Autonomous Pop-Up Attack Maneuver Using Imitation Learning

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Introduction

- Autonomous systems are becoming increasingly integral to military operations due to their ability to perform diverse roles:
  - **Surveillance:** Monitoring areas of interest to detect potential threats or gather intelligence.
  - **Reconnaissance:** Collecting detailed information about enemy positions, terrain, and movement.
  - **Combat engagement:** Participating in offensive or defensive missions, often requiring real-time decision-making.
- These systems provide significant **strategic advantages**, such as reducing risks to human personnel and enabling rapid responses in dynamic scenarios.
- Despite these advantages, achieving **human-level proficiency** in decision-making, adaptability, and situational awareness remains a challenge.
- **Imitation learning** methods, such as behavior cloning, are employed to replicate **human expertise** by learning from expert demonstrations (Hussein et al., 2017).
- **Behavior Cloning (BC)**, a specific imitation learning approach, focused on replicating **human decision-making**.
- Integrating these systems offers opportunities to improve **combat efficiency** and **coordination** between **human operators** and **autonomous agents**.

Contributions

- **Development of a BC-Based Autonomous Pop-Up Attack Model:** Implemented a BC model to enable an autonomous agent to perform a precise pop-up attack maneuver, replicating the human pilot behavior.
- **Enhanced Understanding of Autonomous Systems in Dynamic Air Combat:** Investigated the performance and adaptability of autonomous systems in highly dynamic air combat environments.

Pop-up Attack Maneuver

- **Critical air-to-ground air combat technique** (Figure 1), essential for modern military operations where precision and speed are key to mission success.
- Designed to **maximize the probability of successfully striking a ground target** by optimizing the attack trajectory and minimizing vulnerabilities.
- Involves a **rapid ascent** to achieve an advantageous position, followed by precise **target engagement** to neutralize threats, and concluding with a **quick descent** to minimize exposure to enemy defenses (Wang et al., 2022).
- Requires exceptional **precision** in maneuvering and targeting, combined with **adaptability** to react dynamically under extreme conditions.

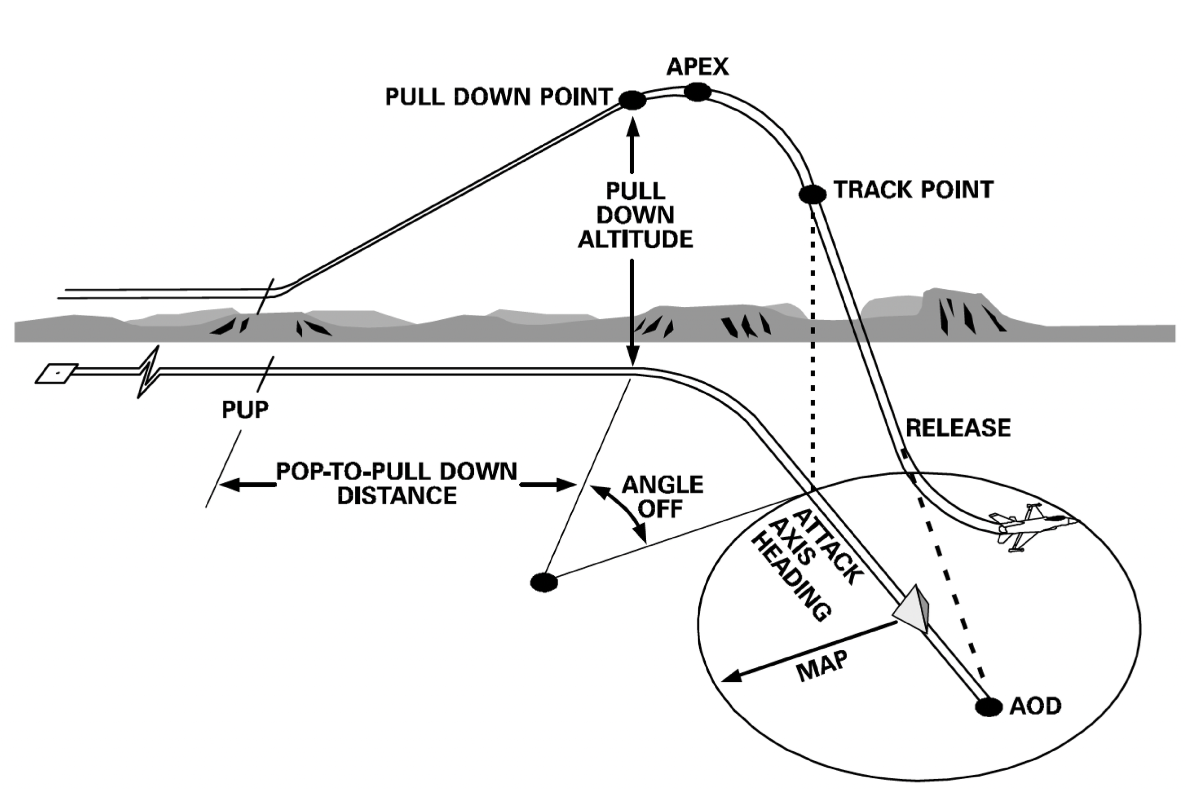

Figure 1. Flight profile for offset pop-up delivery. Source: Foo et al. (2009)

Simulation Data

- **30 flight recordings** of pop-up attack maneuvers, providing an initial dataset for analysis and modeling (Figure 2).
- Executed by a **Brazilian Air Force fighter pilot**, ensuring realistic and operationally relevant flight dynamics.
- Data collected using **AEROGRAF**, a **6DOF flight simulator** designed for high-fidelity simulation of aircraft .
- Based on the **F-16 Fighting Falcon dynamic model**, widely recognized in air combat scenarios.
- All flights begin from the **same point**, positioned **5.9 NM** from the target, with a **146-meters** altitude difference.

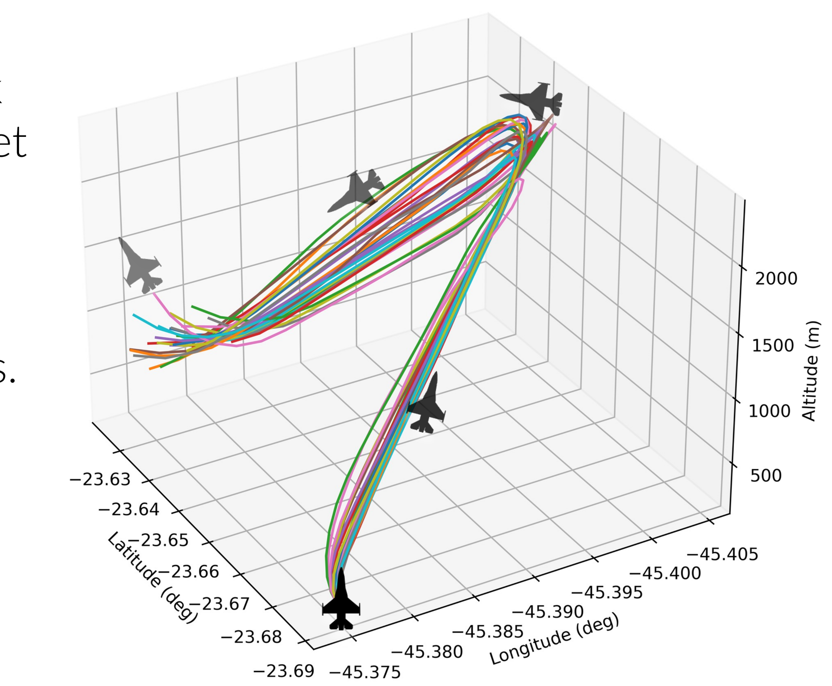

Figure 2. Adjusted flight data for the 30 flights of the pop-up attack maneuver executed by the human pilot.

State and Action Spaces

- The **state vectors**, defined relative to the aircraft's body frame, included key variables: **altitude**, **pitch**, **roll**, and **yaw angles**, along with the **radial angle**, **distance to the target**, and **altitude difference** between the aircraft and the target.
- The **action vectors** represented the control inputs commanded by the pilot, including **pitch**, **roll**, and **throttle**, reflecting the pilot's direct influence on the aircraft's trajectory.

Table 1. State and action variables used in the imitation learning model.

Variable	Units	Description	Type
ALT (m)	Meters	Altitude in meters	State
Phi (deg)	Degrees	Pitch angle (positive for nose-up)	State
Theta (deg)	Degrees	Roll angle (positive for left roll)	State
Psi (deg)	Degrees	Yaw angle	State
Vx (m/s)	Meters/second	Velocity in the pitch direction	State
Vy (m/s)	Meters/second	Velocity in the roll direction	State
Vz (m/s)	Meters/second	Velocity in the yaw direction	State
P (deg/s)	Degrees/second	Pitch angular velocity	State
Q (deg/s)	Degrees/second	Roll angular velocity	State
R (deg/s)	Degrees/second	Yaw angular velocity	State
Nx (m/s^2)	Meters/second^2	Lateral acceleration	State
Ny (m/s^2)	Meters/second^2	Longitudinal acceleration	State
Nz (m/s^2)	Meters/second^2	Vertical acceleration	State
Radial (deg)	Degrees	Radial angle	State
Distance (m)	Meters	Distance in meters	State
DeltaAlt:Anv-Tgt (m)	Meters	Altitude difference between aircraft and target	State
JX	–	Positive for nose-up pitch	Action
JY	–	Positive for left roll	Action
Throttle	–	Throttle position	Action

Imitation Learning Model

- Used **Long Short-Term Memory (LSTM) networks** to capture temporal dependencies effectively (Figure 3).
- Training conducted with **5-fold cross-validation**, incorporating **early stopping** for regularization.
- Performance evaluation utilized **Root Mean Squared Error (RMSE)** and **Coefficient of Determination (R^2)**.
- **Flight trajectories generated** using a **sliding window approach** to handle time-series predictions (Figure 4).

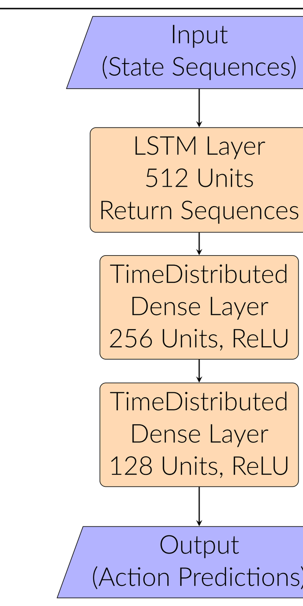

Figure 3. Architecture of the proposed LSTM model.

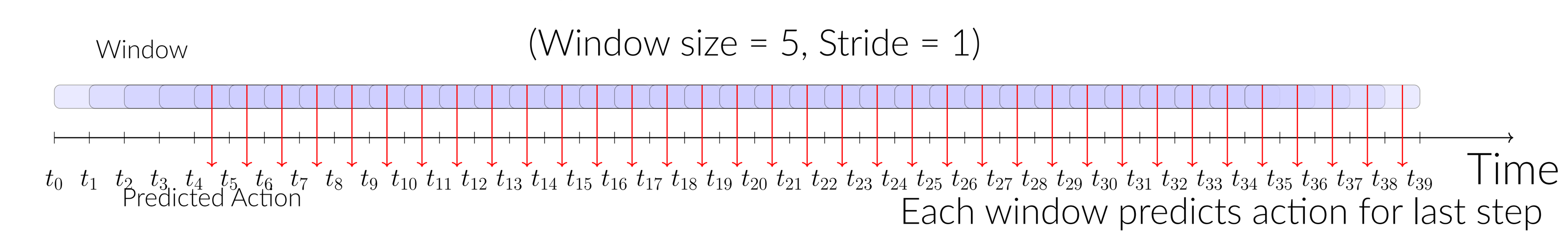

Figure 4. Sliding window approach with overlapping sequences to predict flight trajectory.

Results

- **Best model performance:** Attained an **R^2 of 0.73** and an **RMSE of 1.55** on the test group, confirming the model's ability to generalize effectively.

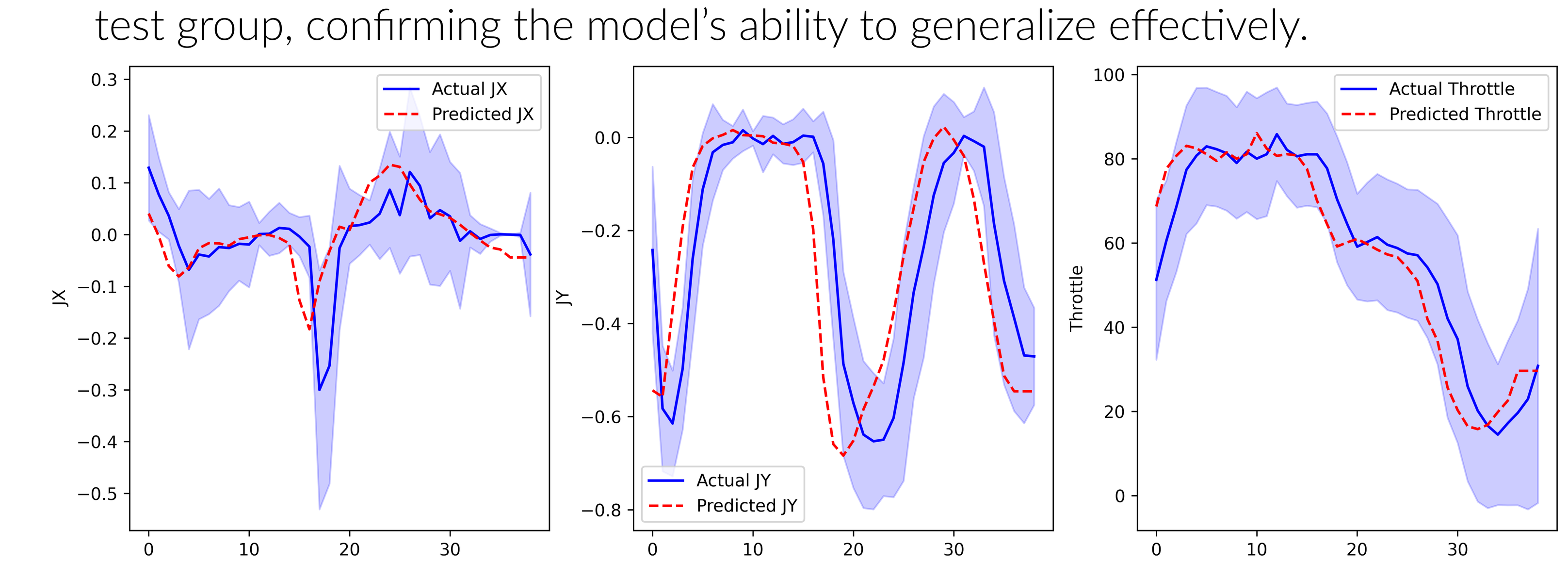

Figure 5. Trajectory Comparison – Actual vs Predicted with Mean and Standard Deviation.

Conclusion and Future Work

- **Developed a model** to replicate the **pop-up attack maneuver** using real pilot data colleted from a **high-fidelity flight simulator**.
- The model showed potential to **predict aircraft control inputs**, mimicking the actions of an experienced pilot.
- **Future work includes:**
  - **Expanding the dataset** with diverse pilot profiles, while exploring additional maneuvers.
  - **Using generative learning** to create synthetic data, aiming to improve the model accuracy.
  - **Testing alternative imitation learning models**, including the **Gated Recurrent Unit (GRU)**.

References

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