

StarLander

A (WIP) Framework for Arbitrary Lumped-Mass Lander Simulation

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StarLander Background: Goals

- Excited by optimal control theory and implementation
- Approx. 1 month of free-time work
- Closed-loop control system simulation for non-convex soft-landing problem
 - Followed research out of UW ACL
 - Specifically 3DOF ...for now
- Goal was to develop a modular system to simulate control systems
 - Focus on trajectory-following vehicles
 - Further personal research into stochastic optimal control
 - Simple to abstract to generic systems

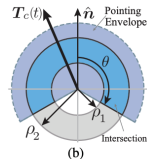
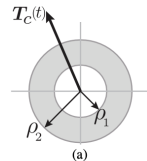


Figure: Non-Convex Thrust Bounds (Top) and Pointing Constraints (Bottom)[1]

StarLander Background: Scope and Technologies

- Independent research project
 - Written in C++17
- Used community libraries
 - Matplot++ (supports 3D plotting unlike Matplotlib-cpp)
 - Epigraph (C++ wrapper for ECOS, SOCP solver)
 - Eigen (Matrix, Vector, Linear Algebra)
- Git for version control, submoduling components
 - Each control block has its own repository
 - Can submodule/fork for other use cases
- CMake for compiling, dependency management



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Control System Architecture

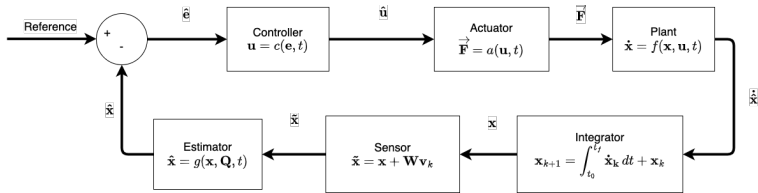


Figure: Closed Loop Feedback Control System Architecture

- Traditional control system architecture
- Each "block" is a unique C++ class with an abstract base class and several derived classes

Control System Explained: Sensor

- True state is unobservable
- Sensors measure empirical reality and return a (noisy) measurement
- Sensor Class allows selection of different noise profiles
- **Notice:** Noise simulation is technically interesting
 - White Noise (Gaussian) is unrealistic (inf. energy at high frequencies)
 - Pink/Colored Noise is more apt for real systems
 - Simulates random walk, bias

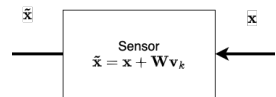


Figure: Sensor Block; Noisy State is Computed

Control System Explained: Estimator

- Measured state is too noisy; estimators reduce noise in a variety of ways based on measurements and inputs
- State Estimator Class allows for various styles
- **Kalman Filters** are interesting
 - Optimal linear estimators
 - Requires knowledge of system
 - Luckily we do!
 - Derived from “Spacecraft Dynamics and Control”, DeRuiter

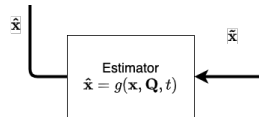


Figure: Estimator Block;
Noise is Minimized

Control System Explained: Controller

- Controllers provide a signal based on difference on state and reference
- Several types (e.g., PID)
- **LQRs** are interesting
 - Optimal linear controllers
 - Requires knowledge of system
 - Combining an LQR with a Kalman Filter results in a **LQG**
- StarLander “cheats”
 - Inputs are calculated as part of trajectory generation for free

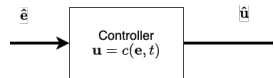


Figure: Controller Block; Control Signal to Actuators is Computed

Control System Explained: Plant

- Controllers (and Actuators together) provide an input e.g., a Force, Momentum, etc.
- Plant represents the system and contain system dynamic information
- Control input influences next state
- Plant class will contain state transition information to compute change in state
- Plant Class supports LTI systems currently
 - Non-Linear support is simple to add

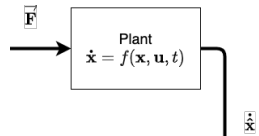


Figure: Plant Block;
Derivative of State is
Computed

Control System Explained: Integrator

- Plant computes derivative of state
- Next state computed as...

$$\mathbf{x}_{k+1} = \int_{\Delta t} \dot{\mathbf{x}}_k dt + \mathbf{x}_k$$

- ODESovler Class allows selection to trial different methods
- ForwardEuler is unstable:

$$\mathbf{x}_{k+1} = \dot{\mathbf{x}}_k \Delta t + \mathbf{x}_k$$

- **Runge-Kutta-4/5** is relatively simple and stable for non-stiff systems

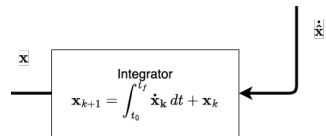


Figure: Integrator Block;
New State is Computed

Control System Explained: Reference Trajectory

- Control system aligns Plant state with some reference
- Landing trajectories in the context of StarLander
- TrajectoryGenerator Class opens interface for computing path given initial point and returning closest point along path
- SplineTrajectory performs soft-landing kinematically but ignores constraints
- GFOLD performs soft-landing and abides by constraints

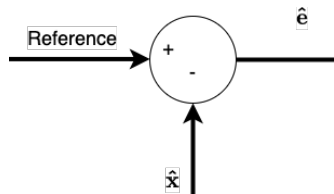


Figure: Reference Block; Deviation in State is Computed

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Software Implementation: System Overview

- Abstract classes provide public interfaces
 - Computation methods are overridden in derived class
- Instantiate each block:
 - $\begin{cases} \in [1, n] & \text{if Sensor} \\ 1 & \text{otherwise} \end{cases}$
- Initialize ControlSystem Class
 - System wrapper to control signal flow
 - Stores bus data at each time step
- Call simulate method

```
1 while ((t <= time) && (t_step > SIM_CONST::SMALL)) {  
2     // apply control  
3     actuation = reference->world.PLANET_G;  
4     if (col_idx < reference->input().cols()) {  
5         actuation = reference->input().col(col_idx) + reference->world.PLANET_G;  
6     }  
7     // update state (use true state for propagation)  
8     true_state = plant->update(truth_bus.col(col_idx - 1), actuation, t);  
9     truth_bus.col(col_idx) = true_state;  
10    // measure state vector  
11    for (Sensor *sensor : sensor_set) {  
12        int state_id = (int)sensor->sensor_id / SENSOR_IDENT - 1;  
13        meas_state[state_id] = sensor->sample(true_state[state_id]);  
14    }  
15    measurement_bus.col(col_idx) = meas_state;  
16    // estimate state  
17    est_state = estimator->estimate(meas_state, actuation);  
18    estimation_bus.col(col_idx) = est_state;  
19    // get reference signal  
20    ref_state = reference->get_reference(est_state);  
21    reference_bus.col(col_idx) = ref_state;  
22    // update time  
23    time_bus.col(col_idx) = t;  
24    // check time bounds  
25    t_step = (t + t_step > time) ? (time - t) : (t_step);  
26    t += t_step;  
27    col_idx++;  
28 }
```

Figure: ControlSystem simulate Method to Run Control System Over Timespan

Software Implementation: Sensor

- Derived IdealSensor, WhiteSensor, and PinkSensor from abstract Sensor Class
 - Abstract class “samples” reality
 - Derived class overrides how noise is generated
- Pink Noise generation transcribed from MATLAB IMU model process

$$\beta_k = \frac{1}{2}\beta_{1,k-1} + Bw_k$$
$$+ \beta_{2,k-1} + w_k \left(\frac{RW}{\sqrt{\frac{1}{2}T_s}} \right)$$

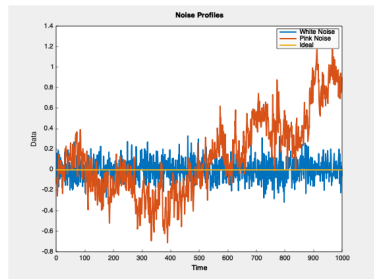


Figure: Ideal, White, and Pink Noise Profiles

Software Implementation: Estimator

- Derived NULLEstimator and (LTI) KalmanFilter from abstract StateEstimator Class
 - NULLEstimator does not estimate (returns measurement)
 - KalmanFilter employs Kalman Filter with provided state transition matrices s/t
$$\mathbf{x}_{k+1} = \mathbf{F}\mathbf{x}_k + \mathbf{G}\mathbf{u}_k \text{ and } \mathbf{y}_k = \mathbf{H}\mathbf{x}_k + \mathbf{M}\mathbf{v}_k$$
- Can assume $\mathbf{F} = \mathbf{A}\Delta t + \mathbf{I}$, $\mathbf{G} = \mathbf{B}\Delta t$ but will lead to error (see *Results, Appendix* section)

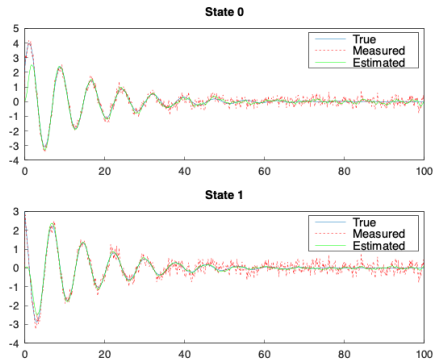


Figure: Measured VS KF Estimated State for Mass-Spring-Dampener 🔍 ↻ 🔗

Software Implementation: Plant

- Derived (LTI) LinearSystem from abstract Plant Class
 - Plant exposes interface for propagating state using integrator
 - LinearSystem accepts constant state transition matrices
 - NonLinearSystem is simple to implement (see Integrator)
- Plant classes store key information for simulation
 - Number of States
 - Number of Inputs

```
// enum to specify ode type
enum ODE_TYPE { FE, RK45 };

class Plant {
public:
    // returns x_dot
    virtual Eigen::VectorXd update(Eigen::VectorXd state, Eigen::VectorXd input,
                                   double time) = 0;

protected:
    void init_ode_system(ODE_TYPE ode_type, int num_states, double dt);

    // applies xdot = f(x, u, t)
    virtual Eigen::VectorXd apply_transition(double time, Eigen::VectorXd state,
                                              Eigen::VectorXd input) = 0;

protected:
    ODESolver::ODESolver *n_ode;

public:
    int num_states;
    int num_inputs;
    double t_step;
};
```

Figure: Implementation of Plant Abstract Base Class

Software Implementation: Integrator

- Derived ForwardEuler and RKF45 from abstract ODESolver
- ForwardEuler is unstable but simple
- RKF45 is stable (for most systems)
- User supplied ODE, tolerance, time-span
 - Heavy influence from MATLAB ode45 or Python solve_ivp

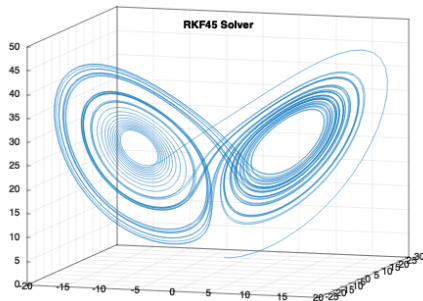


Figure: Lorenz Attractor Integrated via RKF45 Solver

Software Implementation: Reference Trajectory

- Derived SplineTrajectory and GFOLD from abstract TrajectoryGenerator Class
 - SplineTrajectory will solve kinematically (**0** at end) but does not consider constraints
 - GFOLD uses Convex Optimization to solve constrained problem
- TrajectoryGenerator exposes interfaces:
 - Compute trajectory
 - Determine optimal reference state

```
1 // abstract base class
2 class TrajectoryGenerator {
3 public:
4     // main method to override
5     Eigen::VectorXd get_reference(Eigen::VectorXd state);
6
7     const Eigen::MatrixXd &state() const;
8     const Eigen::MatrixXd &input() const;
9     const Eigen::MatrixXd &mass() const;
10
11 protected:
12     virtual void compute_trajectory(Eigen::VectorXd position,
13                                     Eigen::VectorXd velocity) = 0;
14
15 public:
16     lander_data lander;
17     trajectory_constraint traj_init;
18     env_data world;
19     double time_of_flight;
20     const std::string name = "Abstract Trajectory Generator";
21
22 protected:
23     // member variables
24     Eigen::MatrixXd m_trajectory, m_input, m_mass;
25     Eigen::Vector3d m_rf{{0.0, 0.0, 0.0}};
26     Eigen::Vector3d m_vf{{0.0, 0.0, 0.0}};
27 };
```

Figure: Implementation of Trajectory Abstract Base Class

Software Implementation: Spline Trajectory

- Cubic Spline with initial conditions and final conditions set
- Assume linear acceleration profile
 - Integrate for velocity, position
 - Use boundaries for coefficients
- Generalize to 3-dimensions
- See Appendix

$$j = A \quad (1)$$

$$a = At + B \quad (2)$$

$$v = \frac{1}{2}At^2 + Bt + C \quad (3)$$

$$x = \frac{1}{6}At^3 + \frac{1}{2}Bt^2 + Ct + D \quad (4)$$

$$A = \frac{6v}{t^2} + \frac{12r}{t^3} \quad (5)$$

$$B = -\frac{v}{t} - \frac{1}{2}At \quad (6)$$

$$C = v_0 \quad (7)$$

$$D = r_0 \quad (8)$$

Software Implementation: GFOLD

- “Guidance for Fuel Optimal Large Diverts”
- First researched by Acikmese (UW), Blackmore (SpaceX)
- Pose constraints at each time step, use SOCP Solver

$$\mathbf{x}[0 : 3, 0], [4 : 6, 0] = \mathbf{r}_0, \mathbf{v}_0 \quad (9)$$

$$\mathbf{x}[0 : 3, ToF], [4 : 6, ToF] = \mathbf{0}, \mathbf{0} \quad (10)$$

$$\text{while } t > ToF: \quad (11)$$

$$\mathbf{x}_{k+1} = (\mathbf{A}\mathbf{x}_k + \mathbf{B}(\mathbf{g} + \mathbf{u}_k)) \Delta t + \mathbf{x}_k \quad (12)$$

$$\mathbf{z}_{k+1} = \mathbf{z}_k - \alpha \sigma_k \quad (13)$$

$$\mathbf{u}_k^T \mathbf{n}_z \geq \cos \theta_{\max} \quad (14)$$

$$\mathbf{r}_k^T \mathbf{n}_z \geq \sigma_k \cos \gamma \quad (15)$$

$$\|\mathbf{u}_k\| \leq \sigma_k \dots \quad (16)$$

Software Implementation: Compiling and Linking

- Learned basics of CMake
- Each component has its own CMake
- Flags set at compile time for build targets:
 - Executable (compiling examples)
 - Libraries (linking to StarLander)
- Links community libraries

```
1 cmake_minimum_required(VERSION 3.26)
2 project(ControlSystem)
3
4 set(CMAKE_CXX_STANDARD 17)
5 set(CMAKE_RUNTIME_OUTPUT_DIRECTORY ${CMAKE_BINARY_DIR}/..)
6 set(CMAKE_EXPORT_COMPILE_COMMANDS 1)
7
8 # Plotting library
9 find_package(Matplotlib REQUIRED)
10
11 # Source subproject (submodule)
12 set(ENABLE_ECOS TRUE)
13
14 # ODE Library
15 set(BUILD_ODE_LIB ON CACHE BOOL "Build as a library" FORCE)
16 add_subdirectory(ODEsolver)
17
18 # Sensor Library
19 set(BUILD_SENS_LIB ON CACHE BOOL "Build as a library" FORCE)
20 add_subdirectory(Sensor)
21
22 # State Estimator Library
23 set(BUILD_EST_LIB ON CACHE BOOL "Build as a library" FORCE)
24 add_subdirectory(StateEstimator)
25
26 # Trajectory Generator Library
27 set(BUILD_TRAJ_LIB ON CACHE BOOL "Build as a library" FORCE)
28 add_subdirectory(TrajectoryGenerator)
29
30 add_executable(example.out landing_simulation.cpp plant.cpp control_system.cpp)
31 target_link_libraries(example.out Matplotlib::matplotlib)
32 target_link_libraries(example.out odesolver_lib)
33 target_link_libraries(example.out sensor_lib)
34 target_link_libraries(example.out stateestimator_lib)
35 target_link_libraries(example.out trajectorygenerator_lib)
36
```

Figure: CMake File for Top Level StarLander

Software Implementation: All Together Now

- ControlSystem initialized with proper components
- Sensor “measures” reality with noise profile
- Estimator attempts to remove all noise
- Controller compares against Trajectory
- Plant reacts to input
- Integrator propagates to next state
- ControlSystem provides plotting interface

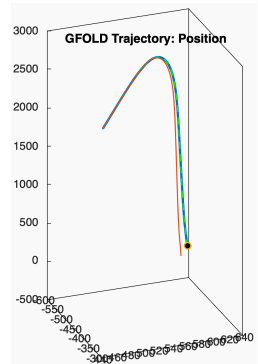


Figure: GFOLD
Trajectory Example

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Results: Parameters

Case A

- 6 IdealSensors
- NULLEstimator
- SplineTrajectory
- Trajectory-based Input
- RK-45 System Integrator

Case B

- 6 PinkSensors
- KalmanFilter
- GFOLD Trajectory
- Trajectory-based Input
 - To-be LQR
- RK-45 System Integrator

$$\mathbf{x}_0 = [-330m, 450m, 2400m, -30m/s, 20m/s, 40m/s]^T$$

Case A: Spline Trajectory

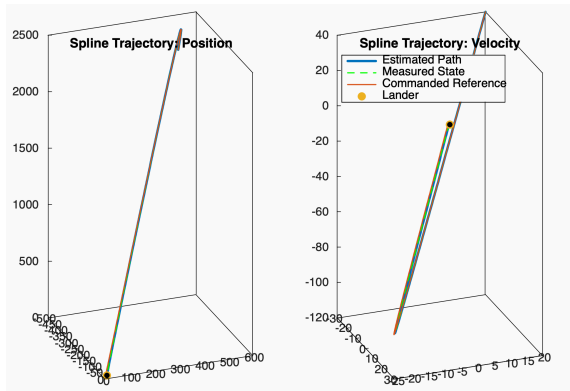


Figure: Spline-based Trajectory with Ideal State Knowledge;

$$\mathbf{x}_F = [0m, 0m, 0m, 0m/s, 0m/s, 0m/s]^T$$

Case B: GFOLD Trajectory

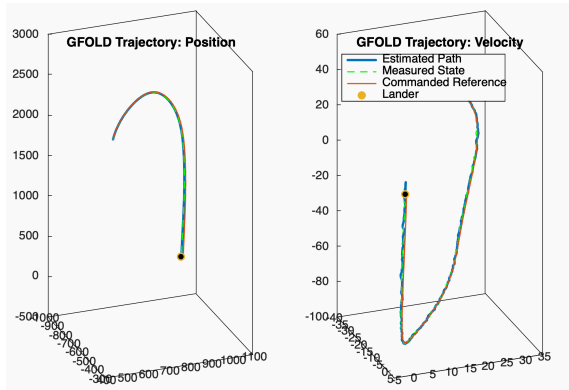


Figure: GFOLD-based Trajectory with Estimated State Knowledge;

$$\mathbf{x}_F = [-979.59, 1032.24, -5.96e-5, -7.48e-5, 7.32e-5, 1.20e-3]^T$$

Case B: GFOLD Trajectory

See GIF

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Conclusion

- Landing rockets is hard!
- Simulation architecture is important!
 - Post-Processing
 - Debugging
- Currently Open-Loop Control
 - LQR Coming Soon
- Important not to “optimize early”
 - Focus on the project and not the broader application
- StarLander is a huge Work in Progress
 - Strong foundation will make the future easier
 - Fix bugs and add features before it gets complicated

Future Work

- Implement LQR Controller
- Fix GFOLD Exit Codes
 - Likely a conflicting constraint
- Implement multi-threading
- Investigate landing under stochastic conditions
- Improve memory usage
 - References and pointers instead of copies where possible
- Add additional block options for wider support
- Improve animation generation pipeline

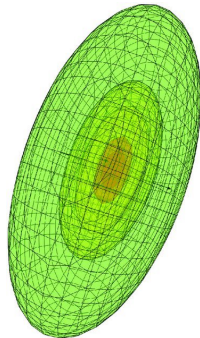


Figure: Probability Ellipsoid of Lumped Mass[2]

References

- 1 “Lossless Convexification of Nonconvex Control Bound and Pointing Constraints of the Soft Landing Optimal Control Problem”, Acikmese et al. (2013)
- 2 “Calculating collision probability for long-term satellite encounters through the reachable domain method”, Wen et al. (2022)

Questions?

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Appendix A: Lossless Convexification

- 1 “Lossless Convexification of Nonconvex Control Bound and Pointing Constraints of the Soft Landing Optimal Control Problem”, Acikmese et al. (2013)
- 2 “In Search of the Material Composition of Refuse-Derived Fuels by Means of Data Reconciliation and Graphical Representation”, Schwarzback et al. (2023)

Appendix B: Kalman Filter State Transition Matrices

$$\mathbf{x}_{k+1} = \mathbf{F}\mathbf{x}_k + \mathbf{G}\mathbf{u}_k + \mathbf{L}\mathbf{w}_k \quad ; \quad \mathbf{w} \in \mathcal{N}(0, \mathbf{Q}^2) \quad (17)$$

$$\dot{\mathbf{x}}_k = \mathbf{A}\mathbf{x}_k + \mathbf{B}\mathbf{u}_k \quad (18)$$

$$\text{NOTE} : \text{Using Forward Euler...} \quad (19)$$

$$\mathbf{x}_{k+1} = \dot{\mathbf{x}}_k \Delta t + \mathbf{x}_k \quad (20)$$

$$\mathbf{x}_{k+1} = (\mathbf{A}\mathbf{x}_k + \mathbf{B}\mathbf{u}_k) \Delta t + \mathbf{x}_k \quad (21)$$

$$\mathbf{x}_{k+1} = (\mathbf{A}\Delta t + \mathbf{I})\mathbf{x}_k + \mathbf{B}\Delta t\mathbf{u}_k \quad (22)$$

$$\mathbf{F} = \mathbf{A}\Delta t + \mathbf{I} \quad (23)$$

$$\mathbf{G} = \mathbf{B}\Delta t \quad (24)$$

Appendix C.1: Spline Trajectory Coefficients

$$j = A \quad (25)$$

$$a = At + B \quad (26)$$

$$v = \frac{1}{2}At^2 + Bt + C \quad (27)$$

$$x = \frac{1}{6}At^3 + \frac{1}{2}Bt^2 + Ct + D \quad (28)$$

$$x(0) = D = r_0 \quad (29)$$

$$v(0) = C = v_0 \quad (30)$$

Appendix C.2: Spline Trajectory Coefficients

$$\frac{v_0 + v_f}{2} = \frac{A}{4}(t_0^2 + t_f^2) + \frac{B}{2}(t_0 + t_f) + C \quad (31)$$

$$\frac{x_f - x_0}{t_f - t_0} = \frac{A}{6}(t_0^2 + t_0 t_f + t_f^2) + \frac{B}{2}(t_0 + t_f) + C \quad (32)$$

$$A = 6 \frac{v_0 + v_f}{(t_f - t_0)^2} - 12 \frac{r_f - r_0}{(t_f - t_0)^3} \quad (33)$$

$$B = \frac{v_f - v_0}{t_f - t_0} - \frac{1}{2} A t \quad (34)$$

$$v_f = r_f = t_0 = 0 \quad (35)$$

$$A = \frac{6v_0}{t^2} + \frac{12r_0}{t^3} \quad (36)$$

$$B = -\frac{v_0}{t} - \frac{1}{2} A t \quad (37)$$