Parameter Analysis of an Adaptive, Fault-Tolerant
Attitude Control System Using Lazy Learning

Matthew Russell

A Senior Thesis submitted in partial fulfillment of the requirements for graduation in the Honors Program
Liberty University
Spring 2018
Acceptance of Senior Honors Thesis

This Senior Honors Thesis is accepted in partial fulfillment of the requirements for graduation from the Honors Program of Liberty University.

______________________________
Kyung Bae, Ph.D.
Thesis Chair

______________________________
Frank Tuzi, Ph.D.
Committee Member

______________________________
David Wang, Ph.D.
Committee Member

______________________________
David Schweitzer, Ph.D.
Assistant Honors Director

______________________________
Date
Abstract

Several key requirements would be met in an ideal fault-tolerant, adaptive spacecraft attitude controller, all centered around increasing tolerance to actuator non-idealities and other unknown quantities. This study seeks to better understand the application of lazy local learning to attitude control by characterizing the effect of bandwidth and the number of training points on the system’s performance. Using NASA’s 42 simulation framework, the experiment determined that in nominal operating scenarios, the actuator input/output relationship is linear. Once enough information is available to capture this linearity, additional training data and differing bandwidths did not significantly affect the system’s performance.
Parameter Analysis of an Adaptive, Fault-Tolerant Attitude Control System Using Lazy Learning

Since the first satellite was launched into space in 1958, both spacecraft and mission complexity have increased dramatically. While early satellites might be able to function effectively with limited, spin-stabilized attitude control, more recent missions such as the Hubble Space Telescope, the upcoming James Webb Space Telescope, or the International Space Station must dynamically manage their attitude to achieve the mission objectives. Several active and passive methods have been developed to control attitude. Mechanical reaction wheels leverage conservation of angular momentum to exert torques on the spacecraft’s body. However, these wheels often fail or degrade over time, leading to changes in the movement model of the satellite. Furthermore, the inertial characteristics of the spacecraft could be unknown or varying. An adaptive, fault-tolerant attitude control system could mitigate the effect of these factors on pointing accuracy and overall mission success.

Background

Spacecraft Attitude Control

Almost all spacecraft require some level of pointing control to accomplish their mission (Russell & Straub, 2017). Imaging satellites in Earth orbit must accurately manage their attitude, or orientation, to produce photographs of desired regions, and the necessary precision increases with the resolution of the imaging sensors. Deep space probes rely on attitude control to maintain communication with NASA's Deep Space Network (DSN) while those closer to the Sun must ensure the spacecraft is rotated to
expose solar arrays to the maximum amount of light. The system responsible for
monitoring and adjusting the orientation of the spacecraft is the Attitude Determination
and Control System (ADCS). As this study focuses on control techniques, the discussion
of attitude determination falls outside the scope of this work.

Reference frames. The primary reference frame used in spacecraft attitude
dynamics is the Earth Centered Inertial (ECI) frame (Stoneking, 2014). The origin of ECI
is at the center of the earth, and the $x$-axis extends along the vernal equinox. The $z$-axis
runs through the north pole, and the $y$-axis lies on the equator and is orthogonal to both
the $x$ and $z$ axes (Hall, n.d.). According to Stoneking (2014) the attitude of a spacecraft is
defined as the rotation from the ECI frame to the body frame, which are the axes fixed
relative to the spacecraft’s structure (see Figure 1).

*Figure 1.* Spacecraft reference frames. The red $n$ axes are the inertial axes, while the
green $b$ axes are the body axes. The orientation or attitude of the spacecraft can be
specified as the rotation from the inertial axes to the body axes.
ADAPTIVE, FAULT-TOLERANT ATTITUDE CONTROL

Equations of motion. Wiesel (2010) describes rigid-body rotation as

\[ \tau = \frac{d}{dt} \mathbf{H} \]  

(1)

where \( \mathbf{H} \) is the angular momentum, and \( \tau \) is the net torque on the rigid body. The angular momentum itself can be written in matrix form as

\[ \mathbf{H} = \mathbf{J} \omega \]  

(2)

where \( \mathbf{H} \in \mathbb{R}^{3 \times 1} \) is the angular momentum vector, \( \mathbf{J} \in \mathbb{R}^{3 \times 3} \) is the moment of inertia matrix, and \( \omega \in \mathbb{R}^{3 \times 1} \) is the angular velocity vector in the inertial frame. The moment of inertia (MOI) matrix can be found using

\[ \mathbf{J} = \begin{bmatrix} \int (y^2 + z^2)dm & -\int yx \, dm & -\int zx \, dm \\ -\int xy \, dm & \int (x^2 + z^2)dm & -\int zy \, dm \\ -\int xz \, dm & -\int yz \, dm & \int (x^2 + y^2)dm \end{bmatrix} \]  

(3)

where \( m \) is the mass of the spacecraft.

Passive attitude control. Attitude control can be either active or passive. Active control allows the orientation to be arbitrarily set by the ADCS while passive control relies on exploiting external forces for stabilization. Starin and Eterno (2011) state that passive attitude control for Earth-orbiting satellites can be achieved via a permanent magnet that pulls the satellite in line with the Earth’s magnetic field. Alternatively, the
satellite could be provided an initial angular velocity when ejected from the launch vehicle, relying on gyroscopic effects to constrain the orientation in a method known as spin stabilization.

**Thrusters.** Instead of passive techniques, systems may use an active method or combination of methods. Thrusters are one active approach suitable for coarse attitude control. When a thruster produces a force vector that does not pass through the spacecraft’s center of mass, it applies a torque to the rigid body (Starin & Eterno, 2011). Wiesel (2010) notes that by adding a second thruster which applies an opposite torque, the two torques can be used to point the spacecraft along one axis. Although allowing rapid change of orientation, thruster-based systems suffer a few key disadvantages. A limited supply of propellant means that attitude control will be lost when all the propellant has been expended. Thrusters also cannot completely stop the rotation of the spacecraft since they fire at discrete levels.

**Magnetorquers.** Magnetorquers utilize the Earth’s magnetic field to create a torque on the spacecraft (Starin & Eterno, 2011). Using three-axis solenoids, magnetorquers create a virtual magnetic dipole. The Earth’s magnetic field then acts on this dipole just like it does on a compass needle, pulling the dipole parallel to the magnetic field lines. Although magnetorquers do not require propellant, their performance is restricted by the direction of local field lines; the desired torque may not be possible given the field vector at a specific location. Combined with the small magnitude of torque possible, magnetorquers are often used for small, long-duration attitude maneuvers. One commonly-used maneuver is the B-dot algorithm, which seeks
to prevent the buildup of angular momentum from external disturbances (e.g., gravity gradient).

**Reaction wheels, momentum wheels, and CMGs.** Finer pointing can be achieved using reaction wheels, momentum wheels, or control moment gyroscopes (CMGs). All three of these techniques apply torque to the spacecraft through the conservation of angular momentum, which states that the total angular momentum in a closed system remains constant (Wiesel, 2010). The wheels generally consist of a flywheel driven by an electric motor.

For reaction and momentum wheels, the angular momentum stored in the device is varied by increasing or decreasing the spin rate of the flywheel whose axis coincides with the desired axis of rotation (Wiesel, 2010). Since the overall angular momentum in the system including the spacecraft and the flywheel must remain constant, changing the angular momentum in the flywheel causes the angular momentum of the spacecraft to change in the opposite direction. The rotational analog of Newton’s Second Law of Motion states that torque is simply a change in momentum:

\[ \tau = J \alpha = J \dot{\omega} = \dot{H} \] (4)

where \( \tau \) is the torque, \( J \) is the moment of inertia, \( \alpha \) is the angular acceleration, \( \dot{\omega} \) is the change in angular velocity, and \( \dot{H} \) is the change in angular momentum. Thus, changing the wheel’s speed (and therefore momentum) applies a torque to the wheel. Since momentum is conserved, the rotational analog of Newton's First Law of Motion states
that an equal and opposite torque will be applied to the spacecraft. The conservation of angular momentum can be described as

\[ \sum \tau = \sum \dot{H} = 0 \]  

(5)

i.e., the total change in momentum in the system must be zero. Thus, by precisely controlling the spin rate of the flywheels, reaction and momentum wheels can apply a variable torque to the spacecraft, allowing much finer attitude control than thrusters. Reaction wheel modules can be controlled via torque commands (i.e., desired torque) instead of raw motor current (Carrara & Kuga, 2013). Carrara, da Silva, and Kuga (2012) and Carrara and Kuga (2013) point out that the presence of friction means that the relationship between the current supplied to the reaction wheel motor and the resulting speed is nonlinear.

Although only three reaction wheels (one for each axis) are required for full attitude control, many spacecraft include four or more wheels. By using four wheels in a tetrahedral structure, the ADCS will be able to maintain full three-axis control of the spacecraft even with the complete failure of one of the wheels (Hacker, Ying, & Lai, 2015). For additional redundancy, six reaction wheels will be used to control attitude on the forthcoming James Webb Space Telescope (Space Telescope Science Institute, n.d.).

CMGs operate on a slightly different principle. Instead of changing the spin rate of the flywheel, the axis of the wheel is rotated (Wiesel, 2010). Conservation of angular momentum causes a torque to be applied to the spacecraft. According to NASA (n.d.),
International Space Station (ISS) uses four, 98-kilogram CMGs to stabilize the orbiting laboratory.

**Momentum dumping.** Flywheel methods suffer from momentum saturation, which occurs when the wheel has maximized the amount of momentum it can store (i.e., reached its maximum spin rate) (Starin & Eterno, 2011; Wiesel, 2010). The momentum of the wheel cannot be increased, and it cannot provide any more torque in that direction. If the spacecraft was truly a closed system, this situation could be avoided. However, external torques act on the spacecraft through the Earth’s gravity gradient, its magnetic field, solar pressure, initial spin from the launch vehicle, etc. Thus, as these external torques affect the spacecraft, the wheels must be used to counteract the additional momentum added to the system. In addition to introducing the possibility of momentum saturation, this counteraction requires the wheels to spin continuously, negatively affecting power consumption.

To mitigate this problem, most spacecraft use a process known as momentum dumping or desaturation in which the excess momentum is shed from the system (Starin & Eterno, 2011). Thrusters or magnetorquers are generally used in this process. Since thrusters eject propellant and magnetorquers rely on external forces, these methods can remove angular momentum from the system, allowing the speed of the reaction wheels to be reduced. The James Web Space Telescope and the ISS both use thrusters for momentum dumping (NASA, n.d.; Space Telescope Science Institute, n.d.).
Adaptive, Fault-Tolerant Attitude Control

A standard proportional-integral-derivative (PID) controller can be used for three-axis attitude control with reaction wheels (Li, Post, Wright, & Lee, 2013; Sahay et al., 2017). The control algorithm can be summarized as

$$M_i = K_{P_i} \beta_{l,err} + K_{D_i} \frac{d}{dt} \beta_{l,err} + K_{I_i} \int_0^t \beta_{l,err} \, dt$$

(6)

where $M_i$ is the output torque command for the $i$th inertial axis, $\beta_{l,err}$ is the angular position error for the $i$th inertial axis, $K_{P_i}$ is the proportional gain, $K_{D_i}$ is the derivative gain, and $K_{I_i}$ is the integral gain (Snider, 2010). All three gains may not be used; some instances use a proportional-derivative (PD) controller and rely on Kalman filtering to eliminate noise in the input parameters (Van Buijtenen, Schram, Babuska, & Verbruggen, 1998). In either case, Straub (2015) argues that the underlying dynamics model of the satellite’s rotation is often assumed a priori. Since this dynamics model may change during a spacecraft’s lifetime, due to propellant depletion or hardware failures, a PID control system is not necessarily fault tolerant.

**Need for adaptive fault-tolerant control.** KrishnaKumar, Rickard, and Bartholomew (1995) state that a spacecraft can benefit from using adaptive control algorithms because of the unique operating environment and uncertainties of spaceflight. They point out this need in the context of space station-class spacecraft, observing that the incremental construction of the station and the docking and removal of visiting vehicles significantly alters the rotational dynamics of the system. An adaptive controller
could compensate for these variations. Although KrishnaKumar et al. (1995) focuses on the application of adaptive neural network controllers to the space station problem, the justifications for the study are equally valid for all spacecraft. These can be summarized as follows: (a) environmental uncertainty, (b) flaws in the kinematics model, and (c) system failure. As described by Hu, Xiao, and Friswell (2011), system failure includes not only complete malfunction, but also the degradation of component performance. Cruz and Bernstein (2013) support the position that adaptive controllers are beneficial when a “sufficiently accurate” (p. 4832) kinematics model of the spacecraft is not known.

The mechanical nature of reaction wheels and CMGs makes them vulnerable to degradation and failure over the life of the mission. High-profile examples include the Hubble Space Telescope, the Kepler telescope, the ISS, the Dawn spacecraft, and the Far Ultraviolet Spectroscopic Explorer (FUSE). FUSE was crippled and left with a single, functioning reaction wheel (Burt & Loffi, 2003; Cowen, 2013; Rayman & Mase, 2014; Sahnow et al., 2006; Space Telescope Science Institute, n.d.).

Some actuator failure can be linked to difficulties in maintaining proper lubrication in a space-based system (Krishnan, Lee, Hsu, & Konchady, 2011). Control algorithms must account for increasing friction in the wheel assemblies which introduces high levels of nonlinearity into the system (Dinca, 2004). In the recent case of reaction wheel failure on a Globalstar second generation satellite, Hacker et al. (2015) states that “the bearing friction is considered the most effective data to monitor for early detection of any hardware degradation” (p. 255). Furthermore, the study identified a sudden
increase in calculated dry friction (i.e., reduced performance) as characteristic of hardware failure.

**Existing adaptive control work.** Existing adaptive techniques examine ways to initially adjust and tune the controller. Van Buijtenen et al. (1998) explores the usage of reinforcement learning to constrain the limit cycle of a ADCS fuzzy logic controller without a priori information about the spacecraft. Similarly, Shi, Allen, & Ulrich (2015) and Tang (1995) discuss adaptive tuning of the controller but do not address the possibility of deeper changes to the inertial model of the spacecraft.

Yoon and Tsiotras (2002) recognize the need for an adaptive controller capable of reacting to changes in the spacecraft’s inertial model due to mission operations but differentiate from existing literature by developing adaptive methods for systems using variable speed single-gimbal control moment gyroscopes (VSCMGs), a hybrid of typical CMGs and reaction wheels which can cause the inertial model to vary.

Straub (2015) and Yoon and Agrawal (2009) highlight that the problem of actuator misalignment, in addition to performance degradation, has not been adequately studied. Yoon and Agrawal (2009) describe this issue as follows:

Most (if not all) of the previous research, however, deals only with uncertainties in the inertia, centripetal/Coriolis [sic], and gravitational terms, assuming that an exact model of the actuators is available. This assumption is rarely satisfied in practice because the actuator parameters may also have uncertainties due to installation error, aging and wearing out of the mechanical and electrical parts, etc.
Adaptive control with actuator uncertainty does not seem to have received much attention in the literature, even though this uncertainty may result in a significant degeneration of controller performance. (p. 900)

Yoon and Tsiotras (2008) attempt to address this problem but rely on many estimated parameters and assume that the inertial model does not change. Cruz and Bernstein (2013) study the application of retrospective cost adaptive control (RCAC) to adapt without requiring information about the spacecraft’s inertial model and the actuator momentums. Although actuator misalignment is considered, they assume the inertial model is constant, which may not be the case for a variety of reasons, including propellant depletion, hardware damage, or payload release (Yoon & Tsiotras, 2008).

**Existing fault-tolerant control work.** Previous fault-tolerant control (FTC) studies have attempted approaches which autonomously detect and potentially mitigate failures, including Hu et al. (2011) and Schreiner (2015). Active FTC systems use a two-step process: detect the problem, and then use this knowledge to adjust the controller (Hu et al., 2011). In contrast, passive FTC systems are structured such that component failure does not introduce instability into the controller. According to Hu et al. (2011), the system is stable, with “an acceptable degradation of performance” (p. 271). They point out that passive FTC research has not targeted nonlinear systems such as those in spacecraft and investigate the development of a control law that guarantees the stability of the system based on Lyapunov functional analysis in situations of actuator degradation and failure. They acknowledge the need for additional work to verify the new control law in attitude tracking applications. Importantly, their work does not address variation in
actuator alignment (i.e., change in actuator axis) and uses a second, separate control law in the case of complete actuator failure when a redundant (e.g., fourth) actuator is available. It is also unclear how the control law would respond to a dynamic, changing inertia matrix.

**Adaptive Control Using Lazy Learning**

From the literature, several key requirements would be met in an ideal fault-tolerant, adaptive attitude controller: (a) no requirement of a priori information regarding the inertial model of the spacecraft or actuators, (b) a resilience to actuator misalignment, (c) robustness against actuator degradation or complete failure, and (d) an ability to adapt to a changing inertial model. Straub (2016) identified the potential application of an expert system or systems that could be used to achieve these goals. Russell and Straub (2017) extended this idea to include the use of lazy local learning to fully achieve the desired system capabilities. Here the author includes a brief overview of locally weighted learning and its advantages over neural networks in fault-tolerant ADCS applications.

**Locally weighted learning.** In lazy learning, a system stores a database of training points from which the desired predictions can be found as needed (i.e., lazily) instead of performing a priori training on the dataset. Atkeson, Moore, and Schaal (1997) state that these “methods defer processing of training data until a query needs to be answered. This usually involves storing the training data in memory, and finding relevant data in the database to answer a particular query” (p. 11). Locally weighted learning answers queries by weighting the data points surrounding the query point based on their proximity (i.e., relevance) to the query.
A key aspect of local learning is bandwidth. This bandwidth determines how many training points or how far from the query point the algorithm should go to build the local model (Atkeson et al., 1997). Several methods exist for finding optimal bandwidths (e.g., fixed width, minimizing cross validation error, point-specific bandwidths, etc.). A description of these methods is deferred to more detailed discussion by Atkeson et al. (1997).

In addition to bandwidth, the amount of training data is another key parameter. By only using training points in close proximity to the query, locally weighted learning can be applied to nonlinear systems. However, the training database must contain enough information to effectively characterize the nonlinearity. According to Atkeson et al. (1997), the number of points needed can be “highly problem dependent” (p. 59), most likely because the nature of the nonlinearities varies greatly from application to application.

Several methods are presented in Atkeson et al. (1997) to achieve locally weighted learning, including nearest neighbor, weighted averages, and locally weighted regression. Local regression involves fitting linear models to data around the query point and using these models to predict the query point result. Weighted regression uses a distance function to increase the contribution of training points to the regression based on their proximity to the query point, suppressing the effects of more distant points.

Bottou and Vapnik (1992) examine the use of neural networks in local learning. Instead of training a neural network on an entire dataset, training examples similar to the query are extracted from the database, and a local neural network is trained on just this
subset. Although effective in improving recognition of handwritten digits over traditional neural networks, this method is very slow since the network must be retrained for each query.

**Advantages over neural networks in adaptive, fault-tolerant controllers.** In theory, a multi-layer perceptron (MLP) artificial neural network (ANN) could be trained on ADCS performance data (i.e., input/output relations) and used in an adaptive controller. In this case, the controller would initially collect a large amount of training data, and then train the ANN for future use. This method suffers in several ways: training neural networks is slow, especially on embedded systems with limited computational resources as is the case in many spacecraft; the ANN is not easily adapted after the initial training (i.e., in the case of hardware failure); and the ANN is vulnerable to overtraining. Atkeson et al. (1997) argues that lazy learning algorithms present themselves as a better-suited adaptive algorithm because they avoid the overtraining problem found in neural networks. Since the training data is not encoded in a complex network of weights, the algorithm also allows for detection and removal of outlier training points that may skew the predictions, as discussed in Straub (2015), opening the door for long term adaption without the need to completely retrain the model.

Russell and Straub (2017) detail an initial implementation of a locally-weighted, lazy learning ADCS control algorithm which collected training points (i.e., input/output pairs) through a sequence of random reaction wheel torque commands. This training data represents the correlation between torque commands supplied to the actuators and the resulting angular acceleration output measured by the spacecraft. The preliminary
ADAPTIVE, FAULT-TOLERANT ATTITUDE CONTROL

Simulations indicate the resilience of the algorithm to actuator misalignments. Furthermore, the self-training aspect of the system allows the algorithm to meet the adaptive, fault-tolerant requirements (a) and (b) described earlier in the Adaptive Control Using Lazy Learning section. Tests also showed that the algorithm was robust against drift of actuator alignment, partially satisfying (c). The implementation of an expert system as described by Straub (2015) would achieve (d). Therefore, lazy local learning appears well-suited to solving the adaptive, fault-tolerant control problem for attitude control systems. Building off the results of Russell and Straub (2017), this study seeks to better understand the algorithm and characterize the effect of bandwidth and the number of training points on the system’s performance.

Methods

Algorithm Design

In Russell and Straub (2017), the role of the adaptive, fault-tolerant algorithm was not clearly described in relation to standard ADCS control laws. No new control law is proposed. Instead, the focus falls on developing an adaptive relationship that transforms the desired responses generated by the control law (e.g., PID) into torque commands for a set of four potentially non-ideal actuators, referred to as torque distribution (Princeton Satellite Systems, 2000). To achieve these goals, the proposed algorithm leverages lazy learning. Each item in the collection of training data stores the initial angular velocity vector, the torque commands sent to the actuators, and the resulting body angular acceleration vector. The initial angular velocity vector is included to account for situations in which a torque along a single axis may induce rotation around a secondary
axis if the initial angular velocity is non-zero. These training maneuvers are collected through a series of random actuator torque commands.

This process achieves initial adaption of the ADCS without a priori knowledge of the spacecraft’s inertial model and accounts for any actuator non-idealities existing during the training period. Although outside the scope of this study, the addition of an expert system as described by Straub (2015) would add active fault-tolerant control to the algorithm, allowing it to continue to adapt outside the training period. The following sections describe the lazy learning algorithm used in this study. It resembles the algorithm from Straub & Russell (2017) with a few key revisions which are noted as they are discussed.

**Collecting the training points.** The training points are collected through a sequence of random actuator torque commands (see Figure 2). The torque commands are generated uniformly and restricted to 10% of the maximum torque capability of the actuator. Since the movements are random, this prevents a large accumulation of angular momentum during the training period. After recording the initial angular velocity vector, the random torque command is stored and then applied to the actuators. Following a brief delay (i.e., 0.25 sec), the resulting angular velocity vector is measured, and the true body torque vector components are calculated:

\[
\tau_i = \frac{\omega_{if} - \omega_{i0}}{\Delta t} \cdot J_i
\] (7)
In Equation 7, \( \tau_i \) is the true body torque, \( \omega_{if} \) is the final body angular velocity, \( \omega_{i0} \) is the initial angular velocity, \( \Delta t \) is the maneuver duration, and \( J_i \) is the spacecraft’s moment of inertia. The initial angular velocity state, torque command, and measured true body torque are then hashed using a locality sensitive hashing (LSH) method which ensures similar training points are grouped together. This algorithm is presented in more detail in later sections.

![Figure 2](image_url)

**Figure 2.** Overview of the training process. The LSH algorithm ensures similar training points are grouped together.

At this point, Equation 7 can be seen to incorrectly depend on the inertial properties of the spacecraft. The correct implementation of Equation 7 would be

\[
\alpha_i = \frac{\omega_{if} - \omega_{i0}}{\Delta t}
\]  

(8)
where $\alpha_i$ is the resulting body angular acceleration. In the correct version, the database stores data points relating the torque commands to the output angular acceleration, not the output torque. This error was made in the implementation; however, it does not impact the results of this study. In the method tested by this study, the PID algorithm generates the desired body torques with which to query the lazy learning database. In the correct method (which does not rely on a priori knowledge of the spacecraft), the PID algorithm would generate the desired body angular accelerations with which to query the database. That is, instead of querying with $M_i$, it would query with $\alpha_i = M_i/J_i$, where $J_i$ can be unknown. Adjusting the existing PID implementation to generate $\alpha_i$ instead of $M_i$ is simply a matter of adjusting the PID gain constants. Thus, even though the inclusion of $J_i$ appears to make the system dependent on knowing the spacecraft’s inertial characteristics, it acts only as a scaling constant. The results of the correct implementation would match the current implementation with the proper PID tuning. With this knowledge, the remainder of this discussion will assume the correct implementation.

**PID control law.** A PID control law generates the body axis torque commands given the angular position vector and the target angular position vector:

$$
M = K_p e + K_d \frac{de}{dt} + K_i \int_0^t e \, dt
$$

(9)

In this study, the PID gain constants were experimentally set to $K_p = 5$, $K_i = 0$, and $K_d = 2$. The PID angular acceleration commands and the current angular velocity vector
are used to query the lazy learning training database. The algorithm returns the optimal set of actuator torque commands to achieve the desired body acceleration vector according to a user-defined mathematical heuristic function which numerically rates a maneuver based on power consumption or other mission-critical factors. Since a four-reaction-wheel system is over-actuated, the heuristic function provides a mechanism to select an optimal solution from the solution space. In most applications, this heuristic would be designed to minimize power consumption. The actuator torque commands are then sent to the reaction wheels.

**Responding to a query.** When the PID control law calculates the desired angular acceleration, the result is passed to the lazy learning algorithm. The query contains six values: the three components of angular velocity and three components of the desired angular acceleration. Figure 3 summarizes the process of querying the model.

*Figure 3.* Overview of the lazy learning querying process that generates the necessary torque commands to achieve the desired output.
Note that Figure 3 simplifies the algorithm to a single-dimensional angular velocity state, desired torque output, and torque command. The full implementation uses three-dimensional vectors for the angular velocity and torque output, while the torque command has four components, one for each actuator.

Finding nearest neighbors with locality sensitive hashing. To build the local model, the process must first identify which training data points are near the query point. This is a nearest neighbor problem in six dimensions. Russell and Straub (2017) incorrectly used a sorting method to identify points with similar outputs to the desired output. However, that method treats each dimension of the training points separately, which does not account for the interdependency of the rotational axes in three dimensions (e.g., precession or nutation). All six dimensions must be handled together.

One solution is to use locality sensitive hashing (LSH). In contrast to traditional hashing, in which similar items have very different hashes, LSH ensures that similar items have similar hash values (Slaney & Casey, 2008). Each training point is hashed when collected and added to the database. Whereas a typical hash algorithm would seek to avoid collisions (i.e., two items hashing to the same value), the LSH process used in this work leverages collisions to group similar training points together. When searching the database for nearest neighbors, the algorithm must only calculate the LSH code of the query point and return all the training points with the same hash code.

The LSH implementation used in this study is based on the concept of geohashing or spatial keys (Karich, 2012). A geohash converts latitude and longitude coordinates into an alphanumeric code. The more characters in this code, the more precisely the
coordinates are specified. When converted to binary, the even-indexed bits encode the longitude, and the odd-indexed bits encode the latitude. Each code represents a binary search algorithm. Given that latitude ranges from $-90^\circ$ to $90^\circ$, each bit of the latitude code indicates which half of the remaining range the true value falls within. For example, let $x$ be the true latitude. Given the code $1011$, the first bit indicates that $x \in [0^\circ, 90^\circ]$. The second bit narrows the range to $x \in [0^\circ, 45^\circ)$, and the third narrows it further to $x \in [22.5^\circ, 45^\circ)$. Using the final bit, $x$ can be constrained to $[34.75^\circ, 45^\circ)$. The same algorithm can be repeated for the longitude. The two-bit sequences are interleaved so that the latitude and longitude information are integrated together. The interleaved code essentially identifies a region on the surface of the earth containing the original coordinates. By removing bits from the end of the code, the binary search tree for both the latitude and longitude is flattened, and the resulting geographic area is enlarged. Importantly, if two pairs of coordinates fall in the same region, they will generate the same geohash.

This concept can be extended into the six-dimensional space of the training data points. Instead of encoding and interleaving two values (i.e., latitude and longitude), the binary codes of six values are interleaved. The method of calculating each individual code resembles geohashing. For the angular velocity values, the code represents the binary search of the range $(\omega_{\min}, \omega_{\max})$, where $\omega_{\min}$ and $\omega_{\max}$ are the minimum and maximum expected angular velocities during the training period. The exact values of these parameters do not appear to be critical as long as the region encloses the normal operating space of the ADCS. This will ensure that all of the data points are placed into
the most accurate LSH bins. If the range is set too small, more points will be placed in the edge bins, while if the range is set too large, the points will be clustered toward the middle bins. The results of this study, presented later, indicate that the LSH algorithm does not play a significant role in the performance of the system.

In this study, a statistical analysis of the training sequence was used to estimate appropriate values for the range. The training sequence can be modeled as a random walk in which each step has a magnitude of

$$\Delta \omega = \frac{\tau}{J} \Delta t$$

(10)

where $\tau \in [-\tau_{\text{max}}, \tau_{\text{max}}]$ is randomly chosen uniform distribution, $\tau_{\text{max}}$ is the maximum allowed torque magnitude of the actuators during the training phase, $J$ is the spacecraft moment of inertia (MOI), and $\Delta t$ is the maneuver duration. As with a random walk, the final parameter value after $n$ steps will be

$$S_n = \sum_{i=1}^{n} X_n$$

(11)

where $X_n$ is the step size of the $n$th step (Taipale, n.d.). Therefore, the expected final value will be
\[ E(S_n) = E \left( \sum_{i=1}^{n} X_n \right) \]
\[ = \sum_{i=1}^{n} E(X_n) \]
\[ = 0 \]  

(12)

since \( X_n \) will fall uniformly in a range centered around zero. More interesting to this discussion is the standard deviation of the final value. Since the size of each step is uniformly distributed, the variance can be calculated as

\[ \sigma^2 = \text{Var} \left( \sum_{i=1}^{n} \frac{\Delta t}{J} X_n \right) \]
\[ = \sum_{i=1}^{n} \text{Var} \left( \frac{\Delta t}{J} X_n \right) \]
\[ = \frac{\Delta t^2}{J^2} \sum_{i=1}^{n} \frac{1}{\tau_{\text{max}} - (-\tau_{\text{max}})} \int_{-\tau_{\text{max}}}^{\tau_{\text{max}}} x^2 \, dx \]
\[ = \frac{\Delta t^2}{J^2} \sum_{i=1}^{n} \frac{1}{2\tau_{\text{max}}} \left( \frac{1}{3} \tau_{\text{max}}^3 - \frac{1}{3} (-\tau_{\text{max}})^3 \right) \]
\[ = \frac{\Delta t^2}{J^2} \sum_{i=1}^{n} \frac{1}{2\tau_{\text{max}}} \left( \frac{2}{3} \tau_{\text{max}}^3 \right) \]
\[ = \frac{\Delta t^2}{J^2} \sum_{i=1}^{n} \frac{1}{3} \tau_{\text{max}}^2 \]
\[ = \frac{n \tau_{\text{max}}^2 \Delta t^2}{3J^2} \]  

(13)
Therefore, the standard deviation is

\[ \sigma = \sqrt{\frac{n\tau_{\text{max}}^2 \Delta t^2}{3J^2}} \]

\[ = \frac{\tau_{\text{max}} \Delta t \sqrt{3n}}{3J} \] (14)

Since the final value \( S_n \) is normally distributed (Taipale, n.d.), no defined maximum or minimum value exists, and the value of three standard deviations is used instead:

\[ \omega_{\text{max}} = 3\sigma = \frac{\tau_{\text{max}} \Delta t \sqrt{3n}}{J} \] (15)

Note that although \( J \) and actuator characteristics (i.e., \( \tau_{\text{max}} \)) appear in this derivation, they are not required for the LSH algorithm. This limit does not have to be calculated from the parameters but could be taken from the maximum angular velocity constraints of the spacecraft. If the \( \omega_{\text{max}} \) is too high, this only means that there may be many unused LSH bins. Time constraints during this study forced the \( \omega_{\text{max}} \) and \( \tau_{\text{max}} \) to be determined from the spacecraft’s characteristics; however, the results of the experiments indicated that the LSH algorithm does not significantly affect the system’s performance.

Given \( \omega_{\text{max}} \) and \( \tau_{\text{max}} \), the three angular acceleration components of the datapoint can be encoded as
where $\alpha_i$ is the $i$th angular acceleration component, $\alpha_{\text{max}} = \frac{\tau_{\text{max}}}{J}$, and $B_{\text{dim}}$ is the number of LSH bins per dimension of the data point. The three angular velocity state components can be similar encoded as

$$b_i = \left\lfloor \frac{\omega_i}{\omega_{\text{max}}} \cdot B_{\text{dim}} \right\rfloor, i = 1, 2, 3$$

(17)

where $\omega_i$ is the $i$th angular velocity state component, and $\omega_{\text{max}}$ is the maximum expected angular velocity. The final step in the LSH algorithm is interleaving the component codes, giving


(18)

where $a_i[k]$ represents the $k$th bit (starting from LSb) of $a_i$, and $b_i[k]$ represents the $k$th bit of $b_i$. Figure 4 shows a simplified version of how the LSH algorithm generates this hash code.
Figure 4. Simplified demonstration of the LSH algorithm with two, one-dimensional quantities. In the implementation, both the initial angular velocity state and the output torque were three-dimensional vectors, so the final, interleaved code was 12 bits long. Although the figure uses output torque, the recommended implementation would use angular acceleration per the discussion of the training point collection.

Notice that the angular acceleration values are used in the LSb of $h$. In the event that the query hash bin is empty during the nearest neighbor search, the LSH code can be incremented to find neighboring bins from which to take the necessary points. Using angular acceleration values as the LSb means that neighboring bins with similar angular accelerations will be searched first. The bins are searched until enough points are found to meet the bandwidth requirements (e.g., 10 points).
Creating the local linear model. Once the nearest neighbors have been found, the algorithm seeks to find a system of three linear equations which relate the actuator torques to the angular acceleration around each of the three body axes, that is,

\[
\begin{align*}
    a_1 x_1 + b_1 x_2 + c_1 x_3 + d_1 x_4 + e_1 &= \alpha_x \\
    a_2 x_1 + b_2 x_2 + c_2 x_3 + d_2 x_4 + e_2 &= \alpha_y, \\
    a_3 x_1 + b_3 x_2 + c_3 x_3 + d_3 x_4 + e_3 &= \alpha_z
\end{align*}
\]  

(19)

where \(x_i\) is the torque command for the \(i\)th actuator and \(a_j, b_j, c_j, d_j\) are the linear coefficients of the torque commands for the \(j\)th axis, and \(e_j\) the bias for the \(j\)th axis. Each of the three equations is determined from the nearest neighbor points. For example, to calculate the coefficients \(a_1, b_1, c_1, d_1,\) and \(e_1\) from Equation 19, linear regression with the normal equations is used. The local nearest neighbors form a system of equations

\[
\begin{bmatrix}
    x_{11} & x_{12} & x_{13} & x_{14} & 1 \\
    x_{21} & x_{22} & x_{23} & x_{24} & 1 \\
    \vdots & \vdots & \vdots & \vdots & \vdots \\
    x_{n1} & x_{n2} & x_{n3} & x_{n4} & 1 \\
\end{bmatrix}
\begin{bmatrix}
    a_1 \\
    b_1 \\
    c_1 \\
    d_1 \\
    e_1 \\
\end{bmatrix}
= \begin{bmatrix}
    \alpha_{1x} \\
    \alpha_{2x} \\
    \vdots \\
    \alpha_{nx}
\end{bmatrix},
\]  

(20)

where \(x_{ij}\) is the \(j\)th actuator torque command used in the \(i\)th local training point, \(\alpha_{ix}\) is the angular acceleration around the \(x\)-axis resulting from the \(i\)th local training point, and \(n\) is the bandwidth of the local learning algorithm. The normal equations provide a method of solving for values of \(a_1, b_1, c_1, d_1,\) and \(e_1\) that give the least-squares approximation of the relationship. Given a matrix equation of the form \(Ax = b,\)
the normal equations become $A^T Ax = A^T b$, where $A^T A$ is known as the normal matrix.

Solving this matrix equation for $x$ gives the values of the coefficients of the least-squares regression. Using this process, $a_1, b_1, c_1, d_1, e_1$ from Equation 20 can be found. By repeating this process, the algorithm can solve for $a_j, b_j, c_j, d_j, e_j$ for each axis.

Once all three equations have been found, the coefficients can be substituted in Equation 19 and $\alpha_x, \alpha_y,$ and $\alpha_z$ are set to the desired angular accelerations generated by the PID control law.

**Solving for actuator torque commands.** To solve for the necessary actuator torque commands, the system from Equation 19 is put in matrix form:

\[
\begin{bmatrix}
a_1 & b_1 & c_1 & d_1 & e_1 \\
a_2 & b_2 & c_2 & d_2 & e_2 \\
a_3 & b_3 & c_3 & d_3 & e_3 \\
\end{bmatrix}
\begin{bmatrix}
x_1 \\
x_2 \\
x_3 \\
x_4 \\
1
\end{bmatrix}
= 
\begin{bmatrix}
\alpha_x \\
\alpha_y \\
\alpha_z
\end{bmatrix}.
\]  

(21)

Instead of finding the inverse of the matrix to solve for the actuator values, Gauss-Jordan elimination can be applied to the augmented matrix:

\[
\begin{bmatrix}
a_1 & b_1 & c_1 & d_1 & e_1 & \alpha_x \\
a_2 & b_2 & c_2 & d_2 & e_2 & \alpha_y \\
a_3 & b_3 & c_3 & d_3 & e_3 & \alpha_z
\end{bmatrix}.
\]  

(22)

After Gauss-Jordan elimination, the matrix takes the form:
This represents the following system:

$$
\begin{align*}
1 & \quad 0 & \quad 0 & \quad d'_1 & \quad e'_1 & | \quad \alpha'_x \\
0 & \quad 1 & \quad 0 & \quad d'_2 & \quad e'_2 & | \quad \alpha'_y \\
0 & \quad 0 & \quad 1 & \quad d'_3 & \quad e'_3 & | \quad \alpha'_z
\end{align*}
$$

(23)

If only three actuators were used, the system would be determined, and there will be a single solution. However, four or more actuators will create an overdetermined system. This study investigates a four-actuator system, but the results can be extended to any number of actuators.

**Handling overdetermined equations.** An overdetermined system means that three of the actuator commands are dependent on the fourth command and the constant term. The fourth actuator command is a free variable and can take on any value within the actuator’s operating range. This solution space can be searched for the optimal set of actuator commands. Rearranging Equation 24 gives

$$
\begin{align*}
\dot{x}_1 + d'_1 x_4 + e'_1 &= \alpha'_x \\
\dot{x}_2 + d'_2 x_4 + e'_2 &= \alpha'_y \\
\dot{x}_3 + d'_3 x_4 + e'_3 &= \alpha'_z
\end{align*}
$$

(24)

Returning Equation 27 to matrix form allows easy calculation of the solution space.
Expanding the matrix multiplication in Equation 28 confirms that it equals Equation 27. Optimality is determined by a heuristic function. In this study, the heuristic was designed to minimize the magnitude of torque applied to the spacecraft, i.e.,

$$h(x) = \sum_{i=1}^{4} x_i^2$$

where $$x = [x_1, x_2, x_3, x_4]^T$$. By stepping through the solution space, the actuator commands with the smallest heuristic value can be found. Once the optimal result has been reached, the torque commands are applied to the reaction wheels.

**Simulation Using NASA’s 42**

In order to test the lazy learning algorithm, simulations were run using 42, an open-source simulation software developed at NASA’s Goddard Space Flight Center (see Appendix A). Configuration files are used to specify aspects of the simulation, such as which environmental effects to simulate, the spacecraft’s 3D model and characteristics, starting orbit and time, etc. (see Appendix B). The simulations in this study were run with aerodynamic forces and torques, solar pressure forces and torques, gravity gradient torques, gravity perturbation forces, and reaction wheel imbalance forces and torques. To control the simulated spacecraft, users develop a custom flight software (FSW) function
in C that is called at each step of the simulation and implements custom control algorithms.

**C Software Architecture**

The implementation of the algorithm was developed in C. The code can be divided into three primary sections: (a) matrix operations, (b) ADCS functions, and (c) main flight software loop (see Appendix C).

**Matrix operations.** It is advantageous to create a set of matrix manipulation functions to facilitate building the lazy learning model. Although existing C/C++ libraries for matrix operations exist, the decision was made to create a custom lightweight implementation that only included what was needed (Free Software Foundation, n.d.). This library would be more practical than a complete library of numerical operations when porting the code to an embedded target. The matrix content and dimensions are stored in a structure which is modified by a set of matrix operation functions. The datatype of the matrices is fixed to double. The matrix functions include initializing matrices, getting and setting elements, matrix addition, matrix multiplication, scalar multiplication, row multiplication, row addition, transposition, horizontal and vertical concatenation, horizontal splitting, reduced row echelon form, duplication, deletion, and debug printing.

**ADCS functions.** Building off of the matrix operations, a set of ADCS functions provides locality sensitive hashing, manages the training sequence, and handles lazy learning queries. Training data points are stored in a data structure that has fields for the initial angular velocity state, the actuator commands, and the resulting angular
acceleration. The lazy learning database is stored as a list of LSH bins. Each bin is represented by a structure holding an array of data points, the size of the bin, and the number of points in the bin. An ADCS structure holds the LSH bins, a pointer to the heuristic function, and the current state of the ADCS. The ADCS has four states: IDLE, TRAIN, MOVE, and RESET.

**Main flight software loop.** The main flight software loop transitions the system between the four ADCS states to test the performance of the algorithm. The program flow is summarized in Figure 5.

![Flowchart of the C flight software used in the simulations with NASA’s 42](attachment:flowchart.png)

*Figure 5. Flowchart of the C flight software used in the simulations with NASA’s 42*
Training data collection. The flight software initializes by creating the ADCS structure and starting in the TRAIN state. During training, the system performs four actions: (a) initialize the training sequence, (b) generate a random torque command, (c) wait for maneuver completion, and (d) store the results in the database. After storing the result, the training loop returns to step (b) to gather another data point. Once all the data points have collected, the ADCS state is changed from TRAIN to IDLE.

Return to initial orientation. Once reaching the IDLE state for the first time, the flight software changes the state to RESET. This function seeks to use the newly acquired training data to reset the spacecraft’s orientation back to $\theta_0 = \langle 0,0,0 \rangle$. More importantly, this phase allows the test maneuver that follows to be started from same position for all the trials. Once the angular velocity and position are reset within the required thresholds, the flight software advances the ADCS to the MOVE state.

Rotation to target orientation. In the MOVE state, the spacecraft attempts to rotate to the target orientation of $\theta_f = \langle \pi/4 , \pi/4 , \pi/4 \rangle$. In quaternion form, this orientation becomes $q_f = 0.462\hat{i} + 0.191\hat{j} + 0.462\hat{k} + 0.733$. Using a PID control law in combination with the lazy learning algorithm, the spacecraft applies torques to the four actuators to reach the target attitude. During this movement, the angular position error for each axis is written to a log file.

Test parameters. This study focuses on evaluating the effect of the lazy learning database size and bandwidth on the performance of the ADCS as measured by the time required to rotate from $\theta_0$ to $\theta_f$. Five different values were tested for each parameter, and each test consisted of 100 trials. Since two configurations overlapped, nine total
parameter combinations were tested. The training database size was tested with 10, 50, 100, 500, and 1000 points while the bandwidth was held constant at 10 points. Then, the bandwidth was varied with values of 1, 5, 10, 15, and 20 points while the training database size was held constant at 100 points.

**Results**

Figures 6 through 14 show representative samples of the rotation to the target orientation for each of the nine parameter combinations. Figures 6 through 10 cover the variation of the training point database size while Figures 11 through 14 show the remaining results for the bandwidth tests. Table 1 contains the statistical results of the simulations for each configuration.

Table 1

<table>
<thead>
<tr>
<th>Test</th>
<th>Training Points</th>
<th>Bandwidth</th>
<th>Avg. Time (sec)</th>
<th>S (sec)</th>
<th>Failures</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>10</td>
<td>10</td>
<td>3.8171</td>
<td>0.0095</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>50</td>
<td>10</td>
<td>3.8173</td>
<td>0.0145</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>100</td>
<td>10</td>
<td>3.8157</td>
<td>0.0188</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>500</td>
<td>10</td>
<td>3.8074</td>
<td>0.0294</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>1000</td>
<td>10</td>
<td>3.8025</td>
<td>0.0316</td>
<td>0</td>
</tr>
<tr>
<td>6</td>
<td>100</td>
<td>1</td>
<td>-</td>
<td>-</td>
<td>100</td>
</tr>
<tr>
<td>7</td>
<td>100</td>
<td>5</td>
<td>3.8241</td>
<td>0.0952</td>
<td>2</td>
</tr>
<tr>
<td>8</td>
<td>100</td>
<td>15</td>
<td>3.8151</td>
<td>0.0138</td>
<td>0</td>
</tr>
<tr>
<td>9</td>
<td>100</td>
<td>20</td>
<td>3.8143</td>
<td>0.0135</td>
<td>0</td>
</tr>
</tbody>
</table>

Interestingly, once the bandwidth was at least five data points, the average time required to rotate to the target remained largely the same across all the tests. Adding more points to the database in an attempt to more precisely capture any nonlinearity or expanding the bandwidth to smooth the lazy linear approximation did not impact the overall performance of the algorithm. This seems to indicate that the relationship between
actuator commands and resulting angular acceleration was linear. Once enough points were used to capture this relationship, no additional points in either the training database or the bandwidth were needed.

Figure 6. Rotation to target attitude with 10 training points and a lazy learning bandwidth of 10.

Figure 7. Rotation to target attitude with 50 training points and a lazy learning bandwidth of 10.
**Figure 8.** Rotation to target attitude with 100 training points and a lazy learning bandwidth of 10.

**Figure 9.** Rotation to target attitude with 500 training points and a lazy learning bandwidth of 10.
Figure 10. Rotation to target attitude with 1000 training points and a lazy learning bandwidth of 10.

Figure 11. Rotation to the target attitude with 100 training points and a lazy learning bandwidth of 1. This was the only set of tests to significantly fail.
Figure 12. Rotation to the target attitude with 100 training points and a lazy learning bandwidth of 5.

Figure 13. Rotation to the target attitude with 100 training points and a lazy learning bandwidth of 15.
The linearity present in the results was not expected based on the original understanding of spacecraft attitude dynamics and control systems. This prodded a deeper investigation into rotational dynamics and the architecture of attitude control systems to see if this linearity could have been predicted. As described by both Snider (2010) and by Princeton Satellite Systems (2000), satellite attitude dynamics are nonlinear due to the interaction between the three separate axes.

To control this nonlinear plant, attitude control systems linearize the problem by reducing the range around an operating point and apply a linear control law, such as PID (Princeton Satellite Systems, 2000; Snider, 2010). Developed via control system theory, these laws determine the stability of the system, and the previous adaptive studies
discussed in the literature review have researched the stability of various control laws when encountering partial or complete actuator failure.

The expectation that reaction wheels would have a nonlinear response to torque commands, especially in the presence of friction, justified the exploration of using lazy local learning to intelligently adapt the control system in the presence of changing nonlinearity in the actuator’s response. The lazy learning algorithm described in this study improves on Russell and Straub (2017) by using LSH instead of treating each axis of the training point independently. LSH allows for the algorithm to account for the interdependence of the rotation axes by including all six elements of the training point at once in the hashing algorithm. In addition, using the normal equations for linear regression allows the algorithm to use varying bandwidths (i.e., numbers of training points) when constructing the local linear models, a flexibility that was not present in the methods presented by Russell and Straub (2017). These modifications would increase the flexibility of the lazy local learning algorithm in the presence of nonlinearities, such as those expected in the actuators.

Although the relationship between electrical current and reaction wheel speed is truly nonlinear, both Carrara and Kuga (2013) and Princeton Satellite Systems (2000) note that when operated in speed control mode, reaction wheels have an internal feedback loop which ensures they produce the required torque response, removing this nonlinearity. Therefore, the nonlinearity of rotational dynamics is removed by linearizing the system around an operating point, and the nonlinearity of actuator response is removed via an internal feedback loop.
With this improved knowledge, the system described in this study is better understood as an adaptive torque distribution system. After the control law has calculated the torques that should be applied to the system, the torques must be distributed among the actual actuators located on the spacecraft (Princeton Satellite Systems, 2000). In effect, the torque distribution process projects the desired torques from the body axes onto the actuator axes. If the spacecraft has more than three actuators, their axes will not be linearly independent (four axis vectors in three dimensions), and a cost function similar to the heuristic within the lazy learning algorithm can be used to find an optimal projection. Since the reaction wheel feedback control removes the nonlinearity from the actuator response, this projection is linear, matching the results of this study. This means that instead of searching the training database for relevant points and creating a local linear model for each query, the linear torque distribution matrix could be calculated once initially. A fault detection system could identify degradation and failure of actuators, triggering a new linear distribution matrix to be calculated. Such a system would be valuable since it would allow the distribution matrix to be calculated during mission operations without previous knowledge of the spacecraft, mitigating actuator misalignment and inertial issues.

If the reaction wheels used current control instead of speed control, the nonlinearity of the wheels would emerge. In this scenario, the torque distribution process would translate the desired torques from the control law into current levels to supply to the wheels. A lazy local learning system could potentially be used in this application to account for the nonlinearity.
Conclusions

This study seeks to further investigate the application of lazy local learning to adaptive, fault-tolerant attitude determination and control systems for spacecraft. The results show that the input/output relationship for reaction wheels is predominately linear in nominal operating scenarios and is not significantly impacted by the number of training points or local learning bandwidth. This reflects the linear nature of the torque distribution process. The expected nonlinearity of the rotational dynamics is limited by the control law design, while the nonlinearity of the actuator response is removed by an internal feedback control loop within the reaction wheels. From these results, the torque distribution process can be simplified by removing the lazy learning aspect while retaining the training process to account for actuator misalignments. Future work could explore the application of the lazy local learning algorithm to current-controlled reaction wheels or the continued adaptation of the linear torque distribution matrix in the presence of actuator degradation and failure.
REFERENCES


http://hubblesite.org/the_telescope/team_hubble/servicing_missions.php


http://hdl.handle.net/2060/20110007876


Getting Started with NASA’s 42 Simulation Framework on a UNIX-based Machine

1. Download the 42 archive from the official Sourceforge page:
   https://sourceforge.net/projects/fortytwospacecraftsimulation/

2. Unzip the archive and navigate to the folder from the command line (e.g., “cd Downloads/42”)

3. Edit the Makefile to ensure that the proper build platform is selected. 42 will attempt to auto-detect the platform, but the manual backup should be set to the correct value in case the auto-detect fails. The default is Linux. Find the AUTOPLATFORM lines at the top of the Makefile, uncomment the line corresponding to the current platform, and comment out the lines for the other platforms (see bolded text in the Makefile in Appendix B). The Makefile from Appendix B is configured for macOS.

4. Build the executable by running “make” in the 42 folder from the command line. If linker errors are encountered while trying to build the executable, use “make clean” to clean the output folders.

5. Test the build by running the executable (“./42”). Several windows should open including a 3D view of the spacecraft and a ground track. If using the Inp_Sim.txt from Appendix B, change the time mode to REAL and the graphics front-end to TRUE to see these windows appear.

6. This study added additional source files to the framework (see Appendix C). A folder named “adcs” with “src” and “build” subfolders was created in the main 42 directory.
The Makefile was changed to add these source files to the build process (see bolded text in the Makefile in Appendix B).

Additional documentation can be found in the Docs folder of the 42 main directory or within the configuration files themselves.
Appendix B

42 Simulator Configuration Files

Inp_Sim.txt

<<<<<<< 42: The Mostly Harmless Simulator >>>>>>>
Simulation Control

FAST
! Time Mode (FAST, REAL, or EXTERNAL)
300.0 0.001
! Sim Duration, Step Size [sec]
0.01
! File Output Interval [sec]
FALSE
! Graphics Front End?
Inp_Cmd.txt
! Command Script File Name

Reference Orbits

1
! Number of Reference Orbits
TRUE Orb_LEO.txt
! Input file name for Orb 0

Spacecraft

1
! Number of Spacecraft
TRUE 0 SC_CubeSat1U_Custom.txt
! Existence, RefOrb, Input file for SC 0

Environment

USER_DEFINED
! Model Date Interpolation for Solar Flux and AP values?(TWOSIGMA_KP, NOMINAL or USER_DEFINED)
230.0
! If USER_DEFINED, enter desired F10.7 value
100.0
! If USER_DEFINED, enter desired AP value
IGRF
! Magfield (NONE,DIPole,IGRF)
8 8
! IGRF Degree and Order (<10)
2 0
! Mars Gravity Model N and M (<18)
2 0
! Luna Gravity Model N and M (<18)
TRUE
! Aerodynamic Forces & Torques
TRUE
! Gravity Gradient Torques
TRUE
! Solar Pressure Forces & Torques
TRUE
! Gravity Perturbation Forces
FALSE
! Passive Joint Forces & Torques
FALSE
! Thruster Plume Forces & Torques
TRUE
! RWA Imbalance Forces and Torques
TRUE
! Contact Forces and Torques
FALSE
! CFD Slosh Forces and Torques
FALSE
! Output Environmental Torques to Files

Celestial Bodies of Interest

FALSE
! Mercury
FALSE
! Venus
TRUE
! Earth and Luna
FALSE
! Mars and its moons
FALSE
! Jupiter and its moons
FALSE
! Saturn and its moons
FALSE
! Uranus and its moons
FALSE
! Neptune and its moons
FALSE
! Pluto and its moons
FALSE
! Asteroids and Comets

Lagrange Point Systems of Interest

FALSE
! Earth-Moon
FALSE
! Sun-Earth
FALSE
! Sun-Jupiter

Ground Stations

5
! Number of Ground Stations
TRUE EARTH -77.0 37.0 "GSFC"
! Exists, World, Lng, Lat, Label
TRUE EARTH -155.6 19.0 "South Point"
! Exists, World, Lng, Lat, Label
TRUE EARTH 115.4 -29.0 "Dongara"
! Exists, World, Lng, Lat, Label
TRUE EARTH -71.0 -33.0 "Santiago"
! Exists, World, Lng, Lat, Label
TRUE LUNA 45.0 45.0 "Moon Base Alpha"
! Exists, World, Lng, Lat, Label
ADAPTIVE, FAULT-TOLERANT ATTITUDE CONTROL

SC_CubeSat1U_Custom.txt

<<<<<<<<<<<  42: Spacecraft Description File  >>>>>>>>>>

1-U Cubesat  ! Description
"Cube 1"  ! Label
GenScSpriteAlpha.ppm  ! Sprite File Name
AD_HOC_FSW  ! Flight Software Identifier

************************* Orbit Parameters ***************************
ENCKE  ! Orbit Prop FIXED, EULER_HILL, or ENCKE
CM  ! Pos of CM or ORIGIN, wrt F
0.00000 0.00000 2.50000 ! Pos wrt F
0.00566 0.00283 -0.00000 ! Vel wrt F

*************************** Initial Attitude ***************************
NAN  ! Ang Vel wrt [NL], Att [QA] wrt [NLF]
0.0 0.0 0.0  ! Quaternion
0.0 0.0 0.0 1.0  ! Ang Vel (deg/sec)
0.0 0.0 0.0 123  ! Angles (deg) & Euler Sequence

*************************** Dynamics Flags ***************************
KIN_JOINT  ! Rotation STEADY, KIN_JOINT, or DYN_JOINT
TRUE  ! Assume constant mass properties
FALSE  ! Passive Joint Forces and Torques Enabled
FALSE  ! Compute Constraint Forces and Torques
REFPT_CM  ! Mass Props referenced to REFPT_CM or REFPT_JOINT
FALSE  ! Flex Active
FALSE  ! Include 2nd Order Flex Terms
2.0  ! Drag Coefficient

*************************** Body Parameters ***************************
1  ! Number of Bodies

************** Body 0 **************
1.0  ! Mass (kg)
0.0017 0.0017 0.0017  ! Moments of Inertia (kg-m^2)
0.0 0.0 0.0  ! Products of Inertia (xy,xz,yz)
0.0 0.0 0.0  ! Location of mass center, m
0.0 0.0 0.0  ! Constant Embedded Momentum (Nms)
Cubesat_1U.obj  ! Geometry Input File Name
NONE  ! Flex File Name

*************************** Joint Parameters ***************************
(Number of Joints is Number of Bodies minus one)

************** Joint 0 **************
0 1  ! Inner, outer body indices
213 GIMBAL  ! RotDOF, Seq, GIMBAL or SPHERICAL
1 123  ! TrnDOF, Seq
FALSE FALSE FALSE  ! RotDOF Locked
FALSE FALSE FALSE  ! TrnDOF Locked
0.0 0.0 0.0  ! Initial Angles [deg]
0.0 0.0 0.0  ! Initial Rates, deg/sec
0.0 0.0 0.0  ! Initial Displacements [m]
0.0 0.0 0.0  ! Initial Displacement Rates, m/sec
0.0 0.0 0.0 312  ! Bi to Gi Static Angles [deg] & Seq
0.0 0.0 0.0 312  ! Go to Bo Static Angles [deg] & Seq
0.0 0.0 0.0  ! Position wrt inner body origin, m
0.0 0.0 0.0  ! Position wrt outer body origin, m
0.0 0.0 0.0  ! Rot Passive Spring Coefficients (Nm/rad)
0.0 0.0 0.0  ! Rot Passive Damping Coefficients (Nms/rad)
0.0 0.0 0.0  ! Trn Passive Spring Coefficients (N/m)
0.0 0.0 0.0  ! Trn Passive Damping Coefficients (Ns/m)

*************************** Wheel Parameters ***************************
4  ! Number of wheels

************** Wheel 0 **************
0.0  ! Initial Momentum, N-m-sec
0.5 0.5 0.5  ! Wheel Axis Components, [X, Y, Z]
0.004 0.015  ! Max Torque (N-m), Momentum (N-m-sec)

(http://bluecanyontech.com/wp-content/uploads/2017/03/DataSheet_RW_06.pdf)
## Adaptive, Fault-Tolerant Attitude Control

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wheel Rotor Inertia</td>
<td>~ = 0.00003 kg m^2</td>
</tr>
<tr>
<td>Static Imbalance</td>
<td>~ = 0.12 g cm</td>
</tr>
<tr>
<td>Dynamic Imbalance</td>
<td>~ = 0.20 g cm^2</td>
</tr>
<tr>
<td>Flex Node Index</td>
<td>~ = 0.0</td>
</tr>
</tbody>
</table>

### Wheel 1
- Initial Momentum: 0.0 N m sec
- Wheel Axis Components: [X, Y, Z]
- Max Torque: 0.004 N m, Momentum: 0.015 N m sec
- Wheel Rotor Inertia: 0.00003 kg m^2 (estimated)
- Static Imbalance: 0.12 g cm
- Dynamic Imbalance: 0.20 g cm^2
- Flex Node Index: 0

### Wheel 2
- Initial Momentum: 0.0 N m sec
- Wheel Axis Components: [X, Y, Z]
- Max Torque: 0.004 N m, Momentum: 0.015 N m sec
- Wheel Rotor Inertia: 0.00003 kg m^2 (estimated)
- Static Imbalance: 0.12 g cm
- Dynamic Imbalance: 0.20 g cm^2
- Flex Node Index: 0

### Wheel 3
- Initial Momentum: 0.0 N m sec
- Wheel Axis Components: [X, Y, Z]
- Max Torque: 0.004 N m, Momentum: 0.015 N m sec
- Wheel Rotor Inertia: 0.00003 kg m^2 (estimated)
- Static Imbalance: 0.12 g cm
- Dynamic Imbalance: 0.20 g cm^2
- Flex Node Index: 0

### MTB Parameters
- Number of MTBs: 3
- Saturation (A m^2): 180.0
- MTB Axis Components: [X, Y, Z]
- MTB Axis Components: [X, Y, Z]
- MTB Axis Components: [X, Y, Z]

### Thruster Parameters
- Number of Thrusters: 0
- Thrust Force (N): 1.0
- Location in B0, m: 1.0

### CMG Parameters
- Number of CMGs: 0
- CMG DOF: Typically 1 or 2
- Initial Gimbal Angles [deg] and Seq: 0.0 0.0 0.0 123
- Initial Gimbal Angle Rates, deg/sec: 0.0 0.0 0.0
- Static Mounting Angles [deg] and Seq: -90.0 0.0 -54.74 123
- Rotor Inertia, kg m^2: 0.12
- Momentum, Nms: 75.0
- Max Gimbal Angle Rates, deg/sec: 1.0 0.0 0.0

---

### Makefile

```makefile
# Let's try to auto-detect what platform we're on.
# If this fails, set 42PLATFORM manually in the else block.
AUTOPLATFORM = Failed
ifeq ($(PLATFORM),apple)
  AUTOPLATFORM = Succeeded
  42PLATFORM = __APPLE__
```
endf
ifeq ($(PLATFORM), linux)
  AUTOPLATFORM = Succeeded
  42PLATFORM = __linux__
endif
ifeq ($(MSYSTEM), MINGW32)
  AUTOPLATFORM = Succeeded
  42PLATFORM = __MSYS__
endif
ifeq ($(AUTOPLATFORM), Failed)
  # Autodetect failed. Set platform manually.
  # 42PLATFORM = __APPLE__
  # 42PLATFORM = __linux__
  # 42PLATFORM = __MSYS__
endif

GUIFLAG = -D _USE_GUI_
#GUIFLAG =

SHADERFLAG = -D _USE_SHADERS_
#SHADERFLAG =

#TIMEFLAG =
TIMEFLAG = -D _USE_SYSTEM_TIME_

CFDFLAG =
#CFDFLAG =

FFTBFLAG =
#FFTBFLAG = -D _ENABLE_FFTB_CODE_

# Basic directories
HOMEDIR = ./
PROJDIR = ./
KITDIR = $(PROJDIR)Kit/
OBJ = $(PROJDIR)Object/
INC = $(PROJDIR)Include/
SRC = $(PROJDIR)Source/
KITINC = $(KITDIR)Include/
KITSRC = $(KITDIR)Source/
INOUT = $(PROJDIR)InOut/
PRIVSRC = $(PROJDIR)/Private/Source/

#EMBEDDED = -D EMBEDDED_MATLAB
EMBEDDED =

ifeq ($(strip $(EMBEDDED)),)
  MATLABROOT = "C:/Program Files/MATLAB/R2010b/"
  MATLABINC = $(MATLABROOT)extern/include/
  SIMULINKINC = $(MATLABROOT)simulink/include/
  MATLABLIB = -leng -lmx -lmmathutil
  MATLABSRC = $(PROJDIR)External/MATLABSRC/
else
  MATLABROOT =
  MATLABINC =
  SIMULINKINC =
  MATLABLIB =
  MATLABSRC =
endif

ifeq ($(42PLATFORM), __APPLE__)
  # Mac Macros
  CINC = -I /usr/include
  EXTERNDIR =
  GLINC = -I /System/Library/Frameworks/OpenGL.framework/Headers/ -I
  /System/Library/Frameworks/GLUT.framework/Headers/
  # ARCHFLAG = -arch i386
  ARCHFLAG = -arch x86_64
ADAPTIVE, FAULT-TOLERANT ATTITUDE CONTROL

#SOCKETFLAG =
SOCKETFLAG = -D _ENABLE_SOCKETS_

ifneq ($(strip $(EMBEDDED)),)
  LFLAGS = -bind_at_load -m64 -L$(MATLABROOT)bin/maci64
  LIBS = -framework System -framework Carbon -framework OpenGL -framework GLUT
  $(MATLABLIB)
else
  LFLAGS = -bind_at_load
  LIBS = -framework System -framework Carbon -framework OpenGL -framework GLUT
endif
GUIOBJ = $(OBJ)42GlutGui.o $(OBJ)glkit.o
EXENAME = 42
CC = gcc
endif

ifeq ($(42PLATFORM),__linux__)
  # Linux Macros
  CINC =
  EXTERNDIR =
  #SOCKETFLAG =
  SOCKETFLAG = -D _ENABLE_SOCKETS_
  ifneq ($(strip $(GUIFLAG)),)
    GUIOBJ = $(OBJ)42GlutGui.o $(OBJ)glkit.o
    #GLINC = -I /usr/include/
    GLINC = -I $(KITDIR)/include/GL/
    LIBS = -lglut -lGLU -lGL
    LFLAGS = -L $(KITDIR)/GL/lib/
    ARCHFLAG =
  else
    GUIOBJ =
    GLINC =
    LIBS =
    LFLAGS =
    ARCHFLAG =
  endif
  EXENAME = 42
  CC = g++
endif

ifeq ($(42PLATFORM),__MSYS__)
  CINC =
  EXTERNDIR = /c/42ExternalSupport/
  #SOCKETFLAG =
  SOCKETFLAG = -D _ENABLE_SOCKETS_
  ifneq ($(strip $(GUIFLAG)),)
    GLEW = $(EXTERNDIR)Glew/
    GLUT = $(EXTERNDIR)freenglut/
    LIBS = -lopengl32 -lglu32 -lfreeglut -lws2_32 -lglew32
    LFLAGS = -L $(GLEW)lib/ -L $(Glew)lib/
    GUIOBJ = $(OBJ)42GlutGui.o $(OBJ)glkit.o
    GLINC = -I $(GLEW)include/GL/ -I $(Glew)include/GL/
    ARCHFLAG = -D GLUT_NO_LIB_PRAGMA -D GLUT_NO_WARNING_DISABLE -D GLUT_DISABLE_ATEXIT_HACK
  else
    GUIOBJ =
    GLINC =
    LIBS =
    LFLAGS =
    ARCHFLAG =
  endif
  ifneq ($(strip $(EMBEDDED)),)
    LFLAGS = -L $(GLUT)lib/ -m64 -L$(MATLABROOT)bin/win32
LIBS = -lopengl32 -lglu32 -lfreeglut $(MATLABLIB)
endif
EXENAME = 42.exe
CC = gcc
endif

# If not using GUI, don't compile GUI-related files
ifeq ($($(strip $(GUIFLAG))),)
    GUIOBJ =
endif

# If not using IPC, don't compile IPC-related files
ifneq ($(strip $(SOCKETFLAG))),
    IPCOBJ = $(OBJ)42ipc.o
else
    IPCOBJ =
endif

# If not in FFTB, don't compile FFTB-related files
ifneq ($(strip $(FFTBFLAG))),
    FFTBOBJ = $(OBJ)42fftb.o
else
    FFTBOBJ =
endif

CFLAGS = -Wall -Wshadow -Wno-deprecated -g $(GLINC) $(CINC) -I $(INC) -I $(KITINC) -I $(KITSRC) -I $(MATLABINC) -I $(MATLABINC) -I $(SIMULINKINC) -O0 $(ARCHFLAG) $(GUIFLAG) $(SHADERFLAG) $(TIMEFLAG) $(SOCKETFLAG) $(ITEMFLAG) $(CFDFLAG) $(FTFBUFLAG)

42OBJ = $(OBJ)42main.o $(OBJ)42exec.o $(OBJ)42actuators.o $(OBJ)42cmd.o \ $(OBJ)42dynams.o $(OBJ)42environ.o $(OBJ)42ephem.o $(OBJ)42fsw.o \ $(OBJ)42init.o $(OBJ)42perturb.o $(OBJ)42report.o \ $(OBJ)42sensors.o
ifneq ($(strip $(CFDFLAG))),
    SLOSHOBJ = $(OBJ)42CfdSlosh.o
else
    SLOSHOBJ =
endif

KITOBJ = $(OBJ)dcmkit.o $(OBJ)envkit.o $(OBJ)fswkit.o $(OBJ)geomkit.o \ $(OBJ)ikit.o $(OBJ)mthkit.o $(OBJ)nrmsise0kit.o $(OBJ)nis86kit.o \ $(OBJ)orbkit.o $(OBJ)sigkit.o $(OBJ)sphkit.o $(OBJ)timekit.o
ifneq ($(strip $(EMBEDDED))),
    MATLABOBJ = $(OBJ)DetectorFSW.o $(OBJ)OpticsFSW.o
else
    MATLABOBJ =
endif

# custom ADCS
ADCSOBJ = ./adcs/build/ADCS_main.o ./adcs/build/Matrix.o

# Rules to link 42
$(OBJ)42main.o : $(SRC)42main.c
    $(CC) $(CFLAGS) -c $(SRC)42main.c -o $(OBJ)42main.o

$(OBJ)42exec.o : $(SRC)42exec.c $(INC)42.h
    $(CC) $(CFLAGS) -c $(SRC)42exec.c -o $(OBJ)42exec.o
ADAPTIVE, FAULT-TOLERANT ATTITUDE CONTROL

$(OBJ)42actuators.o : $(SRC)42actuators.c $(INC)42.h $(INC)42fsw.h $(INC)fswdefines.h $(INC)fswtypes.h
$(CC) $(CFLAGS) -c $(SRC)42actuators.c -o $(OBJ)42actuators.o

$(OBJ)42cmd.o : $(SRC)42cmd.c $(INC)42.h $(INC)42fsw.h $(INC)fswdefines.h $(INC)fswtypes.h
$(CC) $(CFLAGS) -c $(SRC)42cmd.c -o $(OBJ)42cmd.o

$(OBJ)42dynam.o : $(SRC)42dynam.c $(INC)42.h
$(CC) $(CFLAGS) -c $(SRC)42dynam.c -o $(OBJ)42dynam.o

$(OBJ)42environs.o : $(SRC)42environs.c $(INC)42.h
$(CC) $(CFLAGS) -c $(SRC)42environs.c -o $(OBJ)42environs.o

$(OBJ)42ephem.o : $(SRC)42ephem.c $(INC)42.h
$(CC) $(CFLAGS) -c $(SRC)42ephem.c -o $(OBJ)42ephem.o

$(OBJ)42fsw.o : $(SRC)42fsw.c $(INC)42fsw.h $(INC)fswdefines.h $(INC)fswtypes.h
$(CC) $(CFLAGS) -c $(SRC)42fsw.c -o $(OBJ)42fsw.o

$(OBJ)42GlutGui.o : $(SRC)42GlutGui.c $(INC)42.h $(INC)42GlutGui.h $(KITSRC)CamShaders.glsl $(KITSRC)MapShaders.glsl
$(CC) $(CFLAGS) -c $(SRC)42GlutGui.c -o $(OBJ)42GlutGui.o

$(OBJ)42init.o : $(SRC)42init.c $(INC)42.h
$(CC) $(CFLAGS) -c $(SRC)42init.c -o $(OBJ)42init.o

$(OBJ)42ipc.o : $(SRC)42ipc.c $(INC)42.h
$(CC) $(CFLAGS) -c $(SRC)42ipc.c -o $(OBJ)42ipc.o

$(OBJ)42perturb.o : $(SRC)42perturb.c $(INC)42.h
$(CC) $(CFLAGS) -c $(SRC)42perturb.c -o $(OBJ)42perturb.o

$(OBJ)42report.o : $(SRC)42report.c $(INC)42.h
$(CC) $(CFLAGS) -c $(SRC)42report.c -o $(OBJ)42report.o

$(OBJ)42sensors.o : $(SRC)42sensors.c $(INC)42.h $(INC)42fsw.h $(INC)fswdefines.h $(INC)fswtypes.h
$(CC) $(CFLAGS) -c $(SRC)42sensors.c -o $(OBJ)42sensors.o

$(OBJ)dcmkit.o : $(KITSRC)dcmkit.c
$(CC) $(CFLAGS) -c $(KITSRC)dcmkit.c -o $(OBJ)dcmkit.o

$(OBJ)envkit.o : $(KITSRC)envkit.c
$(CC) $(CFLAGS) -c $(KITSRC)envkit.c -o $(OBJ)envkit.o

$(OBJ)fswkit.o : $(KITSRC)fswkit.c
$(CC) $(CFLAGS) -c $(KITSRC)fswkit.c -o $(OBJ)fswkit.o

$(OBJ)glkit.o : $(KITSRC)glkit.c $(KITSRC)glkit.h
$(CC) $(CFLAGS) -c $(KITSRC)glkit.c -o $(OBJ)glkit.o

$(OBJ)geomkit.o : $(KITSRC)geomkit.c $(KITSRC)geomkit.h
$(CC) $(CFLAGS) -c $(KITSRC)geomkit.c -o $(OBJ)geomkit.o

$(OBJ)iokit.o : $(KITSRC)iokit.c
$(CC) $(CFLAGS) -c $(KITSRC)iokit.c -o $(OBJ)iokit.o

$(OBJ)mathkit.o : $(KITSRC)mathkit.c
$(CC) $(CFLAGS) -c $(KITSRC)mathkit.c -o $(OBJ)mathkit.o

$(OBJ)nrlmsise00kit.o : $(KITSRC)nrlmsise00kit.c
$(CC) $(CFLAGS) -c $(KITSRC)nrlmsise00kit.c -o $(OBJ)nrlmsise00kit.o

$(OBJ)msis86kit.o : $(KITSRC)msis86kit.c $(KITSRC)msis86kit.h
$(CC) $(CFLAGS) -c $(KITSRC)msis86kit.c -o $(OBJ)msis86kit.o
ADAPTIVE, FAULT-TOLERANT ATTITUDE CONTROL

$(OBJ)orbkit.o  : $(KITSRC)orbkit.c
 $(CC) $(CFLAGS) -c $(KITSRC)orbkit.c -o $(OBJ)orbkit.o

$(OBJ)sigkit.o  : $(KITSRC)sigkit.c
 $(CC) $(CFLAGS) -c $(KITSRC)sigkit.c -o $(OBJ)sigkit.o

$(OBJ)sphkit.o  : $(KITSRC)sphkit.c
 $(CC) $(CFLAGS) -c $(KITSRC)sphkit.c -o $(OBJ)sphkit.o

$(OBJ)timekit.o : $(KITSRC)timekit.c
 $(CC) $(CFLAGS) -c $(KITSRC)timekit.c -o $(OBJ)timekit.o

$(OBJ)DetectorFSW.o : $(MATLABSRC)DetectorFSW.c
 $(CC) $(CFLAGS) -c $(MATLABSRC)DetectorFSW.c -o $(OBJ)DetectorFSW.o

$(OBJ)OpticsFSW.o : $(MATLABSRC)OpticsFSW.c
 $(CC) $(CFLAGS) -c $(MATLABSRC)OpticsFSW.c -o $(OBJ)OpticsFSW.o

$(OBJ)42CfdSlosh.o : $(PRIVSRC)42CfdSlosh.c $(INC)42.h
 $(CC) $(CFLAGS) -c $(PRIVSRC)42CfdSlosh.c -o $(OBJ)42CfdSlosh.o

$(OBJ)42fftb.o  : $(PRIVSRC)42fftb.c $(INC)42.h
 $(CC) $(CFLAGS) -c $(PRIVSRC)42fftb.c -o $(OBJ)42fftb.o

# Build Custom ADCS
./adcs/build/ADCS_main.o: ./adcs/src/ADCS_main.c ./adcs/src/ADCS_main.h
 $(CC) $(CFLAGS) -c ./adcs/src/ADCS_main.c -o ./adcs/build/ADCS_main.o

./adcs/build/Matrix.o: ./adcs/src/Matrix.c ./adcs/src/Matrix.h
 $(CC) $(CFLAGS) -c ./adcs/src/Matrix.c -o ./adcs/build/Matrix.o

# Miscellaneous Rules
clean:
ifeq ($(42PLATFORM),_WIN32)
del .\Object\*.o .\$(EXENAME) .\InOut\*.42
else ifeq ($(42PLATFORM),_WIN64)
del .\Object\*.o .\$(EXENAME) .\InOut\*.42
else
rm $(OBJ)*.o .\$(EXENAME) .\$(INOUT)*.42 .\Demo/\*.42 .\Rx/\*.42 .\Tx/\*.42
endif
Appendix C

Matrix.h

/** @addtogroup Matrix
 *  @{ */
/**
 * @file    Matrix.h
 * Header file for custom Matrix operations code
 */
#ifndef __MATRIX_H__
#define __MATRIX_H__
#include <stdint.h>
#define MATRIX_SUCCESS      0
#define MATRIX_DIMMISMATCH  1
#define MATRIX_ERROR        1

typedef struct
{
  uint32_t rows;  /**< Number of rows in matrix */
  uint32_t cols;  /**< Number of cols in matrix */
  double *data;   /**< Contents of matrix */
} Matrix_t;

/** @brief  Set the value of a matrix entry
 * @param    m: Matrix to edit
 * @param    row: Row of entry to change
 * @param    col: Column of entry to change
 * @param    value: New value of location
 * @returns  result: Matrix with (row, col) set to value
 * @returns  iStatus */
uint32_t Matrix_Set(Matrix_t *m, uint32_t row,
                    uint32_t col, double value);

/** @brief  Get the value of a matrix entry
 * @param    m: Matrix to get value from
 * @param    row: Row of entry
 * @param    col: Column of entry
 * @returns  value: Value of entry in the matrix */
double Matrix_Get(Matrix_t *m, uint32_t row, uint32_t col);

/** @brief  Add two matrices
 * @param    m: First matrix
 * @param    n: Second matrix
 * @returns  result: m + n
 * @returns  iStatus */
uint32_t Matrix_Add(Matrix_t *m, Matrix_t *n, Matrix_t *result);

/** @brief  Multiply a matrix by a scalar
 * @param    m: Matrix to multiply
 * @param    scalar: Scalar value
 * @returns  iStatus */
uint32_t Matrix_ScalarMult(Matrix_t *m, double scalar);
/**
 * @brief  Multiply two matrices
 * @param  m: First matrix
 * @param  n: Second matrix
 * @returns result: m * n
 * @returns iStatus
 */
uint32_t Matrix_Mult(Matrix_t *m, Matrix_t *n, Matrix_t *result);

/**
 * @brief  Multiply a row of the matrix by a scalar
 * @param  m: Matrix to operate on
 * @param  row: Row to operate on
 * @param  scalar: Scalar to multiply the row by.
 * @returns iStatus
 */
uint32_t Matrix_RowMult(Matrix_t *m, uint32_t row, double scalar);

/**
 * @brief  Add row1 of the matrix to row2
 * @param  m: Matrix to operate on
 * @param  row1: The source row
 * @param  row2: The destination row to be added to
 * @param  scale: Coefficient of row1 when adding to row2
 * @returns iStatus
 */
int32_t Matrix_RowAdd(Matrix_t *m, uint32_t row1, uint32_t row2, double scale);

/**
 * @brief  Find the reduced row echelon form of the matrix
 * @param  m: The matrix to be RREFed
 * @returns iStatus
 */
uint32_t Matrix_RREF(Matrix_t *m);

/**
 * @brief  Transpose the Matrix
 * @param  m: The matrix to be transposed
 * @returns iStatus
 */
uint32_t Matrix_Transpose(Matrix_t* m);

/**
 * @brief  Concatenate matrices horizontally
 * @param  m: Left-hand matrix
 * @param  n: Right-hand matrix
 * @returns result: The concatenated matrix
 * @returns iStatus
 */
uint32_t Matrix_hcat(Matrix_t *m, Matrix_t *n, Matrix_t *result);

/**
 * @brief  Concatenate matrices vertically
 * @param  m: Top matrix
 * @param  n: Bottom matrix
 * @returns result: The concatenated matrix
 * @returns iStatus
 */
uint32_t Matrix_vcat(Matrix_t *m, Matrix_t *n, Matrix_t *result);
/**
 * @brief Splits matrix horizontally
 * @param m: The matrix to split
 * @returns n1: Right-hand matrix
 * @returns n2: Left-hand matrix
 * @returns iStatus
 */
uint32_t Matrix_hsplit(Matrix_t *m, uint32_t split_col, Matrix_t *n1, Matrix_t *
*n2);
/**
 * @brief Creates a new matrix
 * @param rows: Number of rows in new matrix
 * @param cols: number of columns in new matrix
 * @param value: Initial value of matrix elements
 * @returns result: The new matrix
 * @returns iStatus
 */
uint32_t Matrix_Init(Matrix_t* result, uint32_t rows, uint32_t cols, double
value);
/**
 * @brief Duplicates a matrix
 */
uint32_t Matrix_Dup(Matrix_t* input, Matrix_t* output);
/**
 * @brief Deletes the matrix contents
 * @param m: Matrix to delete
 */
uint32_t Matrix_DeleteData(Matrix_t *m);
/**
 * @brief Debug prints a matrix
 */
uint32_t Matrix_Print(Matrix_t* m);
#endif /* __MATRIX_H__ */
/**@*/
Matrix.c

/** @addtogroup Matrix
 * @{ */
/**
 * @file Matrix.c
 * Implementation file for custom Matrix operations code
 *
 */
#include "Matrix.h"
#include <stdlib.h>
#include <stdio.h>
#include <string.h>
uint32_t Matrix_Init(Matrix_t* matrix, uint32_t rows, uint32_t cols, double value)
{
    /* populate the matrix struct */
    matrix->rows = rows;
    matrix->cols = cols;
    Matrix_DeleteData(matrix);
    matrix->data = malloc(rows * cols * sizeof(double));
    int i;
for (i = 0; i < rows * cols; i++)
    matrix->data[i] = value;
return MATRIX_SUCCESS;
}

uint32_t Matrix_Dup(Matrix_t* input, Matrix_t* output)
{
    Matrix_Init(output, input->rows, input->cols, 0);
    memcpy(output->data, input->data, sizeof(double)*input->rows*input->cols);
    return MATRIX_SUCCESS;
}

uint32_t Matrix_DeleteData(Matrix_t *m)
{
    if (m->data != NULL)
        free(m->data); /* delete the data array */
    m->data = NULL;
    return MATRIX_SUCCESS;
}

uint32_t Matrix_Print(Matrix_t* m)
{
    int i;
    printf("\nMatrix:");
    for (i = 0; i < m->rows * m->cols; i++)
    {
        if (i % m->cols == 0)
            printf("\n    ");
        printf("%11.5f ", m->data[i]);
    }
    printf("\n\n");
    return MATRIX_SUCCESS;
}

uint32_t Matrix_Set(Matrix_t* m, uint32_t row, uint32_t col, double value)
{
    if (row < m->rows && col < m->cols)
    {
        m->data[row*m->cols + col] = value;
        return MATRIX_SUCCESS;
    }
    return MATRIX_DIMMISMATCH;
}

double Matrix_Get(Matrix_t* m, uint32_t row, uint32_t col)
{
    if (row < m->rows && col < m->cols)
    {
        return m->data[row*m->cols + col];
    }
    return 0.0;
}

uint32_t Matrix_Add(Matrix_t* m, Matrix_t* n, Matrix_t* result)
{
    if (m->rows == n->rows && m->cols == n->cols)
    {
        int i;
        for (i = 0; i < (m->rows * m->rows); i++)
            result->data[i] = m->data[i] + n->data[i];
        return MATRIX_SUCCESS;
    }
    return MATRIX_DIMMISMATCH;
}

uint32_t Matrix_ScalarMult(Matrix_t *m, double scalar)
{
    int i, items;
items = m->rows*m->cols;
for (i = 0; i < items; i++)
{
    m->data[i] *= scalar;
}
return MATRIX_SUCCESS;
}

uint32_t Matrix_Mult(Matrix_t* m, Matrix_t* n, Matrix_t* result)
{
    // check for correct dimensions
    if (m->cols != n->rows)
    {
        // illegal dimensions for multiplication
        return MATRIX_DIMMISMATCH;
    }

    // initialize the result
    Matrix_DeleteData(result);
    Matrix_Init(result, m->rows, n->cols, 0.0);

    int i, j, k, index;
    for (i = 0; i < m->rows; i++)
    {
        for (j = 0; j < n->cols; j++)
        {
            index = i*n->cols + j;
            result->data[index] = 0.0;
            for (k = 0; k < m->cols; k++)
            {
                result->data[index] += m->data[i*m->cols + k] * n->
                                data[k*n->cols + j];
            }
        }
    }

    return MATRIX_SUCCESS;
}

uint32_t Matrix_RowMult(Matrix_t *m, uint32_t row, double scalar)
{
    if (row >= m->rows)
    return MATRIX_DIMMISMATCH;

    int i;
    for (i = 0; i < m->cols; i++)
    m->data[row*m->cols + i] *= scalar;

    return MATRIX_SUCCESS;
}

uint32_t Matrix_RowAdd(Matrix_t *m, uint32_t row1, uint32_t row2, double scale)
{
    if (row1 >= m->rows || row2 >= m->rows)
    return MATRIX_DIMMISMATCH;

    int i;
    for (i = 0; i < m->cols; i++)
    m->data[row2*m->cols + i] += m->data[row1*m->cols + i]*scale;

    return MATRIX_SUCCESS;
}

uint32_t Matrix_Transpose(Matrix_t* m)
{
    Matrix_t* transposed = malloc(sizeof(Matrix_t));
    memset(transposed, 0x0, sizeof(Matrix_t));
    Matrix_Init(transposed, m->cols, m->rows, 0);
}
int i, j;
for (i = 0; i < m->rows; i++)
{
    for (j = 0; j < m->cols; j++)
    {
        Matrix_Set(transposed, j, i, Matrix_Get(m, i, j));
    }
}
/* delete the old matrix */
Matrix_DeleteData(m);
m->data = transposed->data;
m->rows = transposed->rows;
m->cols = transposed->cols;
free(transposed);
/* return the new matrix */
m = transposed;
return MATRIX_SUCCESS;
}

uint32_t Matrix_vcat(Matrix_t *m, Matrix_t *n, Matrix_t *result)
{
    if (m->cols != n->cols)
    return MATRIX_ERROR;
    Matrix_Init(result, m->rows + n->rows, m->cols, 0.0);
    int i, j;
    for (i = 0; i < result->rows; i++)
    {
        for (j = 0; j < result->cols; j++)
        {
            if (i < m->rows)
                Matrix_Set(result, i, j, Matrix_Get(m, i, j));
            else
                Matrix_Set(result, i, j, Matrix_Get(n, i - m->rows, j));
        }
    }
    return MATRIX_SUCCESS;
}

uint32_t Matrix_hcat(Matrix_t *m, Matrix_t *n, Matrix_t *result)
{
    if (m->cols != n->cols)
    return MATRIX_ERROR;
    Matrix_Init(result, m->rows, m->cols + n->cols, 0.0);
    int i, j;
    for (i = 0; i < result->rows; i++)
    {
        for (j = 0; j < result->cols; j++)
        {
            if (j < m->cols)
                Matrix_Set(result, i, j, Matrix_Get(m, i, j));
            else
                Matrix_Set(result, i, j, Matrix_Get(n, i, j - m->cols));
        }
    }
    return MATRIX_SUCCESS;
}

uint32_t Matrix_hsplit(Matrix_t *m, uint32_t split_col, Matrix_t *n1, Matrix_t *n2)
{
    Matrix_Init(n1, m->rows, split_col, 0);
    Matrix_Init(n2, m->rows, m->cols - split_col, 0);
    int i, j;
    for (i = 0; i < m->rows; i++)
    {
        for (j = 0; j < m->cols; j++)
{  
    if (j < split_col)  
        Matrix_Set(n1, i, j, Matrix_Get(m, i, j));  
    else  
        Matrix_Set(n2, i, j-split_col, Matrix_Get(m, i, j));  
}

return MATRIX_SUCCESS;
}

uint32_t Matrix_RREF(Matrix_t *m)
{
    int row = 0;
    int row2 = 0;
    // first we go down...
    for (row = 0; row < m->rows-1; row++)
    {
        // normalize the row
        Matrix_RowMult(m, row, 1.0 / Matrix_Get(m, row, row));
        // remove the leading value from each lower row
        for (row2 = row+1; row2 < m->rows; row2++)
        {
            Matrix_RowAdd(m, row, row2, -Matrix_Get(m, row2, row));
        }
    }
    // normalize the last row
    row = m->rows-1;
    Matrix_RowMult(m, row, 1.0 / Matrix_Get(m, row, row));
    // now go back up!
    for (row = m->rows-1; row > 0; row--)
    {
        // add to rows above
        for (row2 = row-1; row2 >= 0; row2--)
        {
            Matrix_RowAdd(m, row, row2, -Matrix_Get(m, row2, row));
        }
    }
    // should be done...
    return MATRIX_SUCCESS;
}/** @}*/

ADCS_main.h

/** @addtogroup ADCS_main  
* @{ */
/** *
* @file    ADCS_main.h  
* Header file for custom ADCS code  
* */
#include <stdint.h>
#include "42types.h"
#include "Matrix.h"
#define ADCS_TRAINING_POINTS 100 /**< Maximum number of training points */
#define ADCS_SQRT_TRAINING_POINTS 10
#define ADCS_BANDWIDTH 20 /**< Model bandwidth */
#define ADCS_ACT_CNT 4 /**< Number of actuators */
#define ADCS_MAX_TCMD 0.004 /**< Maximum torque cmd for the reaction wheel (N-m) */

#define ADCS_TRAINING_TORQUE_SCALE 0.1
#define ADCS_TRAINING_MOVE_DURATION 0.25
#define ADCS_RESET_TOLERANCE 0.001

/* Error Codes */
#define ADCS_SUCCESS 0 /**< Generic success return code */
#define ADCS_ERROR 1 /**< Generic error return code */
#define ADCS_NOT_ENOUGH_POINTS 2 /**< Not enough points similar to the desired output */
#define ADCS_SOLVE_SUCCESS 0 /**< Indicates successful solution */
#define ADCS_SOLVE_OVERDEFINED 1 /**< Indicates error due to overdefinition */

#define ADCS_LSH_MAX_GYRO (ADCS_SQRT_TRAINING_POINTS*3.1373*ADCS_TRAINING_MOVE_DURATION) /**< 3x std dev for angular rotation amplitude (rad/s) */
#define ADCS_LSH_MAX_TORQUE 0.0092 /**< Max torque around a body axis (N-m) */
#define ADCS_LSH_HASH_BITS_PER_DIM 2 /**< bits per dimension */
#define ADCS_LSH_BINS_PER_DIM (2^(bits per dim)) /**< number of bins per dim = 2^(bits per dim) */
#define ADCS_LSH_TOTAL_NUM_OF_BINS 4096 /**< total bins = (bins per dim)^6 */
#define ADCS_SEARCH_STEP_SIZE 0.002

typedef struct
{
    double state[3]; /**< Stores initial rotation state */
    double inputs[ADCS_ACT_CNT]; /**< Stores input torque cmds to actuators */
    double outputs[3]; /**< Stores output rotation on XYZ body axes */
} ADCS_Point_t;

typedef double (*HEURISTIC_PTR)(ADCS_Point_t*);

typedef struct
{
    double state[3]; /**< Stores initial rotation state */
    double inputs[ADCS_ACT_CNT]; /**< Stores input torque cmds to actuators */
    double outputs[3]; /**< Stores output rotation on XYZ body axes */
} ADCS_Point_t;

typedef enum
{
    IDLE,
    TRAIN,
    MOVE,
    RESET
} ADCS_State_t;

typedef uint8_t actuatorCount; /**< Number of actuators */
uint8_t numPoints; /**< Number of training points */
ADCS_LSH_Bin_t* lshBins[ADCS_LSH_TOTAL_NUM_OF_BINS]; /**< Array of LSH bins. Each bin is an array of points */
HEURISTIC_PTR heuristic; /**< Function pointer to heuristic used to select the "best" movement option */
ADCS_Data_t* state; /**< Current ADCS state */

/* @brief Initialize the ADCS model */
* 
* This function initializes the contents of the ADCS_Data_t structure
ADAPTIVE, FAULT-TOLERANT ATTITUDE CONTROL

uint8_t ADCS_Init(ADCS_Data_t *adcs, HEURISTIC_PTR heuristic);

uint8_t ADCS_Destroy(ADCS_Data_t *adcs);

uint8_t ADCS_AddPoint(ADCS_Data_t *adcs, const ADCS_Point_t* dataPoint);

uint8_t ADCS_ConvertTorqueCmd(const ADCS_Data_t *adcs,
                                const ADCS_Point_t *desiredOutput,
                                ADCS_Point_t *torqueWhlCmds);

uint8_t ADCS_FindNearestNeighbors(const ADCS_Data_t *adcs,
                                    const uint32_t bandwidth,
                                    const ADCS_Point_t *input,
                                    ADCS_Point_t* neighbors, uint32_t* neighborCount);

uint8_t ADCS_FindLSHHash(const ADCS_Point_t *dataPoint);
* @param point: ADCS_Point_t structure to hash
* @param hash: Hash value
*/

uint32_t ADCS_LSH_Hash(const ADCS_Point_t *point);
/**
* @brief Heuristic function for finding "best" solution
* @param point: ADCS_Point_t structure to use as input
* @returns value: Heuristic value for point
*/
double ADCS_Heuristic(ADCS_Point_t* point);
/**
* @brief Main loop function of custom ADCS flight software
* @param Spacecraft - The 42 SCType structure representing the spacecraft
* @return None
*/
void ADCS_FSW(struct SCType *Spacecraft);
#endif /* __ADCS_MAIN_H__ */
/**@*/
ADCS_main.c
/** @addtogroup ADCS_main
* @{ */
/** @file ADCS_main.c
* Implementation file for custom ADCS code
* */
#include "ADCS_main.h"
#include <string.h>
#include "42.h"
#include <math.h>
#include <float.h>
#include <time.h>

uint8_t ADCS_Init(ADCS_Data_t *adcs, HEURISTIC_PTR heuristic)
{
    adcs->actuatorCount = ADCS_ACT_CNT;
    adcs->numPoints = 0;
    adcs->heuristic = heuristic;
    /* initialize the LSH bins */
    memset(adcs->lshBins, 0x00,
           sizeof(ADCS_LSH_Bin_t)*ADCS_LSH_TOTAL_NUM_OF_BINS);
    uint32_t i;
    for (i = 0; i < ADCS_LSH_TOTAL_NUM_OF_BINS; i++)
    {
        adcs->lshBins[i].points = malloc(sizeof(ADCS_Point_t)*8); // start with 8 point size
        adcs->lshBins[i].size = 8;
        memset(adcs->lshBins[i].points, 0x00, sizeof(ADCS_Point_t)*8);
    }
    return ADCS_SUCCESS;
}

uint8_t ADCS_Destroy(ADCS_Data_t *adcs)
ADAPTIVE, FAULT-TOLERANT ATTITUDE CONTROL

```c
{ int i;
  for (i = 0; i < ADCS_LSH_TOTAL_NUM_OF_BINS; i++)
  { free(adcs->lshBins[i].points); // free the bin
    return ADCS_SUCCESS;
  }
}

uint8_t ADCS_AddPoint(ADCS_Data_t *adcs, const ADCS_Point_t* dataPoint)
{
  uint32_t hash;
  /* store the data point */
  /* calculate the hash */
  hash = ADCS_LSH_Hash(dataPoint);
  if (hash > ADCS_LSH_TOTAL_NUM_OF_BINS-1)
      hash = ADCS_LSH_TOTAL_NUM_OF_BINS-1;
  if (adcs->lshBins[hash].nextPoint >= adcs->lshBins[hash].size / 2)
  {
    /* need to expand the array. double the capacity */
    /* create a new array */
    ADCS_Point_t* newArray = malloc(2*adcs->lshBins[hash].size*sizeof(ADCS_Point_t));
    /* copy data to new array*/
    memcpy(newArray, adcs->lshBins[hash].points, adcs->lshBins[hash].size*sizeof(ADCS_Point_t));
    /* free the old array */
    free(adcs->lshBins[hash].points);
    /* use the new array */
    adcs->lshBins[hash].points = newArray;
    /* update to the new size */
    adcs->lshBins[hash].size *= 2;
  }
  /* add the new point */
  adcs->lshBins[hash].points[adcs->lshBins[hash].nextPoint++] = *dataPoint;
  /* increment the end of the list index */
  adcs->numPoints++;
  return ADCS_SUCCESS;
}

uint32_t ADCS_LSH_Hash(const ADCS_Point_t *point)
{
  /* hash the point! */
  char values[6]; /* 3 dimensions for initial state, 3 for output state */
  int i;
  /* copy the values to the array */
  /* quantize as we go to avoid needing another loop */
  for (i = 0; i < 3; i++)
  {
    values[i] = (char)(floor(point->outputs[i] / ADCS_LSH_MAX_TORQUE * ADCS_LSH_BINS_PER_DIM/2)); // convert the torque to integer
    values[i+3] = (char)(floor(point->state[i] / ADCS_LSH_MAX_GYRO * ADCS_LSH_BINS_PER_DIM/2)); // convert the state input to integer
  }
  // calculate the hash
  uint32_t hash = 0;
  /* loop through each bit of the hash from MSb to LSb */
  /* Example: 01 10 01 11 00 10 */
  *
  * 0: hash + 0b1 = 0b1
  * 1: hash + 0b00 = 0b01
  * 2: hash + 0b100 = 0b101
```
ADAPTIVE, FAULT-TOLERANT ATTITUDE CONTROL

```c
* 3: hash + 0b1000 = 0b1101
* 4: hash + 0b00000 = 0b01101
* 5: hash + 0b000000 = 0b001101
* 6: hash + 0b0000000 = 0b0001101
* 7: hash + 0b1000000 = 0b10001101
* 8: hash + 0b000000000 = 0b0010001101
* 9: hash + 0b1000000000 = 0b1010001101
* 10: hash + 0b00000000000 = 0b0101010001101
* 11: hash + 0b100000000000 = 0b10101010001101
* final hash value is 0xA8D
*/

for (i = 0; i < 6*ADCS_LSH_HASH_BITS_PER_DIM - 1; i++)
{
    if (i >= 6*(ADCS_LSH_HASH_BITS_PER_DIM - 1))
    {
        /* here we want the sign bits */
        hash += ((values[i % 6] >> 8) & 0x1) << i;
    }
    else
    {
        hash += ((values[i % 6] >> (i / 6)) & 0x1) << i;
    }
}
return hash;
```

```c
uint8_t ADCS_FindNearestNeighbors(const ADCS_Data_t *adcs, uint32_t bandwidth, const ADCS_Point_t *input, ADCS_Point_t* neighbors, uint32_t* neighborCount)
{
    uint32_t hash, binNum;
    ADCS_LSH_Bin_t bin;
    hash = ADCS_LSH_Hash(input);
    if (hash > ADCS_LSH_TOTAL_NUM_OF_BINS - 1)
        hash = ADCS_LSH_TOTAL_NUM_OF_BINS - 1;
    binNum = hash;
    /* use a moving pointer to add points from bins */
    ADCS_Point_t* nextBinPoints = neighbors;
    /* reset the neighbor count */
    *neighborCount = 0;
    while (bandwidth > 0)
    {
        bin = adcs->lshBins[binNum];
        /* copy up to bandwidth points into the array */
        if (bin.nextPoint < bandwidth)
        {
            /* copy the whole bin */
            memcpy(nextBinPoints, bin.points, sizeof(ADCS_Point_t)*bin.nextPoint);
            /* update the neighbors pointer */
            nextBinPoints += bin.nextPoint;
            /* update the number of neighbors found */
            *neighborCount += bin.nextPoint;
            /* decrement the number of neighbors left */
            bandwidth -= bin.nextPoint;
        }
        else
        {
            /* copy just the points we need */
            memcpy(nextBinPoints, bin.points, sizeof(ADCS_Point_t)*bandwidth);
            nextBinPoints += bandwidth;
        }
    }
    return hash;
}
```
double ADCS_Heuristic(ADCS_Point_t* point)
{
    /* shoot for smallest overall change in wheel speed */
    /* not the best option */
    int i;
    double result = 0;
    for (i = 0; i < ADCS_ACT_CNT; i++)
    {
        result += point->point->inputs[i];
    }
    return result;
}

uint8_t ADCS_ConvertTorqueCmd(const ADCS_Data_t *adcs,
                               const ADCS_Point_t *desiredOutput,
                               ADCS_Point_t *torqueWlCmds)
{
    /* find similar points */
    uint32_t neighborCount;
    ADCS_FindNearestNeighbors(adcs, ADCS_BANDWIDTH, desiredOutput,
                                &neighborCount);
    /* put the information into linear equations */
    Matrix_t modelEquations, augmentedModelEquations;
    memset(&modelEquations, 0x0, sizeof(Matrix_t));
    memset(&augmentedModelEquations, 0x0, sizeof(Matrix_t));
    Matrix_Init(&inputMatrix, neighborCount, ADCS_ACT_CNT+1, 0.0);
    int i,j;
    for (i = 0; i < neighborCount; i++)
    {
        for (j = 0; j < ADCS_ACT_CNT; j++)
        {
            Matrix_Set(&inputMatrix, i, j, neighbors[i].inputs[j]);
        }
        Matrix_Set(&inputMatrix, i, ADCS_ACT_CNT, 1.0);
    }
    Matrix_Dup(&inputMatrix, &inputMatrixTranspose);
    Matrix_Transpose(&inputMatrixTranspose);
/* compute the normal matrix */
Matrix Mult(&inputMatrixTranspose, &inputMatrix, &normalMatrix);
/* solve the equations for the equations for each dimension */
Matrix t rhsMatrix; /**< Matrix for right-hand side, b */
Matrix t inputTrhsMatrix; /**< Matrix for A'b */
Matrix t augmentedMatrix; /**< Matrix for [ A'A | A'b ] */
Matrix t tmp; /**< Matrix for unneeded results */
memset(&rhsMatrix, 0x0, sizeof(Matrix t));
memset(&inputTrhsMatrix, 0x0, sizeof(Matrix t));
memset(&augmentedMatrix, 0x0, sizeof(Matrix t));
memset(&tmp, 0x0, sizeof(Matrix t));

int axis;
for (axis = 0; axis < 3; axis++)
{
    Matrix Init(&rhsMatrix, neighborCount, 1, 0);
    /* put the axis output value in the rhsMatrix */
    for (i = 0; i < neighborCount; i++)
    {
        Matrix Set(&rhsMatrix, i, 0, neighbors[i].outputs[axis]);
    }
    /* left multiply the rhsMatrix by the input transposed */
    Matrix Mult(&inputMatrixTranspose, &rhsMatrix, &inputTrhsMatrix);
    /* horiz concatenate the normalMatrix and the inputTrhsMatrix */
    Matrix hcat(&normalMatrix, &inputTrhsMatrix, &augmentedMatrix);
    /* do RREF on the concatenated matrix */
    Matrix RREF(&augmentedMatrix);
    /* extract the coefficients from the rhs by splitting the RREFed matrix */
    Matrix hsplit(&augmentedMatrix, normalMatrix.cols, &tmp, &rhsMatrix);
    /* transpose the column matrix. this is one row of the final equation matrix */
    Matrix Transpose(&rhsMatrix);
    /* add it to the equation matrix */
    for (i = 0; i < ADCS_ACT_CNT; i++)
    {
        Matrix Get(&modelEquations, axis, i) = Matrix Get(&rhsMatrix, 0, i);
    }
}
/* use the equations to find the torques needed */
/* create a matrix with the desired outputs */
Matrix t outputs; /**< Column matrix of desired outputs */
memset(&outputs, 0x0, sizeof(Matrix t));
Matrix Init(&outputs, 3, 1, 0.0);
memcpy(outputs.data, desiredOutputs, sizeof(double)*3);
/* add the desired outputs to the rhs */
Matrix hcat(&modelEquations, &outputs, &augmentedModelEquations);
/* RREF the matrix to get the solution */
Matrix RREF(&augmentedModelEquations);
/* check for undetermined case */
Matrix t independentMatrix; /**< Matrix of independent variables */
Matrix t dependentMatrix; /**< Matrix containing values of dependent variables */
Matrix t solutionVector; /**< Matrix of both ind. and dep. variable solutions */
memset(&independentMatrix, 0x0, sizeof(Matrix t));
memset(&dependentMatrix, 0x0, sizeof(Matrix t));
memset(&solutionVector, 0x0, sizeof(Matrix t));
if (ADCS_ACT_CNT > 3) {
    /* split the matrix */
    Matrix_hsplit(&augmentedModelEquations, 3, &tmp, &modelEquations);
    /* negate the matrix */
    Matrix_ScalarMult(&modelEquations, -1.0);
    for (i = 0; i < 3; i++)
    {
        Matrix_Set(&modelEquations, i, 1, -Matrix_Get(&modelEquations, i, 1));
    }
    if (ADCS_ACT_CNT == 4) {
        /* handle this special case to avoid need for recursive functions */
        /* with ADCS_ACT_CNT == 4, there will be 1 free variable */
        /* therefore, the independentMatrix will be [ a_3; 1 ] */
        /* find a value of a_3 to minimize the cost heuristic */
        /* a_3 is a torque cmd, and must be within the range of the actuator */
        Matrix_Init(&independentMatrix, 2, 1, 1.0);
        double value, best, bestHeuristicVal, tmpHeuristicVal;
        ADCS_Point_t bestSolution;
        bestHeuristicVal = DBL_MAX;
        Matrix_Init(&solutionVector, 4, 1, 0.0);
        for (value = -ADCS_MAX_TCMD; value <= ADCS_MAX_TCMD; value +=
             ADCS_SEARCH_STEP_SIZE)
        {
            Matrix_Set(&independentMatrix, 0, 0, value);
            Matrix_Mult(&modelEquations, &independentMatrix, &dependentMatrix);
            /* put dependent and independent matrices together */
            /*Matrix_vcat(&dependentMatrix, &independentMatrix, &solutionVector);*/
            memcpy(solutionVector.data, dependentMatrix.data,
                   3*sizeof(double));
            solutionVector.data[3] = value;
            memcpy(torqueWhlCmds->inputs, solutionVector.data,
                   ADCS_ACT_CNT*sizeof(double));
            /* apply heuristic to solution vector */
            tmpHeuristicVal = adcs->heuristic(torqueWhlCmds);
            if (tmpHeuristicVal < bestHeuristicVal)
            {
                best = value;
                bestHeuristicVal = tmpHeuristicVal;
                memcpy(bestSolution.inputs, solutionVector.data,
                       ADCS_ACT_CNT*sizeof(double));
            }
        }
        /* we now have the "best" solution in bestSolution. Return the value */
        memcpy(torqueWhlCmds, &bestSolution, sizeof(ADCS_Point_t));
        /* done */
        return ADCS_SOLVE_SUCCESS;
    }
    /* should not get here in a nominal run */
    return ADCS_ERROR;
}

void ADCS_Train(ADCS_Data_t* adcs, struct FSWType* FSW, char* filename) {
    static uint32_t numberOfPointsRemaining = 0;
    static uint8_t step = 0;
    static ADCS_Point_t trainingPoint;
    static double timer = 0.0;
    static FILE* trainingOutputFile = NULL;
/* set the state */
adcns->state = TRAIN;

if (step == 0)
{
    trainingOutputFile = fopen(filename, "w");
    numberOfPointsRemaining = ADCS_TRAINING_POINTS;
    step++;
}
else if (step == 1)
{
    /* compute the torque cmd */
    memset(&trainingPoint, 0x0, sizeof(ADCS_Point_t));
    int i;
    for (i = 0; i < ADCS_ACT_CNT; i++)
    {
        trainingPoint.inputs[i] = ADCS_TRAINING_TORQUE_SCALE * (-ADCS_MAX_TCMD + ((double)rand()) / ((double)RAND_MAX)) + (2 * ADCS_MAX_TCMD);
        memcpy(trainingPoint.state, FSW->wbn, sizeof(double) * 3);
        memcpy(FSW->Twhlcmd, trainingPoint.inputs, sizeof(double) * ADCS_ACT_CNT);
        numberOfPointsRemaining--;
        step++;
        timer = 0.0;
    }
}
else if (step == 2)
{
    /* wait for delay */
    timer += FSW->DT;
    if (timer >= ADCS_TRAINING_MOVE_DURATION)
    {
        step++;
    }
}
else if (step == 3)
{
    /* save the point data */
    /* calculate the torque */
    int i;
    for (i = 0; i < 3; i++)
    {
        /* calculate torque: \tau = I * \alpha = I * (\omega_f - \omega_i) / \Delta t */
        trainingPoint.outputs[i] = (FSW->wbn[i] - trainingPoint.state[i]) / timer * FSW->MOI[i];
    }
    fprintf(trainingOutputFile, "%5.4f, %5.4f, %5.4f, %5.4f, %5.4f, %5.4f, %5.4f, %5.4f, %5.4f, %5.4f, %5.4f, %5.4f, %5.4f, %5.4f, %5.4f\n",
            trainingPoint.state[0],
            trainingPoint.state[1],
            trainingPoint.state[2],
            trainingPoint.inputs[0],
            trainingPoint.inputs[1],
            trainingPoint.inputs[2],
            trainingPoint.inputs[3],
            FSW->wbn[0],
            FSW->wbn[1],
            FSW->wbn[2],
            trainingPoint.outputs[0],
            trainingPoint.outputs[1],
            trainingPoint.outputs[2]);

    /* add the training point to the database */
    ADCS_AddPoint(adcs, &trainingPoint);

    if (numberOfPointsRemaining > 0)
    {
        /* go back to add another point */
        step = 1;
    }
}
else
{
    /* done training, prep for next time */
    step = 0;
    fclose(trainingOutputFile);
    trainingOutputFile = NULL;
    adcs->state = IDLE;
}
}

void ADCS_FSW(struct SCType *Spacecraft)
{
    struct FSWType *FSW;
    FSW = &Spacecraft->FSW; /* grab the flight software object */

    static double simTime = 0;
    static ADCS_Data_t adcs;
    static uint8_t shouldMove = 1;

    /* variables */
    //double* targetQuat = FSW->Cmd.qrn; /* must be normalized */
    double targetQuat[4] = {0.462, 0.191, 0.462, 0.733};
    double inertialToBodyMat[3][3];
    ADCS_Point_t desired, output;
    double inertialTargetAngles[3], inertialBodyAngles[3],
    Tcmd_desired_inertial[3], Tcmd_desired_body[3];
    double inertialErrorAngles[3];
    static double previousInertialErrorAngles[3], integralInertialErrorAngles[3];
    int i;

    static FILE* file;
    static char filename[64];
    static char trainingFilename[64];
    static double writeTimer = 0;
    static double stepStartTime = 0;

    if (FSW->Init) {
        /* initialize */
        FSW->Init = 0;
        FSW->DT = DTSIM; /* save the sim DT */
        ADCS_Init(&adcs, ADCS_Heuristic);
        adcs.state = TRAIN;

        /* seed the random number generator */
        long startTime = time(NULL);
        srand(startTime);

        /* open the output file */
        sprintf(filename, "output_%ld.txt", startTime);
        sprintf(trainingFilename, "training_%ld.txt", startTime);
        file = fopen(filename, "w");
    }

    switch (adcs.state)
    {
    case IDLE:
        if (shouldMove)
        {
            adcs.state = RESET;
            stepStartTime = simTime;
        }
        shouldMove = 0;
        FSW->Twhlcmd[0] = 0;
        FSW->Twhlcmd[1] = 0;
        FSW->Twhlcmd[2] = 0;
        FSW->Twhlcmd[3] = 0;
        break;
case TRAIN:
  ADCS_Train(&adcs, FSW, trainingFilename);
  break;

case RESET:
  targetQuat[0] = 0;
  targetQuat[1] = 0;
  targetQuat[2] = 0;
  targetQuat[3] = 1.0;
  Q2AngleVec(FSW->qbn, inertialBodyAngles);
  double bodyError = 0.0;
  double omegaError = 0.0;
  for (i = 0; i < 3; i++)
    bodyError += inertialBodyAngles[i]*inertialBodyAngles[i];
  for (i = 0; i < 3; i++)
    omegaError += (FSW->wbn[i]*FSW->wbn[i]);
  if (bodyError < ADCS_RESET_TOLERANCE && omegaError <
  ADCS_RESET_TOLERANCE)
    {
      adcs.state = MOVE;
      stepStartTime = simTime;
      printf("MOVE\n");
    }

case MOVE:
  /* some MOI data from
   * https://www.hindawi.com/journals/jcse/2013/657182/ */
  /* convert target to euler angles */
  Q2AngleVec(targetQuat, inertialTargetAngles);
  /* convert body quat to euler angles */
  Q2AngleVec(FSW->qbn, inertialBodyAngles);
  for (i = 0; i < 3; i++)
    {
      inertialErrorAngles[i] = inertialTargetAngles[i] -
      inertialBodyAngles[i];
      integralInertialErrorAngles[i] += inertialErrorAngles[i]*FSW->DT;
    }
  for (i = 0; i < 3; i++)
    {
      Tcmd_desired_inertial[i] = 5*inertialErrorAngles[i] +
      2*(inertialErrorAngles[i] -
      previousInertialErrorAngles[i])/FSW->DT +
      0*(integralInertialErrorAngles[i]);
      /* save for next loop */
      previousInertialErrorAngles[i] = inertialErrorAngles[i];
    }
  /* convert inertial to body torque command */
  Q2C(FSW->qbn, inertialToBodyMat);
  /* transform the Tcmd */
  MxV(inertialToBodyMat, Tcmd_desired_inertial, Tcmd_desired_body);

  writeTimer += FSW->DT;
  if (writeTimer > 0.01 && file != NULL)
    {
      fprintf(file, "%10.4f, %10.4f, %10.4f, %10.4f\n", simTime,
      inertialErrorAngles[0], inertialErrorAngles[1], inertialErrorAngles[2]);
      writeTimer = 0;
    }
  if (simTime - stepStartTime > 8.0 && file != NULL)
    {
      fclose(file);
      file = NULL;
      exit(0);
    }
memset(&desired, 0x0, sizeof(ADCS_Point_t));
/* copy current state */
memcpy(&desired.state, FSW->wbn, sizeof(double)*3);
memcpy(&desired.outputs, &Tcmd_desired_body, sizeof(double)*3);
/* use new algorithm */
ADCS_ConvertTorqueCmd(&adcs, &desired, &output);

FSW->Twhlcmd[0] = output.inputs[0];
FSW->Twhlcmd[1] = output.inputs[1];
FSW->Twhlcmd[2] = output.inputs[2];
FSW->Twhlcmd[3] = output.inputs[3];
break;
default:
    simTime += FSW->DT;
    break;
}
/*@*/