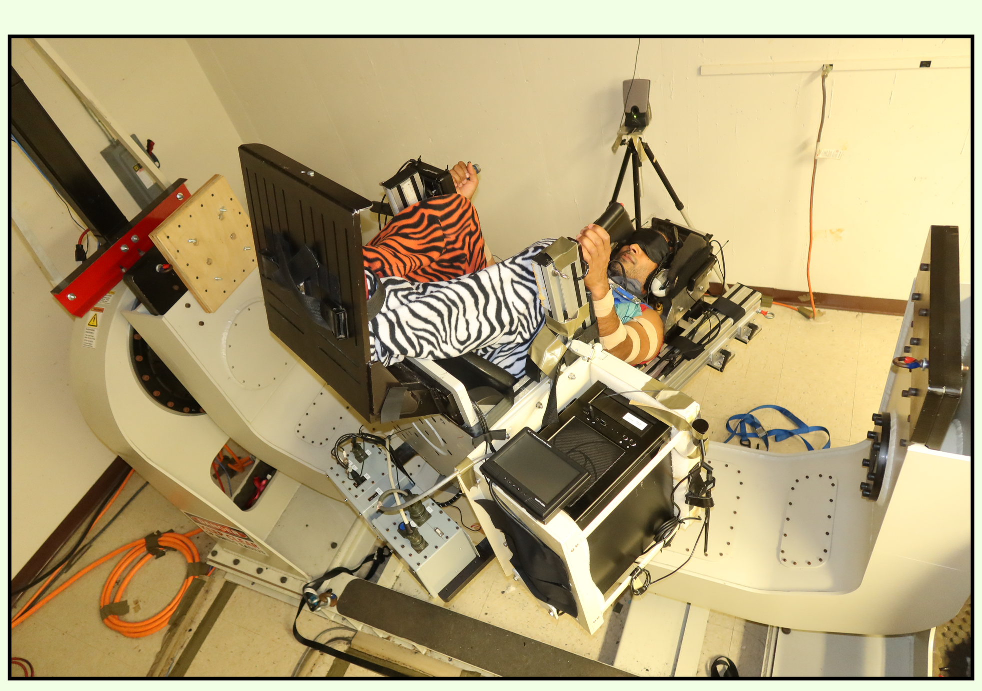
- Maintaining spatial orientation is critical in domains like piloting and spaceflight.
- AI systems could track and maintain human & vehicle's positioning in relevant orientational plane(s).
- AIs may learn task in very different ways from humans, leading to differing *embodiment* of action in the problem space.
  - Exposure to physics vs. modeling sensorimotor data from humans.

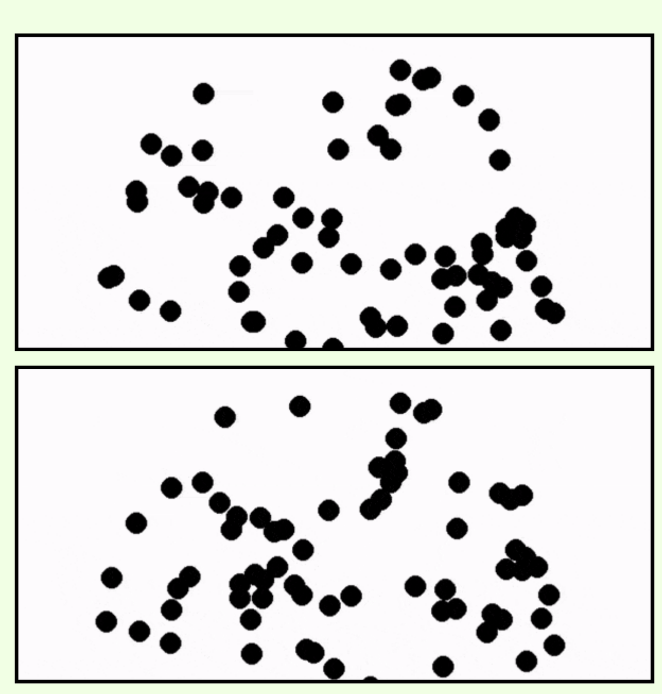


Actions in IP balancing predicted by RL model (blue) and deep learning (DL) model trained over human data (green) compared to an actual 30-sec. participant trial sample (red - human actions, black - angular position).

Task Background

- Multi-axis rotation system (MARS) - documented, realistic simulation of vehicle control in helicopter hovering and spaceflight, programmed with inverted pendulum (IP) dynamics.
  - Supine Roll - disorienting condition denies gravitational position cues placing blindfolded subjects perpendicular to the gravitational vertical.
- Visual inverted pendulum (VIP) task: subjects balance a simulated random dot kinematogram (RDK) with low-level retinal motion cues.
  - Circular array of dots have 50% coherence in every frame.





MARS device in the supine roll condition (left). Two consecutive frames of the VIP 50% coherent RDK display (right).

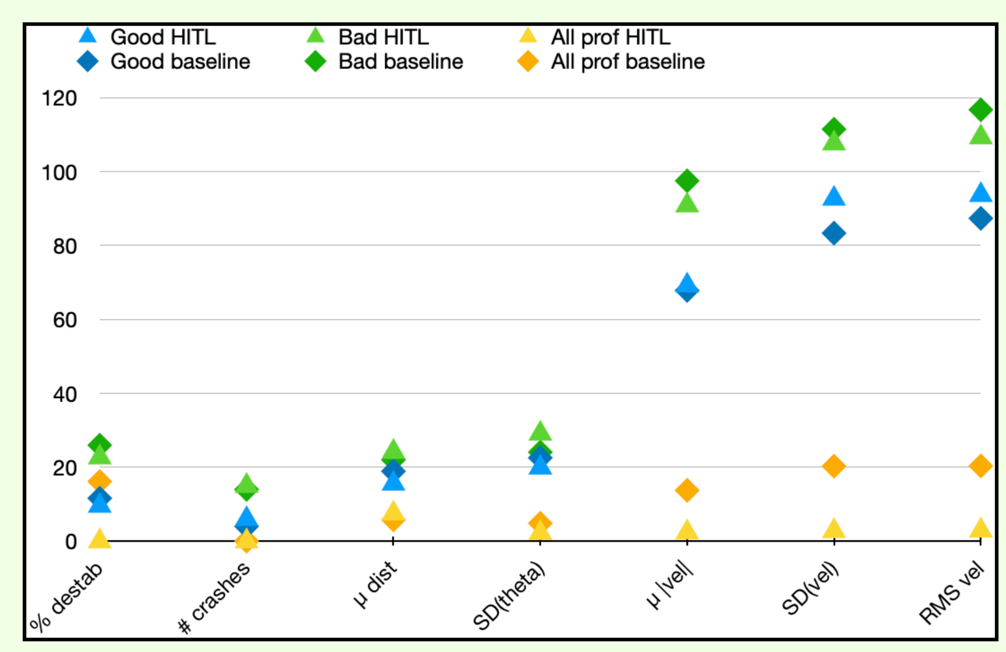
Data & Initial Training

- Data from 34 healthy adult subjects.
- 2 sessions on consecutive days, 20 100-sec. trials each.
  - Angular positions, velocities, and joystick deflections sampled at 50 Hz.
  - Participants clustered into Good, Medium, and Bad using proficiency characteristics (# of crashes, tendency to destabilize and oscillate).
- Trained 3 models: i) LSTM using Good data (Good); ii) MLP using Bad data (Bad); iii) MLP using all data (All prof).
- Predict future joystick actions using sliding windows of past angular positions, velocities, and deflections.

Human-In-the-Loop Training

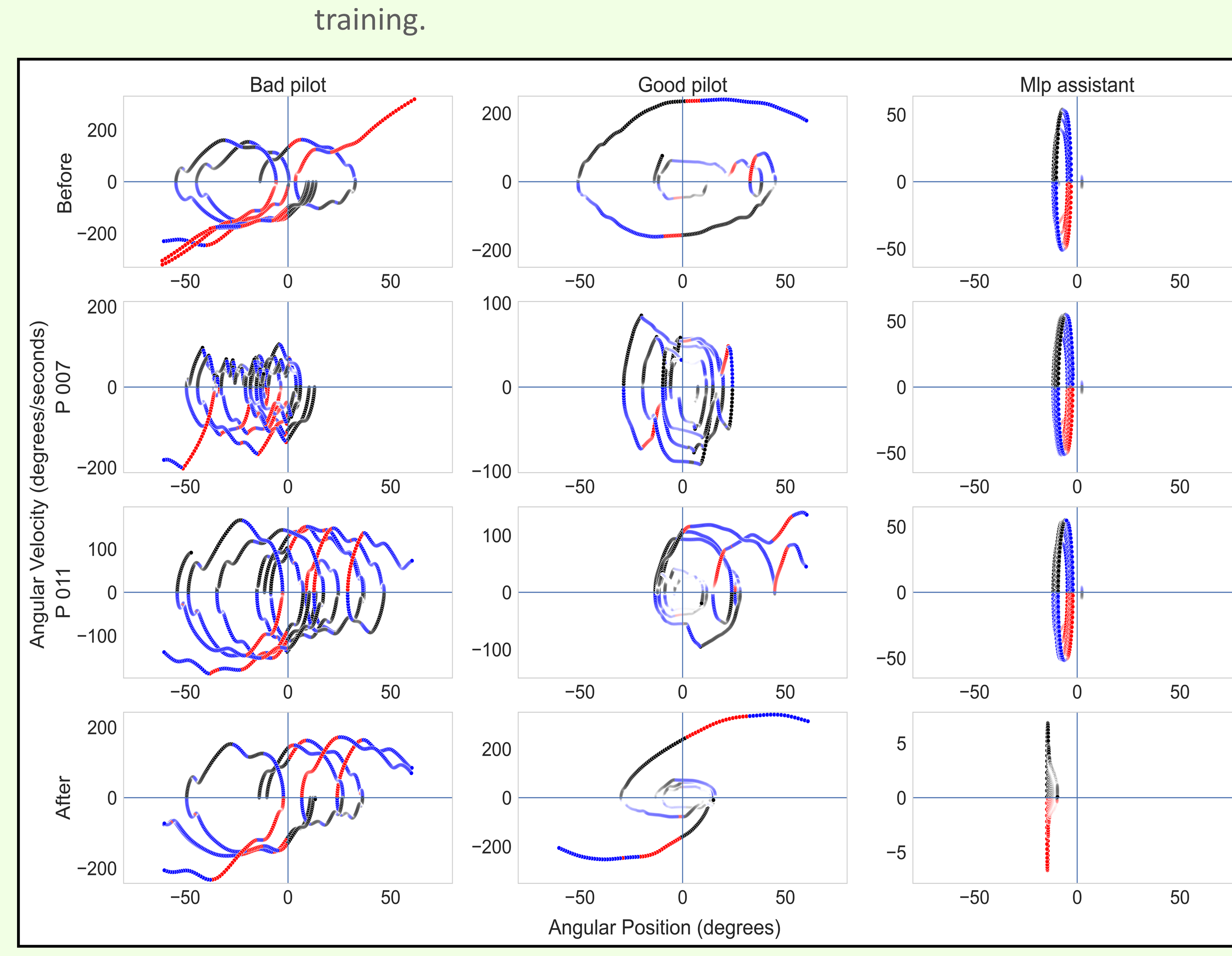
- AI models placed in co-performance with human subjects in VIP task.
- Tests how AI can cue corrective deflections to prevent crashes and how suboptimal AI can learn from human interaction to improve performance.
- 9 subjects recruited, each performed 3 30-sec. trials of:
  - VIP at 50% coherence to establish baseline solo performance.
  - Dyadic human-in-the-loop (HITL) AI training: each AI models performed the VIP task; human provided potential corrections if needed. AI model were fine-tuned using HITL data.
  - AI guidance: subjects performed the VIP task receiving visual cues according to the predictions of the Good AI (original and retrained after HITL).
- Joystick control mode - subjects supplied only direction.

Results



Performance changes in AI before and after HITL training.

- Good - minimal improvement & some degradations.
- Bad - shows <10% diff in metrics improved.
- All prof - substantial improvements, especially oscillation metrics.



Velocity-position scatter plots. Red dots represent destabilizing deflections while blue dots represent "anticipatory" deflections.

- Human trials display behavior patterns, oscillate around center point.
- During HITL, AI reflect more human-like behavior patterns as human subjects provided corrective measures when they deemed necessary.
- After HITL, AI displayed i) decrease in destabilizing deflections as VIP reaches crash condition, prompting more preemptive strategies; ii) more time spent near the DOB for Good and All prof AI models.

Conclusion

- Why shouldn't AI override pilot and take control of vehicle directly if it detects an imminent loss of control?
- Results indicate potential for dyadic HITL training, AI guidance to respectively improve AI and human performance to more agreeable human-like strategies.