Intent Recognition on Fixed-Wing Aircraft

Marie Grace

Sonia Chernova

Dr. Sonia Chernova

Anirban Mazumdar

Dr. Anirban Mazumdar

Introduction:

Human-robot teams have the potential to achieve performance that humans or robots individually would not be capable of. We are particularly interested in how humans and machines could work together to improve the flight performance of an aerial vehicle. While humans can rapidly perceive an environment and make high-level plans, their control performance can be poorer than automated systems. In this circumstance, humans are better at high-level decision-making and strategy than feedback control. Human inconsistency can reduce aircraft performance [3]. For example, a novice pilot can struggle to perform a steady turn without dropping altitude, and even an experienced pilot will suffer from mental fatigue during a long, stressful flight, hurting his or her performance [2]. Additionally, the human body faces fundamental limits on control performance due to the relatively slow response of the neuromuscular system.

This study aims to evaluate the ability of an AI to identify a pilot's intentions, as a first step to creating a shared-control system. We propose an architecture that assumes pilots fly according to the principles of the maneuver automata [5]. The maneuver automaton divides aircraft trajectories into trims states and maneuvers. Trim states are defined as points where the aircraft is in a constant, non-accelerating state. Examples of trims include steady level flight, equilibrium glides, or steady turns. Maneuvers are defined as transitions between two trim states from one trim to another, or to and from the same trim state. Maneuvers can include aggressive turns, pitching behaviors to modulate altitude, or aerobatic motions (barrel roll, hammerhead, Immelmann, etc.). For example, a plane flying straight and level is trimmed, until it executes a sharp turn to change heading (a maneuver). When the maneuver is finishes, the plane returns to flying straight and level, the original trim state. We propose an algorithm for an AI to be able to identify a pilot's intended actions. The AI recognizes the trim state or maneuver the pilot is attempting to execute, by pulling from a graph consisting of trim states as vertices and maneuvers as edges such that every maneuver acts as a transition between two trim states. We hypothesize that this algorithm when implemented with a shared control system, will enable improved aircraft performance by utilizing humans for perception and high-level control and incorporating rapid closed-loop control for lower-level execution of trajectories.

The primary objective of this study is to show that the AI can recognize the pilot's intended actions. We will evaluate our data by comparing the pilot's intended maneuvers and trims, with the maneuvers and trim states that our AI was able to recognize. Previous research has explored intent recognition in cars [9] and intent recognition for multi-rotor drones [15,16]. We expand this by introducing an architecture that can be generalized to many cars, aircraft and watercraft. We also implement and test this architecture on a fixed-wing aircraft. The results of this work can lead to applications such as assisting a pilot to outmaneuver an opponent in an aerial dogfight or reducing mental fatigue on long-haul flights.

The core contributions of this work are 1) an architecture for real-time use of a maneuver intention recognition algorithm based on Frazzoli's Maneuver Automata [5], 2) the experimental evaluation of these concepts using a custom flight simulation environment and human subjects.

Literature Review:

Research indicates that flight control of drones can be improved using a combined human and autonomous agent [15,16]. Fixed-wing aircraft, however, are less maneuverable than drones. We account for this by making our model up of well-defined, prerecorded trim states and maneuvers, giving ourselves a library to work out of to improve flight control. The autonomous agent finds and selects the closest maneuver using the state history of the aircraft. The framework for deciding the closest maneuver is constructing a Hidden Markov Model (HMM) and running Viterbi's algorithm. This implementation has been shown to work for recognition purposes [8], so we expanded them to our framework.

Shared control systems combine human input with an autonomous agent's input. A shared control system with an autonomous agent can assist humans in driving [1,9,10,12] performing daily activities [17] or controlling aircraft. Effective human-robot collaboration in shared control systems requires reasoning about the intentions of the human user. [6] Jain investigates indirect signals that a user implicitly provides when performing shared control tasks [6]. This facilitates more natural interaction with improved accuracy and avoids cognitive fatigue that could happen if relying on vocal signals like commands to express intent.

Shared control systems are often used to enhance the performance of vehicle control. [14] Researchers often explore systems using cars since it offers a strong consumer benefit. Quadrotor drones have also been a study for shared control and intent recognition, but fixed-wing aircraft have not been explored to similar extents. Yang explores improving quadrotor drone operator performance by modeling user intent and adapting that to available moves in a library [15]. Yang's system does not require previous knowledge about the environment, task, or user characteristics which allows for a very flexible system. Yang further explores her system and shows their generalizability of this framework, and that it can work in different applications like exploring using mobile vehicles or walking for humanoid systems [16]. Although this framework shows that a shared control system is possible for flight control, fixed-wing aircraft control cannot be implemented in the same way. The increased maneuverability of a quadrotor drone allows enough flexibility, that at any point the drone can move in any direction. Fixed-wing aircraft are not capable of maneuvering in this way.

Young researches intent recognition that allows for smooth transitions between locomotion modes for a powered leg prosthetic [17]. This research emphasizes accuracy and seamless transitions between defined states such as walking or climbing stairs, but also seamless integration into day-to-day life. The human must not feel inhibited in any way, otherwise, the user could lose trust in the system [17]. Young proposes locomotion states including, walking on a flat surface, and climbing stairs; however, these definitions of states do not adapt well to flight control. Because planes are less maneuverable, they need connecting transition maneuvers between steady states to provide seamless integration.

Viterbi's Algorithm used on a hidden Markov model (HMM) finds the most probable sequence of hidden states, and is a commonly used technique for intent recognition, and can be used effectively in our system. Researchers like Berndt and Li use HMMs for driver intention recognition [1,9]. We can translate this to our system by adapting the techniques used to implement the HMM for a land vehicle to an aerial vehicle. Normally, HMMs are fitted using the Baum-Welch algorithm, which like most machine learning algorithms, requires a lot of raw data. Our approach, however, only uses a trim state or maneuver's reference trajectory which is either acquired from a small sample of raw data or formulated from a system model and control law.

Methodology:

The goal of this research is to show that our algorithm can recognize a pilot's intent. To do this, we first populated our library with trim states. We found these trim states by imputing desired altitude, velocity, roll, and gamma (angle to the horizon), then recorded the state (velocity (V,a,b), angular acceleration (r,p,q) and angles (θ, ϕ) for three minutes. We took the average of the results to get a trim state defined by one point. We chose to use trim states flying straight and level, pitched up and down at varying degrees, and steady-state turns with varying radii. A large library of trim states offers a lot of flexibility to the pilot. The pilot does not need to be aware of the library or the trim states it contains. If they are attempting to fly straight and level, they will likely steer the aircraft close to the level trim state in the library. This study, however, uses a small number of trim states, for proof of concept. We then created maneuvers that connected the trim states in our library. A denser library would feature additional maneuvers like aggressive turns. The library is what the autonomous agent references to quantify how the human is flying.

We then created the HMM from this library. For trim states, we define the hidden states around the reference state vector. Maneuvers are split into multiple hidden states. Each maneuver is split into 1-second intervals, and the hidden states are the average state vector from each interval. The transition probabilities are the probabilities that a hidden state transitions to another hidden state. For every trim state, we define a probability that it either stays in that state or transitions to the first hidden state of one of its maneuvers. The final hidden state of each maneuver has a transition probability to the maneuver's final trim. Refer to Figure 1 for reference.

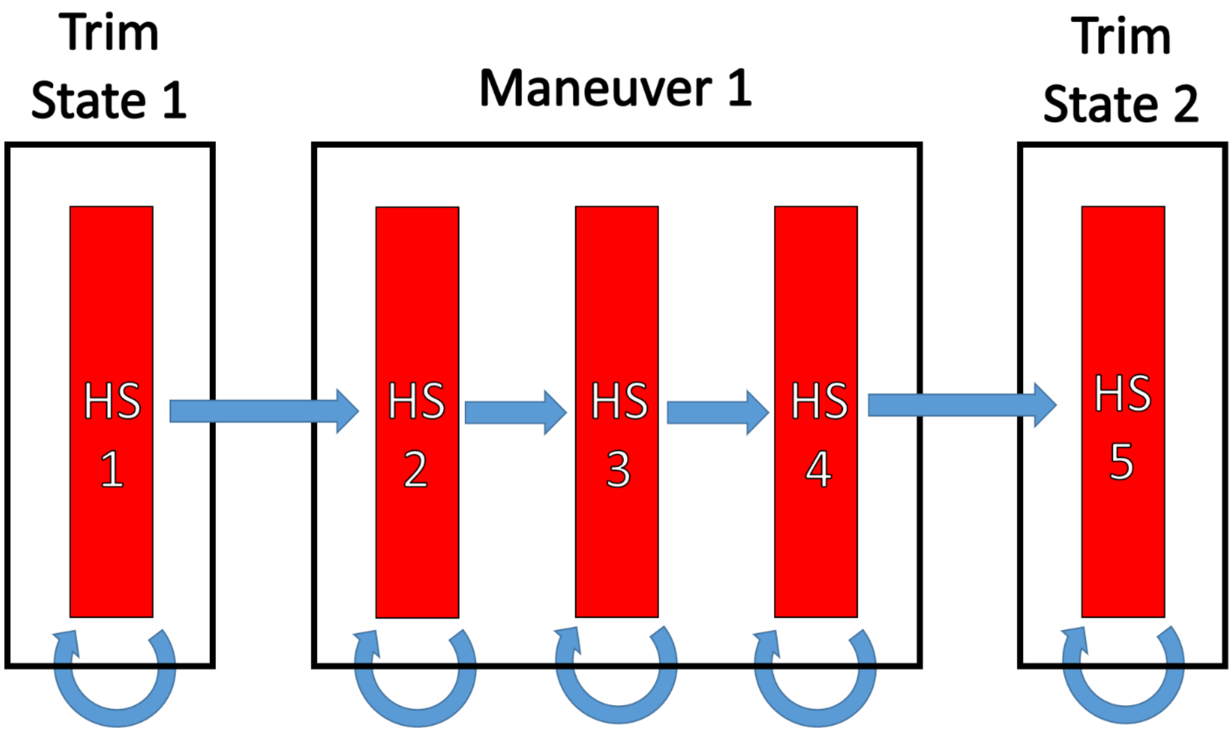

Figure 1: Visualization of hidden states within trim states and maneuvers and how they transition (blue arrows)

We define the emissions model as the probabilities that the aircraft is in each hidden state, given its current state vector. For our HMM, these are calculated as a multivariate Gaussian distribution of the observed state's state vector, and each hidden state's state vector. In our HMM, the emissions model is a multivariate Gaussian distribution. The mean for each hidden state is calculated from our premade library. The mean of the hidden state for a trim state is its state trajectory vector. The mean of the hidden states of maneuvers is the average state trajectory of its 1-second interval and we create a covariance matrix of that 1-second interval. We define the transition model as the probabilities that the plane will transition to each state, given its current state.

Next, we set up and tested our experiments. The first experiment was on automated, simulated data, and uses a 6 degree of freedom model of an F-16 aircraft. We created six trials by recording random combinations of the premade trims and maneuvers and added-in white noise. Then we ran Viterbi's algorithm on each of the trials.

The second experiment used two human participants. The experiments were carried out in accordance with IRB protocol H21061. We generated a series of paths using the premade library and had a "ghost plane" with a highlighted path fly for the human pilot to follow as seen in Figure 2. This path and "ghost plane" are used as the ground truth when evaluating the pilot's intentions. Our setup includes an ultra-wide desktop running a flight simulator with attached joysticks to simulate a realistic environment. The subjects fly flowing the premade path for the different trials. For this experiment, each subject flew 15 different trials, where each trial is 1-2 minutes of flight time. The trials were saved, and then Viterbi's algorithm was run after the experiments.

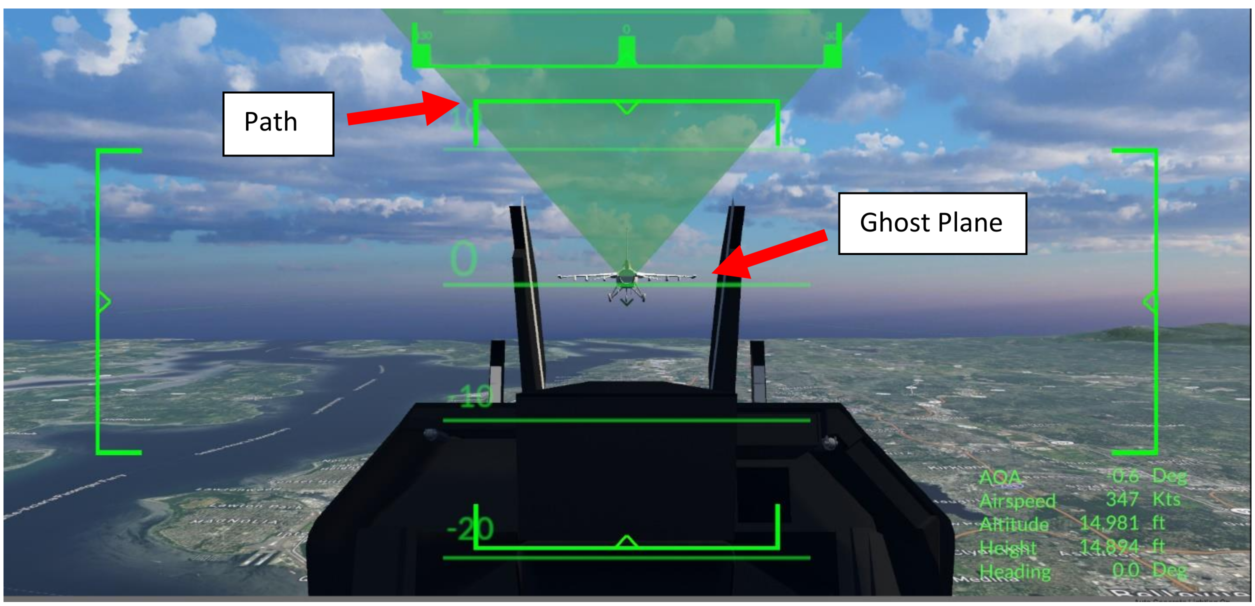

Figure 2: Subject's view of "ghost plane" and highlighted path to follow during trials

Results:

Auto-Generated Data

Each trial of the auto-generated data was between 1-2 minutes long, and we represented our data in 2 different ways. Figure 3 shows the ground truth hidden states and the predicted hidden states against the time interval.

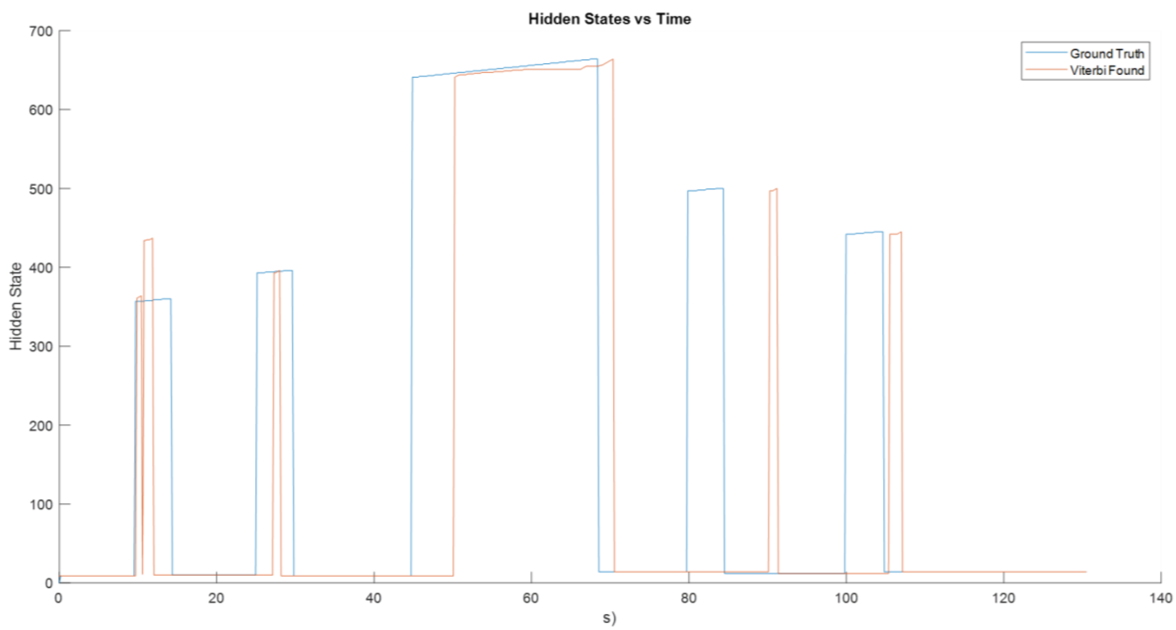

Figure 3: Ground Truth Hidden States and Predicted Hidden States vs. Time

Trim states have lower indices than the maneuvers, so the plot lines alternate between trims, seen as a state close to zero, and maneuvers, the states in the hundreds. Each maneuver is made up of many hidden states, so there is a slight incline to each of the maneuvers as it transitions from state to state. This plot is of one of the trials. Overall, the algorithm does a good job of recognizing the pilot's intentions, but not perfectly. There are some inaccuracies like an incorrect classification, short maneuver classification times, and delayed classification that will be expanded upon in the discussion section.

The next plot (Figure 4) shows the state vectors [velocity (V,a,b), angular acceleration (r,p,q), and attitude angles (roll, pitch)] from the same trial as the previous plot against time. Velocity, roll, and pitch were followed the most closely in this trial, showing that the state vector picked is an accurate representation of the raw data.

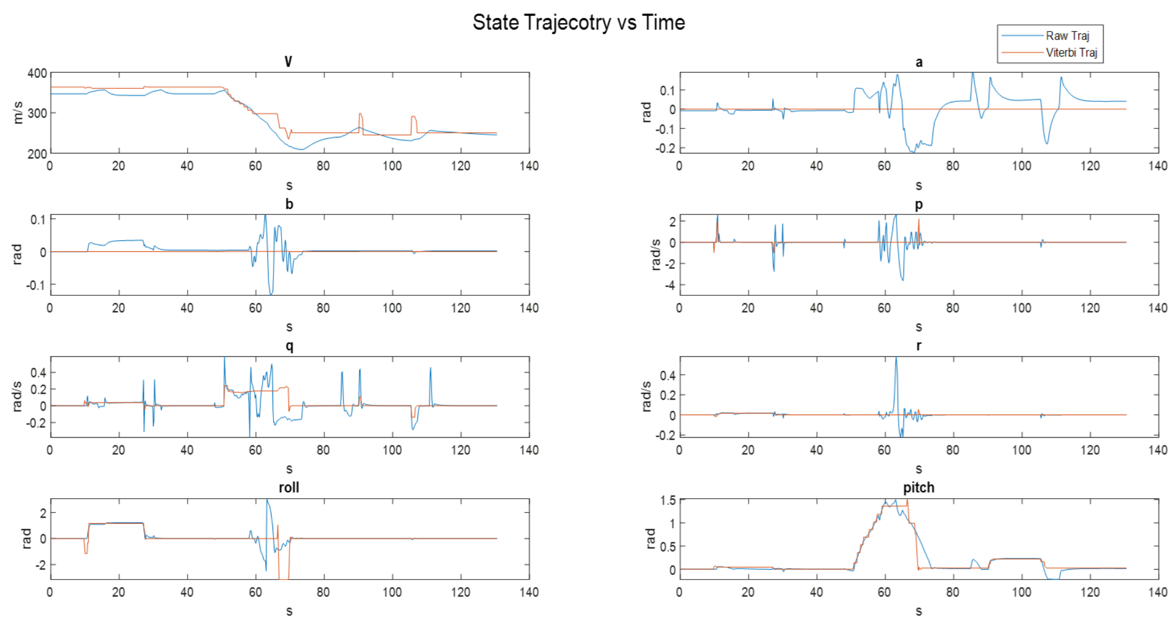

Figure 4: Raw State Vector (Blue) and Predicted Viterbi State Vectors (Red) vs. Time

Human Subject Data

Figure 5 uses the same states vs times format presented in Figure 3 but shows the predicted states for both Subject A and Subject B on the same trial. The most notable takeaway from this graph is the incorrect, but similar classifications of the maneuvers and trims for both Subject A and Subject B.

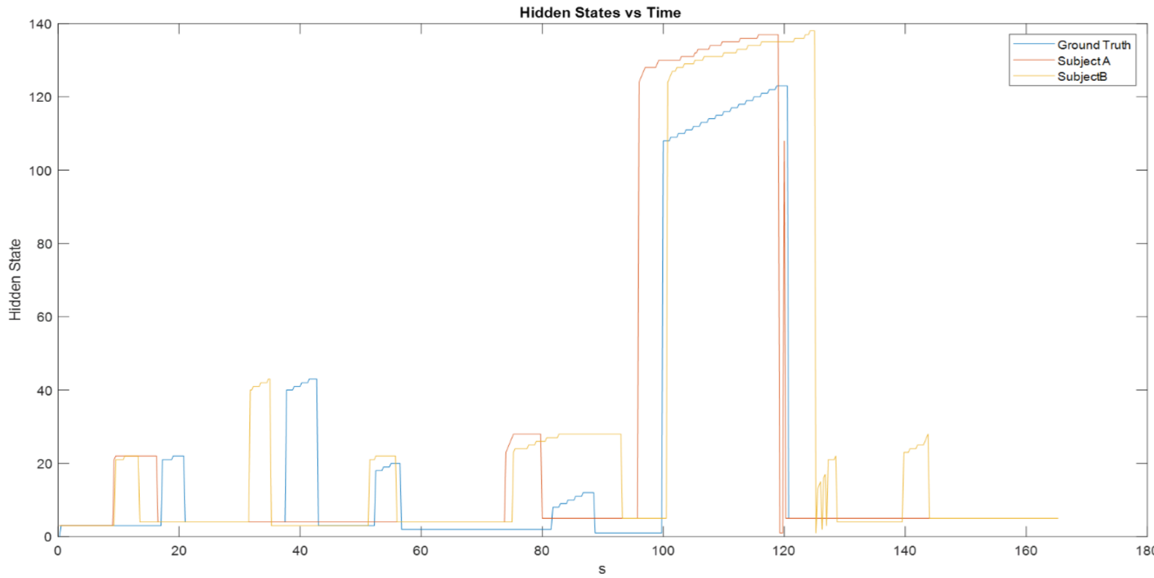

Figure 5: Ground Truth Hidden States (Blue) and Predicted Hidden States of Subject A (Red) and Subject B (Yellow) vs. Time

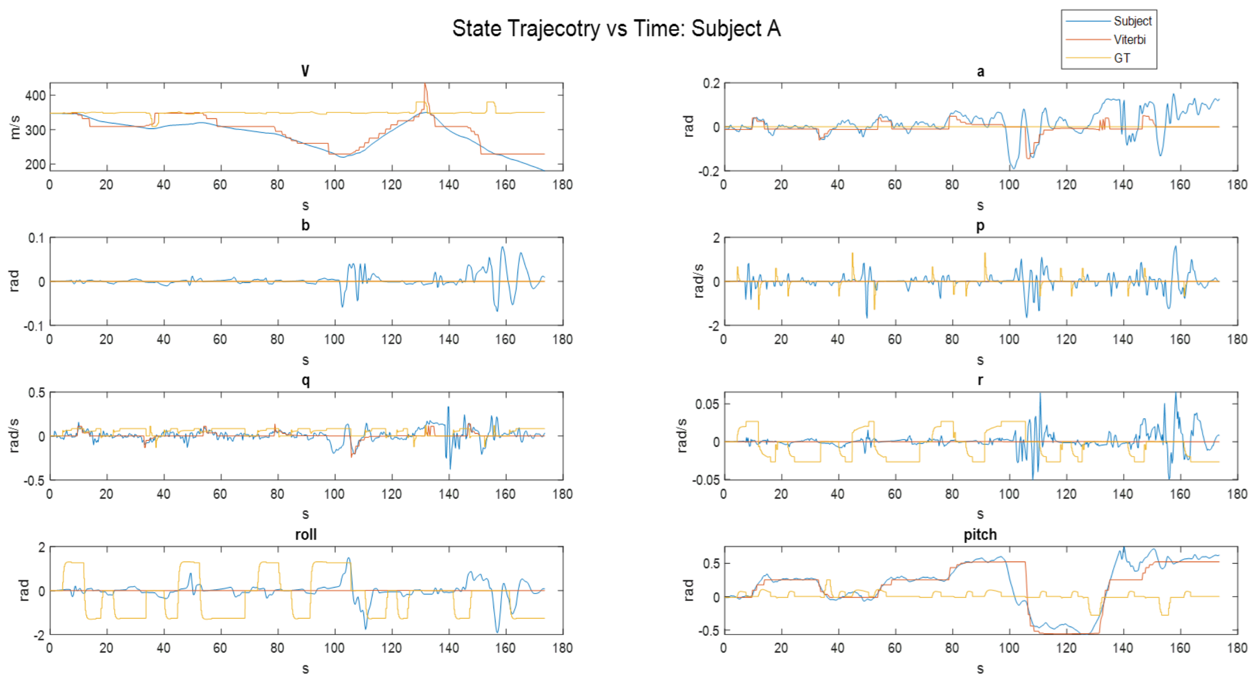

Figure 6: Subject A's Raw State Vector (Blue) and Predicted State Vectors (Red) and Ground Truth Vector (Yellow) vs. Time

Figure 7: Subject B's Raw State Vector (Blue) and Predicted State Vectors (Red) and Ground Truth Vector (Yellow) vs. Time

Figures 6 and 7 show the state vectors for subjects A and B, respectively. The ground truth is the "ghost plane" and path that the subjects following. We see that although the subject's raw state vector data from the participants did not match the ground truth, the predicted state vector stayed close to the subject's raw data.

Discussion:

Auto-Generated Data

The first maneuver of Figure 3 is incorrectly classified, but as we see in Figure 4's state vectors, the predicted maneuver was very close to the raw state data. This incorrect classification can happen when two maneuvers are very similar to each other. These errors would not be a major issue in a shared control system in practice because similar maneuvers will also have similar control inputs. The maneuvers that the algorithm finds tend to be shorter than the ground truth.

This is because the beginning and the end of the transition maneuvers often blend into the connecting trims. Something else to note is that the predicted states happen later than the ground truths. This could be attributed to both the beginning transition period, where the model stays in the trim for longer before transitioning to the maneuver, as well as a small delay between the time that the maneuver time starts, and the maneuver begins to execute. We see the Figure 4 results where the velocities, roll, and pitch match more closely than the other states because they were weighted more in the transmission probabilities of the HMM. The two figures together show that the AI was able to, with reasonable accuracy, recognize the pilot's intent.

Human Subject Data

Figure 5 shows some correct classifications, but many are incorrect. Figure 4 provides insight as to why that is the case. The state vectors of the predicted states match the raw states, but the ground truth states. These two figures together, show us that the recognition algorithm can recognize the raw states of the pilot, but that is not the same as the subject's intended flight path. The subjects' intentions were to follow the ground truth "ghost plane". In many instances, they overcorrected a lot of their movements to follow the path accurately instead of following the attitudes of the plane. The major result that we expected to see was correct classifications of the states, where a correction is the pilot's intended flight path. Although each subject's raw data was matched by the recognition algorithm, the two figures show us, there is a noticeable disconnect between the flight path of the ground truth, (the intended flight path), and the subject's flight path. So, from this experiment, we cannot say that the algorithm was able to recognize the pilot's intentions.

The limitations of these findings are implementing this in a real-world scenario. We are testing using a flight simulator, so it is not as accurate or realistic as a pilot flying an actual aircraft. Another limitation is that this algorithm is run after data is collected, but to practically implement a shared Human-AI control system, the algorithm would need to be able to run in real-time. One possible approach to implement this is by using a beam search algorithm.

Conclusion:

Our research aimed to create a framework for recognizing a human's intended flight path. Using a preconstructed library of trim states and maneuvers, and HMMs, we run Viterbi's Algorithm to identify the most likely flight path a pilot took. The results of this research indicate that for the auto-generated data, the algorithm can predict the intended flight path, but will return inaccurate results when two maneuvers are very similar to each other. For the human experiment, we found that although the predicted states do not reflect the ground truths well, the predicted states follow the raw states of the pilot. Encouraging the subjects to follow the attitudes of the plane more closely than the path trajectory itself could have provided more accurate results.

Future work could run the experiment with more experienced pilots who can follow the path more accurately or redesign the trial to match the attitudes and angular rates of the "ghost plane" instead of following the path. In addition, this research provides a first step to the implementation of a shared control system consisting of Human-AI teaming correcting the intended flight path, which would overall be contributing to greater accuracy and control during a flight.

Funding Statement:

This work was supported by the Laboratory Directed Research and Development program at Sandia National Laboratories, a multimission laboratory managed and operated by the National

Technology and Engineering Solutions of Sandia LLC, a wholly owned subsidiary of Honeywell International Inc. for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525. This paper describes objective technical results and analysis. Any subjective views or opinions that might be expressed in the paper do not necessarily represent the views of the U.S. Department of Energy or the United States Government.

Bibliography:

1. Berndt, H., Emmert, J., & Dietmayer, K. (2008). Continuous Driver Intention Recognition with Hidden Markov Models. *2008 11th International IEEE Conference on Intelligent Transportation Systems*. doi: 10.1109/itsc.2008.4732630
2. Borghini, G., Astolfi, L., Vecchiato, G., Mattia, D., & Babiloni, F. (2014). Measuring neurophysiological signals in aircraft pilots and car drivers for the assessment of mental workload, fatigue and drowsiness. *Neuroscience & Biobehavioral Reviews*, *44*, 58–75. doi: 10.1016/j.neubiorev.2012.10.003
3. Delson, N., & West, H. (1996). Robot programming by human demonstration: the use of human inconsistency in improving 3D robot trajectories. *Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS94)*, *1*, 30–36. doi: 10.1109/iros.1994.407519
4. Dragan, A. D., & Srinivasa, S. S. (2013). A policy-blending formalism for shared control. *The International Journal of Robotics Research*, *32*(7), 790–805. doi: 10.1177/0278364913490324
5. Frazzoli, E., Dahleh, M., & Feron, E. (2005). Maneuver-based motion planning for nonlinear systems with symmetries. IEEE Transactions on Robotics, 21(6), 1077–1091. doi: 10.1109/tro.2005.852260
6. Jain, S., & Argall, B. (2018). Recursive Bayesian Human Intent Recognition in Shared-Control Robotics. 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). doi: 10.1109/iros.2018.8593766
7. Javdani, S., Srinivasa, S., & Bagnell, A. (2015). Shared Autonomy via Hindsight Optimization. *Robotics: Science and Systems XI*. doi: 10.15607/rss.2015.xi.032
8. Kogan, J. A., & Margoliash, D. (1998). Automated recognition of bird song elements from continuous recordings using dynamic time warping and hidden Markov models: A comparative study. *The Journal of the Acoustical Society of America*, *103*(4), 2185–2196. doi: 10.1121/1.421364
9. Li, G., Li, S. E., Liao, Y., Wang, W., Cheng, B., & Chen, F. (2015). Lane change maneuver recognition via vehicle state and driver operation signals - Results from naturalistic driving data. *2015 IEEE Intelligent Vehicles Symposium (IV)*. doi: 10.1109/ivs.2015.7225793
10. Liu, A., & Pentland, A. (1997). Towards real-time recognition of driver intentions. *Proceedings of Conference on Intelligent Transportation Systems*, 236–241. doi: 10.1109/itsc.1997.660481
11. Mack, S., & Kandel, E. R. (2013). Principles of neural science. New York: McGraw-Hill medical.
12. Mars, F., Deroo, M., & Hoc, J.-M. (2014). Analysis of Human-Machine Cooperation When Driving with Different Degrees of Haptic Shared Control. *IEEE Transactions on Haptics*, *7*(3), 324–333. doi: 10.1109/toh.2013.2295095
13. Myers, C., Rabiner, L., & Rosenberg, A. (1980). Performance tradeoffs in dynamic time warping algorithms for isolated word recognition. *IEEE Transactions on Acoustics, Speech, and Signal Processing*, *28*(6), 623–635. doi: 10.1109/tassp.1980.1163491

14. Takano, W., Matsushita, A., Iwao, K., & Nakamura, Y. (2008). Recognition of human driving behaviors based on stochastic symbolization of time series signal. *2008 IEEE/RSJ International Conference on Intelligent Robots and Systems*. doi: 10.1109/iros.2008.4650671
15. Yang, X., Sreenath, K., & Michael, N. (2017). A framework for efficient teleoperation via online adaptation. *2017 IEEE International Conference on Robotics and Automation (ICRA)*. doi: 10.1109/icra.2017.7989701
16. Yang, X., Agrawal, A., Sreenath, K., & Michael, N. (2018). Online adaptive teleoperation via motion primitives for mobile robots. *Autonomous Robots*, *43*(6), 1357–1373. doi: 10.1007/s10514-018-9753-2
17. Young, A. J., & Hargrove, L. J. (2016). A Classification Method for User-Independent Intent Recognition for Transfemoral Amputees Using Powered Lower Limb Prostheses. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *24*(2), 217–225. doi: 10.1109/tnsre.2015.2412461
18. Yu, H., Spenko, M., & Dubowsky, S. (2003). An Adaptive Shared Control System for an Intelligent Mobility Aid for the Elderly. *Autonomous Robots*, *15*(1), 53–66. doi: 10.1023/a:1024488717009