COLD GAS PROPULSION SYSTEM FOR SMALL SATELLITE ATTITUDE CONTROL

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ABSTRACT

Most satellites require the ability to control their attitude, maintain their orbit or maneuver during their missions. This is especially true for small satellites that piggy back as the secondary payload on a launch vehicle because they are forced into the same orbit as the primary payload. The increased availability of flights paired with the decreasing cost of placing an object in orbit provides incredible opportunities for universities to design and build their own small satellites. Cold gas propulsion systems have the unique ability to meet the attitude control and orbital maneuver requirements of a small satellite, all in a simple, compact system that can meet the stringent budget, mass and volume restrictions imposed on small satellites. There has been abundant research on the reliability and miniaturizing of these cold gas systems, but there is insufficient literature on the implementation of a feedback control system utilizing cold gas propulsion. In order to effectively control a satellite, the inherently noisy position data must be filtered. This research focuses on the effects that filtering noisy data have on control system stability. Three filter types, the moving average, linear least squares regression and quadratic least squares regression are explored for various buffer sizes. The result is maneuver accuracy of roughly 5 degrees, a stepping stone on the way to increased maneuver capabilities.

INTRODUCTION

As the cost to place an object in Earth orbit continues to decrease, space exploration will continue to become more accessible to students and educators operating on a meager budget. Small satellites, designed and built by universities, have been successfully launched into orbit; however they are typically not the primary payload on the launch vehicle. As a result, small satellites are typically placed in the same orbit as the larger payload with which they were delivered. In order to change orbits or counteract orbital decay, small satellites must have some sort of propulsion system. Small satellites are typically very limited on volume and weight; as a result, any means of minimizing onboard systems is always pursued. The simplicity of a cold gas propulsion system has much smaller volume and mass requirements than a comparable combustion system. Mass and volume are also conserved by combining the propulsion system with the attitude control system, using the same nozzles to perform rotational maneuvers and also translational movements.

There is a substantial amount of literature available about the development of cold gas propulsion, a system that has been used in satellites since the 1960s. With sufficient flight history to support the reliability of cold gas propulsion, the focus has turned to miniaturizing these systems for use on small satellites. Cold gas micro-propulsion systems have been developed with nozzles small enough to provide as little as 55mN of thrust (Cardin). Other experiments have
explored the physical limitations and reliability of components typically used in cold gas propulsion systems (AL-Sanabawy). Despite the long-standing history of cold gas propulsion in space flight, there is very little to no literature available regarding the actual implementation of cold gas propulsion and its relation with feedback control.

Starting in Fall 2012, John Furumo, Evan Greer, Nathan Walsh and I developed a cold gas propulsion system for small satellites during a yearlong senior design project in mechanical engineering. The propulsion system targets three satellite maneuvers; attitude control, orbit maintenance, and deorbit. The appropriate placement of eight separate thrusters provides the ability to rotate about all three axes and translate along two axes. As a proof of concept, a simplified system with four thrusters was used to demonstrate attitude control about a single axis. Proof of single-axis control is satisfactory because a three-axis maneuver can be decomposed into three single-axis maneuvers.

In order to develop a functioning prototype while minimizing cost, commercial off-the-shelf (COTS) components were researched and acquired. The system is comprised of a high-pressure tank to hold the inert gas, a pressure regulator, a safety valve, four solenoid valves and four custom nozzles. The nozzles are designed for use in the atmosphere, meaning that they have a different expansion ratio than those designed for use in the vacuum of space. The custom nozzles were machined on campus using a precision CNC. Testing was performed using a spherical air bearing at the Hawaii Space Flight Laboratory (HSFL). The final product was a functioning prototype capable of performing open-loop rotational maneuvers via manual user control.

While the open-loop maneuvers performed by the prototype demonstrate the ability of a cold gas propulsion system to move a satellite, they don’t sufficiently demonstrate a controlled maneuver. Adding feedback control to improve the overall system performance is the next step undertaken as part of this space grant funded research. A satellite must be able to determine its own attitude and logically control itself independent of human interaction. There are many types of attitude sensors including star trackers, magnetometers, gyroscopes and horizon trackers. Of particular interest for this project is the inertial measurement unit (IMU); which consists of a 3-axis magnetometer, 3-axis gyroscope and 3-axis accelerometer.

In order to maintain low costs and educational repeatability, a commercially available IMU was selected for use. Although the MPU-9150 has a magnetometer, gyroscope and accelerometer built in, only the magnetometer was successfully used for this project. The onboard chip converts analog signals from the sensors and stores the digital readings in a buffer, which can be read by a computer through an I2C interface. Most sensors provide data with a certain amount of noise; for this IMU it is normally distributed with a standard deviation of about 0.49 degrees. It is important to understand that this IMU is chosen in part for its relatively low cost – an important consideration for small satellites. An IMU with reduced noise can be obtained – but at a substantially higher cost. The question is: what are the limitations of this relatively inexpensive IMU? Can sub-degree control accuracy be obtained from this lower cost option using noise reduction techniques? In order to reduce this noise, various filtering techniques were explored including a moving average, linear least squares regression and
quadratic least squares regression. The theory of each filter type along with the advantages, downfalls and their respective effects on feedback control systems will be discussed.

**EXPERIMENTAL METHODS**

A reliable test setup is the basis for a good experiment; the development of which comprised the majority of our senior design project. The original testing prototype was developed for use on the spherical air bearing at HSFL, in order to utilize its nearly frictionless rotational ability. A rigid 1/8” aluminum plate serves as the platform for mounting all of the propulsion hardware; which includes four solenoid valves, four custom nozzles, a high pressure air tank, a pressure regulator, a safety valve, tubing and the electronics. This plate mounts onto the test bed already in place on the air bearing, shown below (Figure 1). A small electronics stack, which has since been updated, was assembled for wireless communication between a laptop and the Arduino on board the test bed used to control the solenoid valves.

![Figure 1: Cold gas propulsion system mounted on the spherical air bearing at the Hawai‘i Space Flight Laboratory](image)

In order to update the test bed electronics and implement a robust attitude control system, the Arduino was replaced by a Gumstix Overo Airstorm computer-on-module mounted on a Tobi Expansion board. This particular Gumstix has a 1 GHz processor, 8 GB of storage space and runs on a Linux operating system. Communication is established between a laptop and the Gumstix using the built in Wi-Fi antenna. Besides the increased computing power, the Gumstix offers immense expansion capability through the 40 pin header on the Tobi. The Airstorm and Tobi are both mounted on a custom HSFL board capable of regulating power inputs to a suitable level for the Gumstix.

The switches used to control solenoid valves required a 5V signal in order to open and close. We had previously developed a board with 5V switches that were activated by the 3.3V signal from the Arduino. This board had to be rebuilt with different components so that the 5V switches could be activated with the 1.8V signal from the Gumstix, a significant task by itself.

As mentioned before, the raw data collected from the IMU had a standard deviation of 0.49 degrees. In order to accurately perform rotational maneuvers, the error in this data must be
reduced through the use of a filter. Since the filter is applied on board the test bed in real time, the filter can only look backwards at the data, storing previous raw data readings in a buffer. The size of the buffer and the type of filter results in varying system responses, time delays and standard deviations that will be explored later. The response characteristics of three filter types, the moving average, linear least squares regression and quadratic least squares regression were analyzed for buffer sizes from 75 to 300 in increments of 25.

The first filter type is the moving average; it is effective at reducing short term fluctuations while capturing long term changes. This filter type works well for steady-state data sets, however has a slow response to sudden changes. For a moving average filter with buffer size \( n \), each filtered data point \( (\theta_f) \) is determined to be the average of the raw data points \( (\theta_r) \) in the buffer, as show in Equation (1).

\[
\theta_{f,i} = \frac{\sum_{k=0}^{n-1} \theta_{r,i-k}}{n} = \frac{\theta_{r,i} + \theta_{r,i-1} + \cdots + \theta_{r,i-(n-1)}}{n} 
\]

Using the filtered data points calculated by the moving average, the rotational speed of the test bed is then defined by Equation (2).

\[
\omega_i = \frac{\theta_{i} - \theta_{i-1}}{t_i - t_{i-1}}
\]

The second filter type is the linear least squares regression; a method that requires more computing power than the moving average. For a given data set of size \( n \) that is believed to have a linear trend, there exists a line that minimizes the sum of the squares of the error between the data points and the line. That line is defined by Equation (3).

\[
\begin{align*}
\theta_{f,i} &= m_i t_i + b_i \\
\omega_i &= \frac{d\theta_{f,i}}{dt} = m_i
\end{align*}
\]

Where \( m \) is the slope and \( b \) is the vertical intercept of a linear line that defines the angle \( (\theta_f) \) in terms of the time \( (t) \). The filtered data point is calculated using this equation and the rotational speed of the test bed is equal to the slope of the line as seen in Equation (4). The values of \( m \) and \( b \) are calculated using Equation (5), where \( \theta_r \) is the raw position data, \( t \) is the time data and \( n \) is the size of the buffer (Wolfram).

\[
\begin{bmatrix} b_i \\ m_i \end{bmatrix} = \begin{bmatrix} \sum_{k=0}^{n-1} t_{i-k} \left( \sum_{k=0}^{n-1} t_{i-k}^2 \right)^{-1} - \left( \sum_{k=0}^{n-1} \theta_{r,i-k} \right) \\ \frac{1}{\sum_{k=0}^{n-1} t_{i-k}^2} \left( \sum_{k=0}^{n-1} \theta_{r,i-k} t_{i-k} \right) \end{bmatrix}
\]

The third filter type is the quadratic least squares regression; the most computationally intensive calculation of the three. Operating under a similar assumption to the linear least squares regression, there is a quadratic line defined by Equation (6) that minimizes the difference between the quadratic line and the data points. A quadratic is chosen not because it is the next order higher polynomial over linear, but because in the absence of friction the displacement of an inertial body acted on by a constant acceleration should be quadratic. Thus, a quadratic should match the physics of the system. The rotational speed of the test bed is calculated by the derivative of the position function and defined by Equation (7). The values of \( a, b \) and \( c \) are calculated using Equation (8), where \( \theta_r \) is the raw angular position data, \( t \) is the time data and \( n \) is the size of the buffer.
\[
\theta_{f,i} = a_i t_i^2 + b_i t_i + c_i \\
\omega_i = \frac{d\theta_{f,i}}{dt} = 2a_i t_i + b_i
\] (6)

\[
\begin{bmatrix} c_i \\ b_i \\ a_i \end{bmatrix} = \begin{bmatrix} n & \sum_{k=0}^{n-1} t_{r,i-k} & \sum_{k=0}^{n-1} t_{i-k}^2 \\ \sum_{k=0}^{n-1} t_{i-k} & \sum_{k=0}^{n-1} t_{i-k}^2 & \sum_{k=0}^{n-1} t_{i-k}^3 \\ \sum_{k=0}^{n-1} t_{i-k}^2 & \sum_{k=0}^{n-1} t_{i-k}^3 & \sum_{k=0}^{n-1} t_{i-k}^4 \end{bmatrix}^{-1} \begin{bmatrix} \sum_{k=0}^{n-1} \theta_{r,i-k} \\ \sum_{k=0}^{n-1} \theta_{r,i-k} t_{i-k} \\ \sum_{k=0}^{n-1} \theta_{r,i-k} t_{i-k}^2 \end{bmatrix}
\] (8)

In order to analyze the response characteristics of each filter type and buffer size combination, several generic tests were developed. The two main characteristics to be observed were the standard deviation and time delay; measures which define the ability of a filter to eliminate noise and also respond to sudden changes. The standard deviation of the raw data and various filter types were collected for a stationary and rotating test bed. A position step, composed of a 10 second acceleration thrust followed immediately by a 10 second braking thrust of equal magnitude, was used to compare the filters responses to the ideal system response.

![Figure 2: Plots to illustrate the ideal angular position and velocity response of the system to two consecutive equal but opposite thrust impulses](image)

**RESULTS**

In order to fully understand the characteristics of each filter, they must be analyzed for each type of motion that may be experienced by the test bed. One of the most important tests, yet most basic, is performed with the test bed fixed in position. The results are the standard deviation of the position (Figure 3) and speed (Figure 4) of each filter during steady state operation. As a benchmark, the standard deviation of the raw data is included.
As expected, the filters are generally able to reduce the standard deviation below that of the raw data. However, for buffer sizes of 75, 100 and 125 the quadratic filter actually has a higher standard deviation in position than the raw data. This is because the quadratic filter reacts very quickly to short term changes in data; meaning that a random noise spike could trick the filter into thinking that a major change was occurring. The linear filter always has the next lowest standard deviation; however beyond a buffer size of 150, the filter ceases to improve. The moving average filter consistently has the smallest standard deviation.

Since the logic used to control the test bed utilizes both position and speed data, it is important to look at the standard deviation of the speed for each filter type (Figure 4). Since the raw speed data is calculated by differentiating the raw position data, there is a large standard deviation of 2.87deg/s. The quadratic filter again had the highest standard deviation; however the linear filter and moving average filter appear to compete for lowest standard deviation of the speed. The standard deviation values alone are misleading, because they make it seem like both filters do an equivalently good job at reducing the noise in the speed. However, it is important to understand, that since the overall reduction in standard deviation is only 0.4deg/s the seemingly small difference in the standard deviation between a moving average filter and a linear regression filter (at a buffer size of 200) of only about 0.02deg/s still represents about 14% of the overall
reduction. This can easily be seen by referring to a plot of the speed over time for the two filters (Figure 5), it can be seen that at a buffer size of 200 the linear filter provides a much more smooth result than the erratic moving average result. Not only the standard deviation but also the smoothness of the data plays a critical role in deciding which filter best suits the system. For instance, in the example shown, for plus or minus 0.1deg/s of accuracy a control scheme using linear regression would not require any unnecessary gas wasting control inputs but a control scheme using a moving average would.

![Figure 5: Graph to contrast the erratic average filter speed data with the smooth linear filter speed data](image.png)

Another important response characteristic of a filter is the time delay, which affects how quickly a filter can respond to changes in the system. In order to quantify this value, the two step impulse tests described at the end of the introduction were utilized. For the first test, the system accelerates for ten seconds and then immediately switches to ten second of braking thrust. Each filter responds to this input differently (Figure 6).

![Figure 6: The angular response of the raw data and each filter type when subject to ten seconds of acceleration and ten seconds of braking](image.png)

The unique response of each filter type reveals their advantages and disadvantages. For the 10 second acceleration shown above, the test bed rotates through a certain angle. The moving average had a time delay of 1.801 seconds to 7.870 seconds for the various buffer sizes before reaching the defined rotation angle. In contrast, the linear filter only had delays ranging from 0.009 seconds to 1.742 seconds and the quadratic filter only had delays ranging from -0.164
seconds to .227 seconds. The negative delay experienced for several buffer sizes with the quadratic filter means that it responded too quickly and was actually ahead of the real angle of rotation. Another similar test can be performed with a long delay to coast between the acceleration thrust and the braking thrust, during which the filtered signal would have time to catch back up with the actual angular displacement. While the time taken for the filtered signal to return to the correct value after a single acceleration, it is less significant than the time taken to settle after two successive accelerations, which represents the worst case scenario for causing time delay error.

The sluggish response of the moving average filter may at first seem like a disadvantage, but upon inspection of the time required to settle on a final resting position, the tables appear to have turned. The moving average filter slowly approaches the final resting position without overshooting or oscillating. The linear filter way overshoots the final resting position but then eases into a final value with little oscillation. The quadratic filter typically overshoots and the final resting position and then oscillates several times before settling on a final value. It is difficult to determine the absolute time of settling with all the oscillations that take place. However from observing the data, the time required to settle for the moving average ranged from 15 to 25 seconds, while the time to settle for the linear fit ranged from 20 to 25 seconds and the quadratic filter ranged from 25 to 30 seconds.

Without an accurate computer model of the system behavior to test the control stability of combinations of filter type, buffer size and error tolerance, the results must be obtained empirically. In order to test the stability, the control scheme was adjusted to ignore angular position requirements and focus solely on obtaining a predetermined speed while using various filter types, buffer sizes and error tolerances. The plots below (Figure 7) show the results of different target speed and error tolerance combinations for moving average filters with a buffer size of 200. The test shown in the left plot features a target speed of 5 deg/s (shown by the solid line) and error tolerance of 1 deg/s (defined by the dotted lines). For this particular combination, the system was stable and the oscillating speed eventually dampens out. The test shown in the right plot features a target speed of 2 deg/s and error tolerance of 0.5 deg/s. This combination resulted in an unstable system, as shown by the increasing amplitude of each oscillation.

Figure 7: Two speed test plots showing a stable system (left) and an unstable system (right)
CONCLUSION

Picking the correct filter and buffer size is a delicate balance between error reduction and time delay. These experiments have dug deeper into the effects of error and delay on system dynamics; however a connection has yet to be made to control stability. Several maneuvers have been attempted but none have produced results with position error less than 5 degrees.

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REFERENCES

