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EVALUATION OF FILTERS FOR COMPETITION ALTIMETERS

Research and Development Report

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SUMMARY

Altitude contests need accurate results from altimeters. However, altimeter data often contains noise caused by ejection charges, staging, wind, etc.

The objective of this project was to determine which processing methods (filters) work best to provide accurate altitude results from altimeter data. The processing methods should minimize or eliminate major noise and smooth minor noise. The methods should also be robust to handle a wide range of both simple and challenging flight histories.

Seven filters were examined:

- Simple Moving Average (SMA)
- Exponentially Weighted Moving Average (EWMA)
- 2nd order Low Pass (Butterworth) filter
- Kalman filter
- Median filter
- Structural Spline filter
- Savitzky–Golay filter

The results indicated that the Structural Spline filter and the Median filter did well on several challenging flight histories that had significant “spike” noise and other anomalies. The Structural Spline filter was computationally intensive but merits further study. A more computationally efficient approach was to use an Adaptive Median filter (to remove noise) followed by a Savitzky-Golay filter (to smooth the data).

Much more work can be done in this field. More flight histories should be examined to see if there are cases that challenge the robustness of the AM/SG approach. Additional methodology research work can be done including looking at noise/outlier elimination techniques and advanced robust filters.

TABLE OF CONTENTS

NOMENCLATURE

α	Weighting factor for the EWMA filter
ρ	Air density
A	Cross-section area
C_d	Coefficient of drag
F_c	Cutoff frequency (Hz)
F_s	Sampling frequency (Hz)
g	Acceleration due to gravity
H	Altitude
m	Mass
V	Velocity
X	Original (unfiltered) value
Y	Filtered value

ACRONYMS, ABBREVIATIONS, AND INITIALISMS

AMF	Adaptive median filter
AM/SG	Adaptive median / Savitzky-Golay
AI	Artificial intelligence
ARC	American Rocketry Challenge
DOF	Degree of freedom
EMA	Estimated maximum altitude
EWMA	Exponential weighted moving average
FAI	Federation Aeronautique Internationale
FEM	Finite element method
FIR	Finite impulse response
IIR	Infinite impulse response
MAD	Median absolute deviation
MF	Median filter
ML	Machine learning
NAR	National Association of Rocketry
SG	Savitzky–Golay filter
SMA	Simple moving average

UNITS

Hz	Hertz (cycles per second)
Kg	Kilogram
m	Meters

1 INTRODUCTION

Several model rocketry events have altitude contests. These events include national (NAR) and international (FAI) championships, the American Rocketry Challenge (ARC), and the NASA Student Launch. Contests need legitimate altitude results that exclude noise and other non-real artifacts.

In a perfect ideal world, an altitude vs. time history would be a smooth plot. The peak altitude (apogee) could be read easily.

In the real world, many altitude histories have irregularities and noise (see Figure 1-1) caused by staging, ejection, wind/gust, altimeter jostling/vibration, or other events. Determining apogee is not as simple as just reading the maximum altitude value.

This project investigated several methods to obtain the best estimate of altitude from altimeter data.

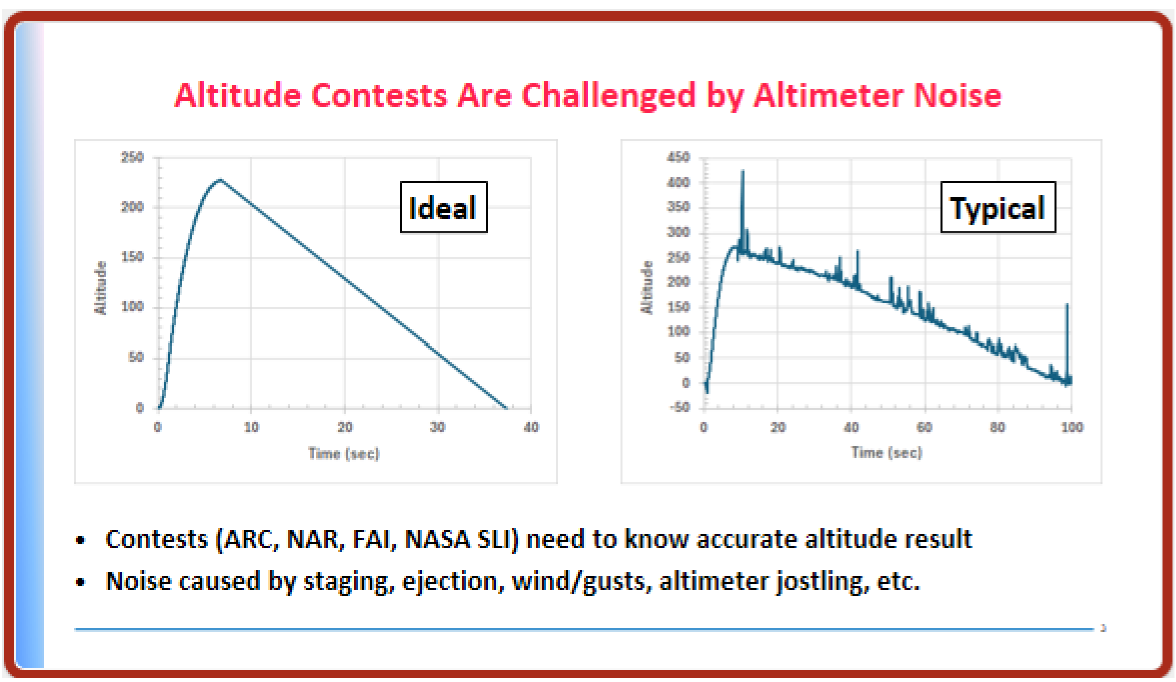

Figure 1-1. Typical altitude histories have noise from ejection, staging, vibration, and other sources.

2 OBJECTIVE AND APPROACH

2.1 OBJECTIVE

The objective of this project was to determine which processing methods (filters) work best to provide accurate altitude results from altimeter data. The processing method should minimize or eliminate major noise and smooth minor noise. The methods should also be robust to handle a wide range of both simple and challenging flight histories.

2.2 TECHNICAL APPROACH

The technical approach for this project included the following steps:

- Review literature and prior R&D reports
- Gather altimeter data from a range of "easy" and "challenging" flights
- Try many filters
- Determine if there is a method or methods that work best

These steps are described in the following sections.

3 LITERATURE REVIEW

Several data sources were searched for existing applicable data:

- Model rocketry R&D reports (NARAM and NARCON)
- Online discussion websites
- Academic publications

3.1 MODEL ROCKETRY R&D REPORTS

There are 27 previous R&D reports in the NAR Digital Archives[1] that are related to "altimeters." Many reports assessed the performance of altimeters compared to optical tracking. Other reports investigated the effect of vent hole size/location.

Three reports related to filtering and noise effects include the following.

- Schultz, David, **"Barometric Apogee Detection Using the Kalman Filter"**, NARAM-45 R&D, 2004. This project was perhaps the first effort to apply a Kalman filter to altimeter data. The main purpose was to more accurately calculate apogee in the presence of electronic noise and bit truncation. The effect of ejection charges or other in-flight noise sources was not addressed.
- Curcio, Larry, **"Using Numerical Methods to Explore Barometric Flight Data"**, NARAM-50, 2008. This project described numerical methods to calculate velocity and acceleration using barometric data (altitude). The effect of ejection charges or other in-flight noise sources was not addressed.
- Wolf, Dan, and Kuzel, Mary, **"Further Studies in Altimeter Performance and Certification"**, NARAM-59, 2017. This project was a continuation of previous work (NARAM-54, -57, and -58) looking at methods to check the operation of altimeters. The work focused on electrical/sensor performance and accuracy of pressure-to-altitude algorithms. The effect of ejection charges or other in-flight noise sources was not addressed.

3.2 ONLINE FORUM

Online discussion sites such as The Rocketry Forum[2] (TRF) have many conversation threads about altimeters and filters. There are many opinions regarding what filters work well.

- There are many recommendations to use Kalman filters, such as https://github.com/denyssene/SimpleKalmanFilter.

[1] https://nar.org, "Digital Archives"
[2] https://www.rocketryforum.com/threads/barometric-altitude-filtering.182592/ and others

- There are also some recommendations to **<u>not</u>** use Kalman filters.
  - "If you are using the Kalman algorithm to filter noise, you are using it for the wrong application."
- "A simple recursive low pass filter is easiest to code and is effective."
- "For filtering baro data, a simple exponential recursive filter is all you need."
- "The problem with an IIR filter is the response from an impulse signal (like the ejection) is, well, infinite."

While TRF has interesting opinions, there are no significant results showing advantages/disadvantages or results using actual flight data.

3.3 ACADEMIC PUBLICATIONS

- Luckett, Edward (ed.), **"Digital Detection of Rocket Apogee"**, Rice University, 2013 https://www.rocketryforum.com/attachments/digital-detection-of-rocket-apogee-1-1-pdf.379843/ This report examined the application of several filters to flight data. The project examined include boxcar, Butterworth, Elliptical Lowpass, and Kalman filters. However, the flight noise was random and did not have discrete "spike" events such as ejection charges.

4 EXAMPLE FLIGHT DATA

Altitude histories were obtained that range from relatively simple to highly challenging data. Four flights represented some of the most challenging cases.

4.1 EJECTION DURING ASCENT

Flights sometimes have ejection occur during ascent, prior to apogee. This can cause large negative or positive spikes in the indicated altitude. An example is shown in Figure 4.1-1.

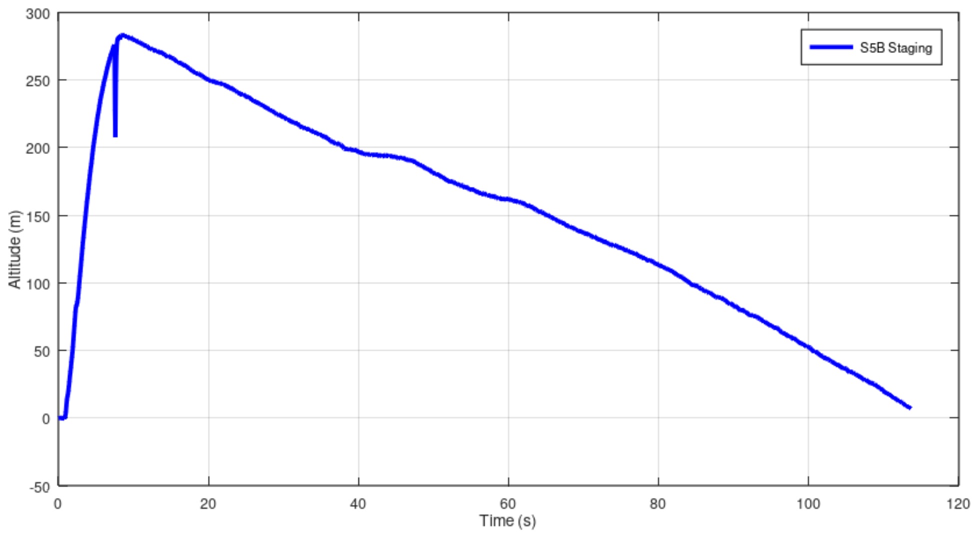

Figure 4.1-1. Ejection during ascent can cause negative or positive spikes in the indicated altitude.

4.2 ASCENT ANOMALY

Staging or other events can produce anomalous results during ascent. An example is shown in Figure 4.2-1.

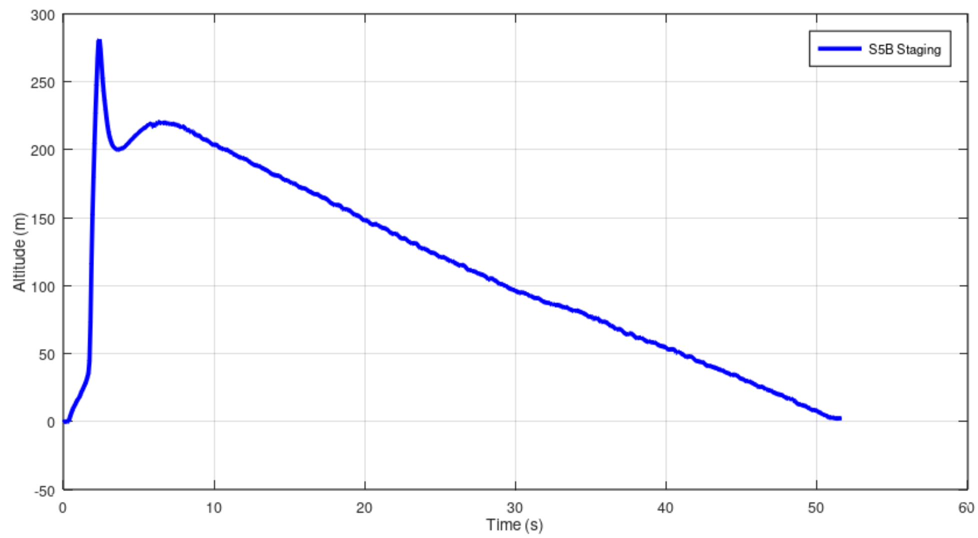

Figure 4.2-2. Anomalies can occur during ascent due to staging issues or payload shifting.

4.3 HIGHER AFTER EJECTION

Altitude after ejection can sometimes be somewhat higher than before ejection. In the example shown in Figure 4.3-1, the "higher after ejection" situation appears to be confirmed by the descent trace. Trying to determine the best estimate of apogee can be difficult due to noise during descent.

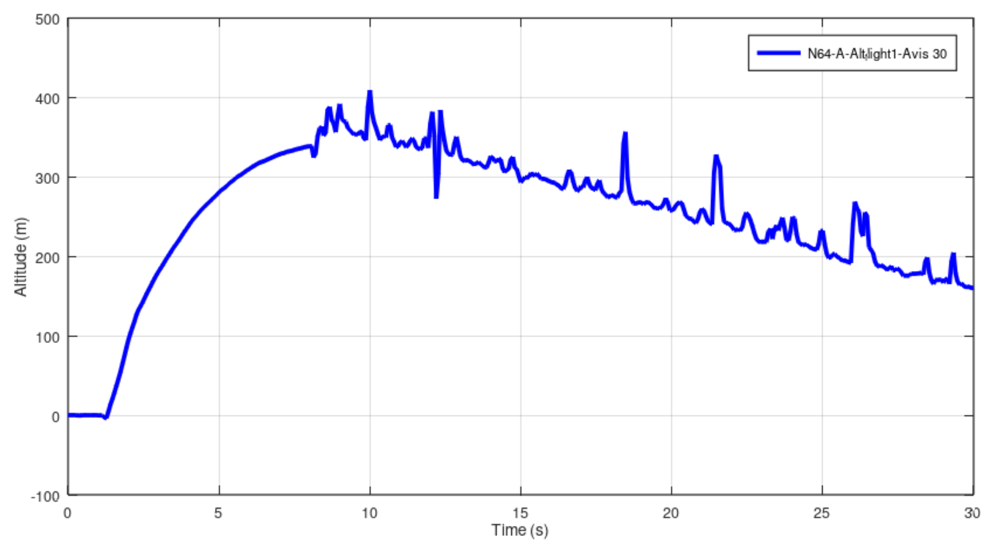

Figure 4.3-1. Altitude can sometimes be somewhat higher after ejection.

4.4 MAJOR NOISE SPIKES

When ejection occurs, there is often a major "snap" as the shock cord reaches full extension. This happens frequently with models that have heavy payloads, such as egglofters and ARC flights. In Figure 4.4-1, the "snap" effect increased the unfiltered altitude by over 50%.

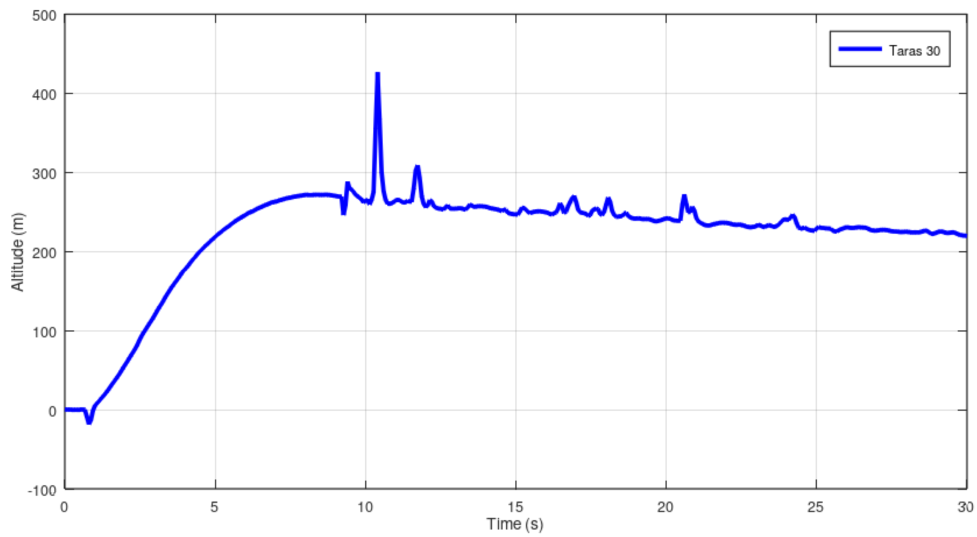

Figure 4.4-1. The "snap" at ejection can sometimes cause major noise spikes.

The altitude history in Figure 4.4-1 was the most challenging example flight examined in this report. It is used in many of the test cases discussed in the next section.

5 PROCESSING METHODS/FILTERS

Seven filters were examined:

- Simple Moving Average (SMA)
- Exponentially Weighted Moving Average (EWMA)
- 2nd order Low Pass (Butterworth) filter
- Kalman filter
- Median filter
- Structural spline filter
- Savitzky–Golay filter

5.1 SIMPLE MOVING AVERAGE (SMA)

A basic filter is called a Simple Moving Average (SMA)[3]. This filter works by calculating a new (filtered) value based on the average of a "window" of nearby original (unfiltered) values.

For example, the equation for a 5-point central SMA is:

$$Y_k = \frac{X_{k-2} + X_{k-1} + X_k + X_{k+1} + X_{k+2}}{5}$$

This calculation is applied to each point in the unfiltered altitude history to produce a filtered history. The size of the window is a trade-off between smoothing and feature retention.

For the example flight shown previously in Figure 4.4-1, the SMA-filtered history is shown in Figure 5.1-1. The SMA-filtered history reduced but did not eliminate the primary noise spike at ~10.5 seconds.

The SMA process can be used in a recursive manner. The output from one pass can be used as the input for the next pass. For the example flight, the results after five passes are shown in Figure 5.1-2. Additional passes provided additional smoothing but did not eliminate the primary noise spike.

[3] https://en.wikipedia.org/wiki/Moving_average#Simple_moving_average

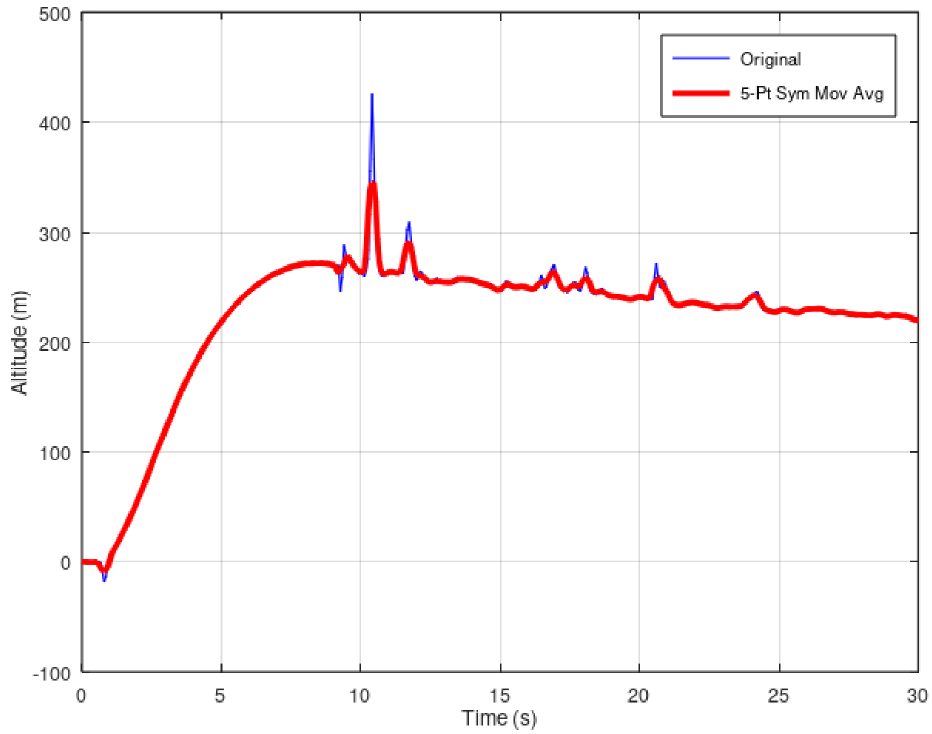

Figure 5.1-1. Applying a SMA filter reduced but did not eliminate the primary noise spike.

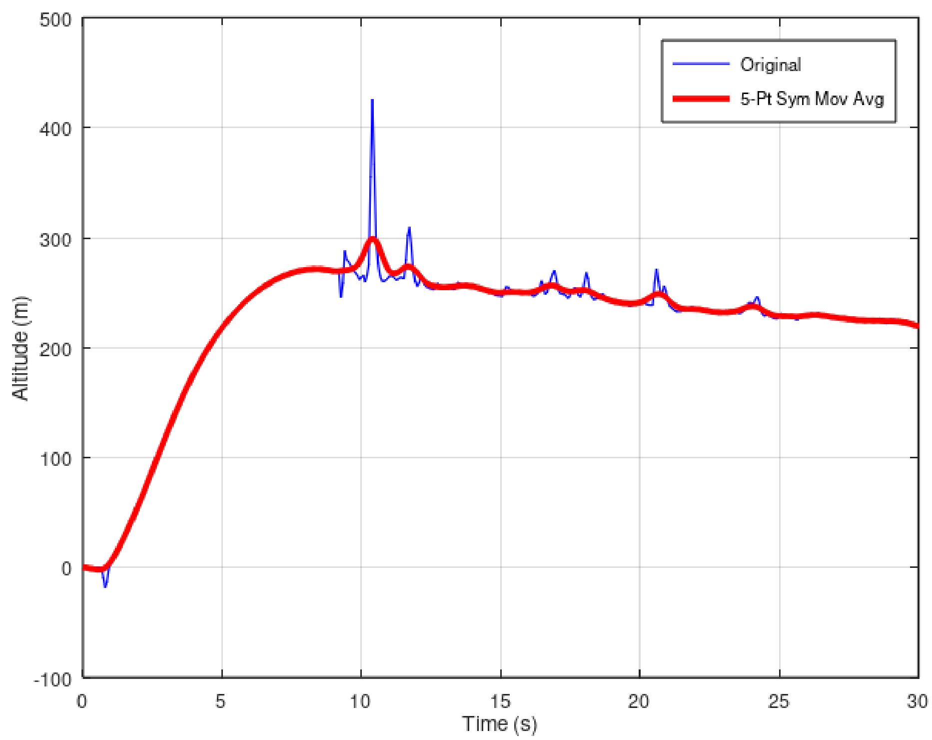

Figure 5.1-2. Applying the SMA filter recursively (5 passes) provided additional smoothing but did not eliminate the noise spike.

Additional passes can provide additional smoothing but will eventually begin to distort the underlying data. The results after 100 and 500 SMA passes are shown in Figures 5.1-3 and 5.1-4, respectively. Some of the primary noise spike was still present after 100 passes. At 500 passes, the filtered results were drifting away from the underlying data.

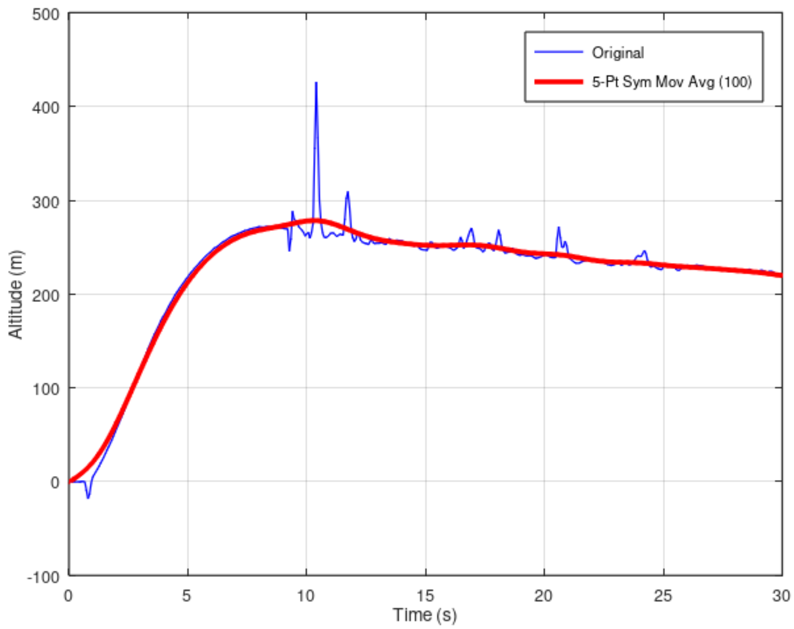

Figure 5.1-3. 100 SMA passed provides additional smoothing but still did not fully eliminate the effect of the primary noise spike.

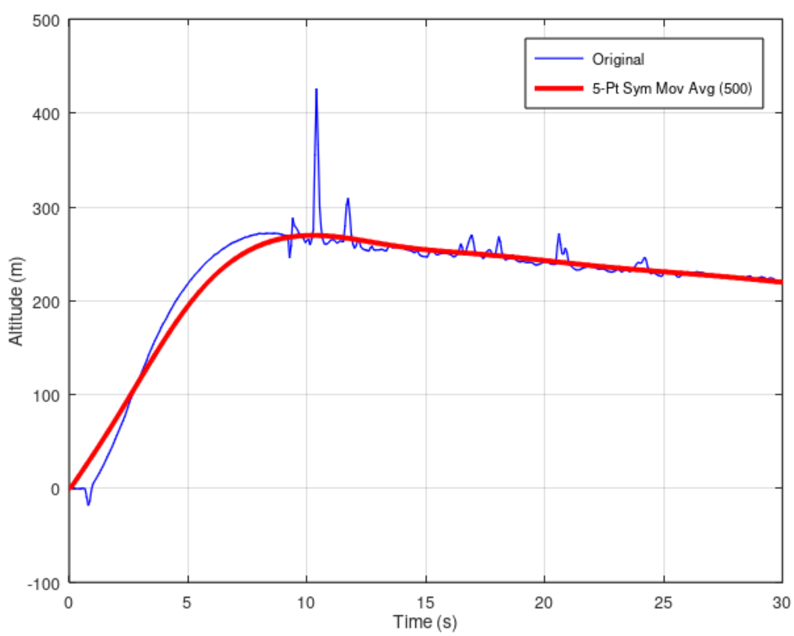

Figure 5.1-4. 500 SMA passes started to distort the original signal.

There does not appear to be an obvious convergence check for the SMA recursion process that can determine how many passes are needed to eliminate the effects of noise spikes but without affecting the underlying results.

5.2 EXPONENTIALLY WEIGHTED MOVING AVERAGE (EWMA)

The SMA filter treats all data points within the window equally. Other averaging methods apply weighting factors to adjust the relative importance of data points.

The Exponentially Weighted Moving Average (EWMA)[4] uses a coefficient "α" to adjust the weighting of recent values relative to earlier values:

$$Y_i = \alpha\, X_i + (1 - \alpha)\, Y_{i-1}$$

The coefficient "α" is between 0 and 1. A small "α" provides much smoothing, while a large "α" provides little smoothing.

EWMA is an Infinite Impulse Response (IIR) filter. New values depend to some extent on all previous values. SMA is a Finite Impulse Response (FIR) filter. New values depend on a finite number of nearby values.

EWMA is computationally efficient, using just one equation and requiring minimal storage. EWMA is also equivalent to a 1st order Low-Pass filter (see Section 5.3).

EWMA was applied to the example flight. Filtered results using light smoothing (α = 0.5) and significant smoothing (α = 0.1) are shown in Figures 5.2-1 and 5.2-2, respectively. The light smoothing case did not do much to eliminate the primary noise spike. The significant smoothing case reduced but did not eliminate the spike. It also caused the filtered results to depart from the underlying flight data.

As with SMA, there does not appear to be convergence check to select the best "α" to eliminate the effects of noise spikes while not affecting the underlying results.

[4] https://en.wikipedia.org/wiki/Moving_average#Exponential_moving_average

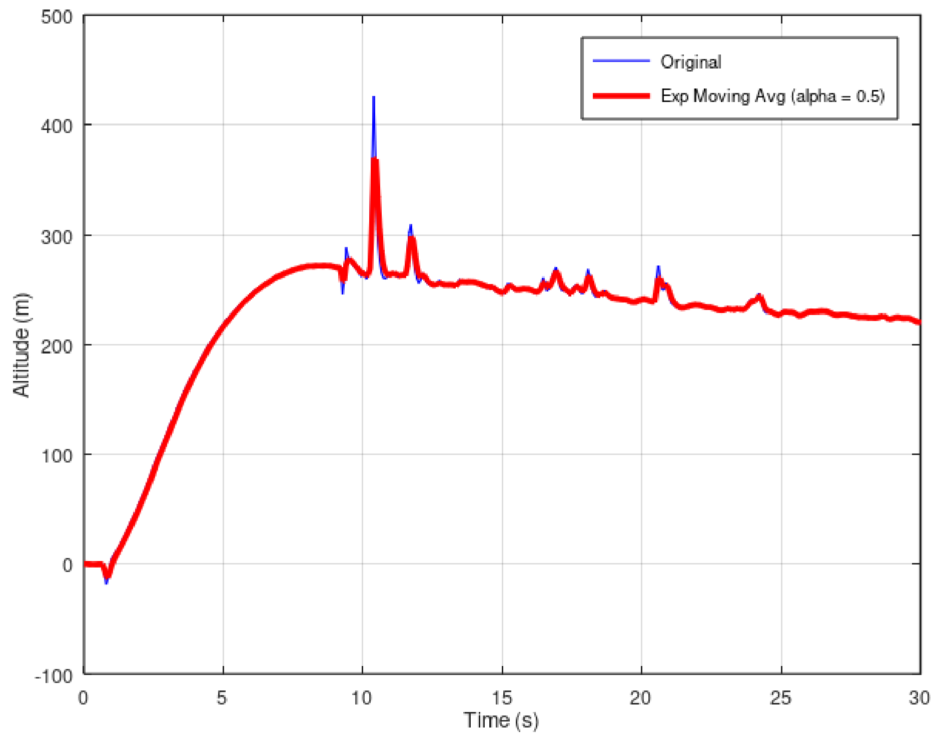

Figure 5.2-1. EWMA using light smoothing (α = 0.5) did not eliminate the noise spikes.

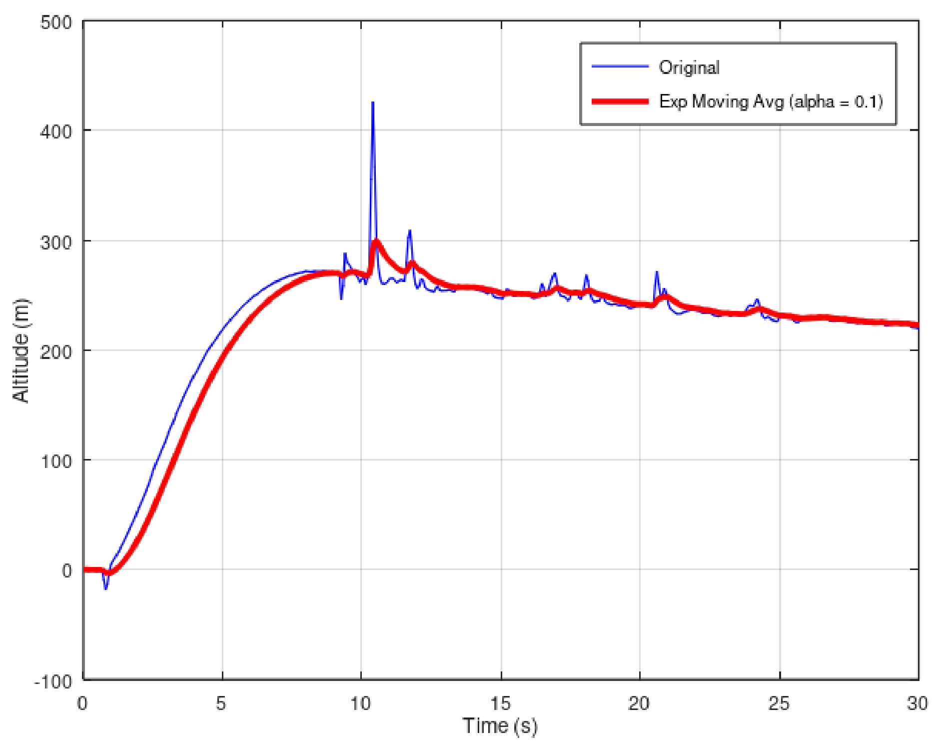

Figure 5.2-2. EWMA using significant smoothing (α = 0.1) reduced the noise spikes but also affected the underlying data.

5.3 2ND ORDER LOW PASS FILTER

"A Low-Pass filter is a filter that allows signals below a cutoff frequency (known as the passband) and attenuates signals above the cutoff frequency (known as the stopband)."[5] For model rocket flight histories, a Low-Pass filter could keep the actual (low frequency) data while eliminating high frequency noise.

The equation for a 1st order Low-Pass filter is the same as EWMA:

$$\mathrm{Y_i} = \alpha\,\mathrm{X_i} + (1-\alpha)\,\mathrm{Y_{i-1}}$$

The coefficient α is related to the cutoff frequency and sampling frequency:

$$\alpha = \frac{1}{1+\left(2\,\pi\,\frac{\mathrm{f_c}}{\mathrm{f_s}}\right)}$$

where:

f_c = cutoff frequency (the frequency at which the output begins to drop off)
f_s = sampling frequency (the rate at which the signal is sampled)

Higher order Low-Pass filters can provide steeper attenuation of high frequency content. A 2nd order Butterworth filter provides "maximally flat frequency response in the passband." A Chebyshev filter can provide "steeper roll-off compared to Butterworth, but with ripples in the passband."

A 2nd order Butterworth filter was applied to the example flight history. Two values of the cutoff frequency (0.5 Hz and 0.1 Hz) (altimeter data sampling rate = 15 Hz) are shown in Figures 5.1-3 and 5.1-4, respectively. Using a cutoff frequency of 0.5 Hz significantly reduced but did not eliminate the primary noise spike. Using a cutoff frequency of 0.1 Hz caused distortion of the underlying data. As with the SMA and EWMA, it's not clear that there is an accuracy or convergence criteria for the selection of the cutoff frequency.

[5] https://www.mathworks.com/discovery/low-pass-filter.html

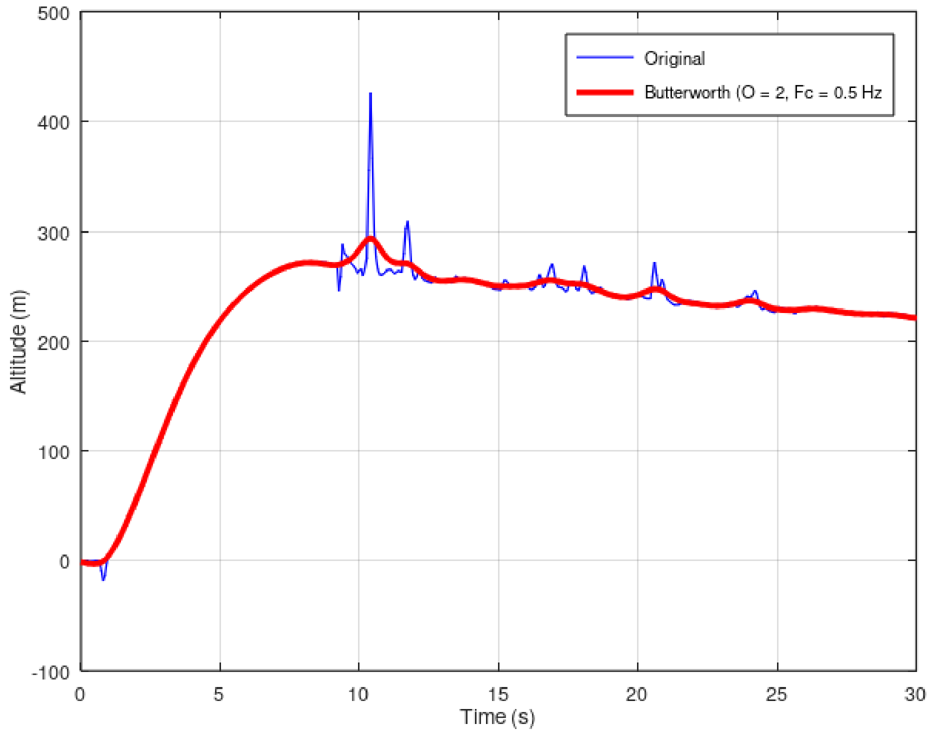

Figure 5.3-1. Applying a 2^{nd} order Butterworth filter (cutoff frequency = 0.5 Hz) noticeably reduced but did not eliminate the primary noise spike.

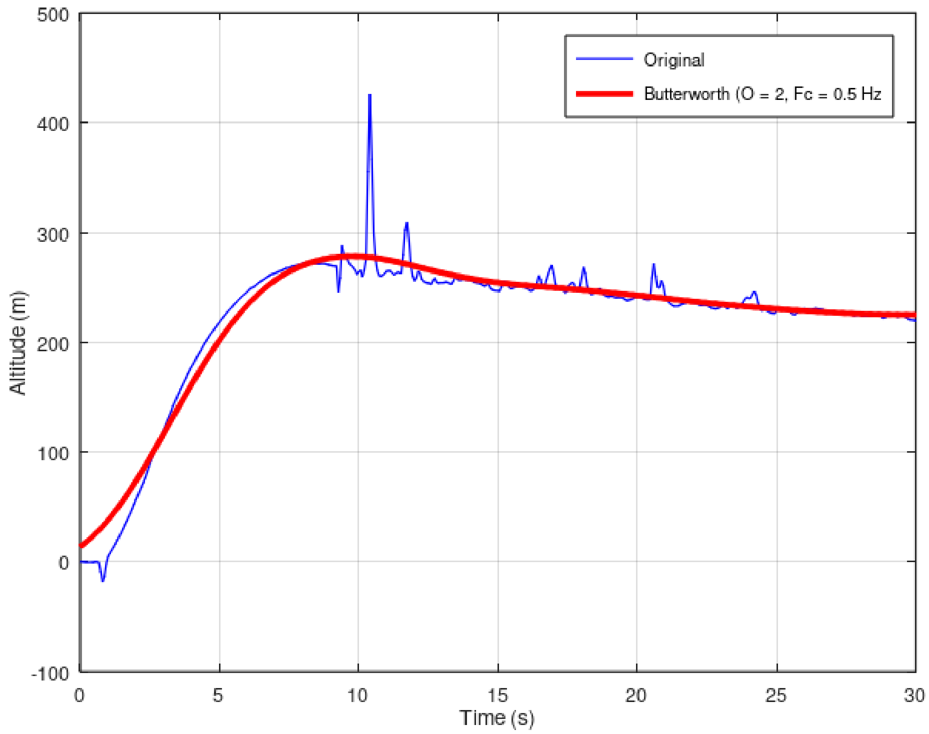

Figure 5.3-2. Decreasing the cutoff frequency to 0.1 Hz) eliminated the noise spike but distorted the underlying data.

5.4 KALMAN FILTER

"The Kalman filter is a digital filter which produces estimates of system variables (called hidden variables, because you cannot know their exact value) based on noisy measurements (data with uncertainty). The Kalman filter is a very common estimation algorithm used in many applications such as GPS/positional measurements, radar, robot kinematics."[6]

The Kalman filter is designed to work optimally under the assumption that the noise is Gaussian. If the noise deviates significantly from this assumption or contains outliers, the filter's performance can degrade, leading to inaccurate state estimates.

A 1-D constant-velocity Kalman filter is the "standard model for smoothing measurements when you don't have direct velocity readings." The Kalman filter can be tuned by adjusting coefficients Q, R, and P:

- Process noise "Q"
    - Controls how much you trust the model vs. the data
    - Increase Q_{11} if altitude changes faster than expected
    - Increase Q_{22} if velocity is noisy or unpredictable
- Measurement noise "R"
    - Represents sensor noise variance
    - If barometric sensor is noisy, increase R
    - If barometric sensor is stable, decrease R
- Initial covariance "P"
    - If starting altitude known well, reduce P_{11}
    - If velocity is unknown, keep P_{22} large

The 1-D constant-velocity Kalman filter was applied to the example flight history using two sets of coefficients:

- "Safe" values: Q_{11} = 0.01, Q_{22} = 0.1, R = 2
- "Tuned by AI" values: Q_{11} = 1E-4, Q_{22} = 1E-3, R = 0.1

Results using Kalman filter with "safe" coefficients looked comparable to those from other filter methods. Results using the "AI-tuned" coefficients started diverging from the underlying data.

[6] https://blog.mbedded.ninja/programming/signal-processing/digital-filters/kalman-filter/

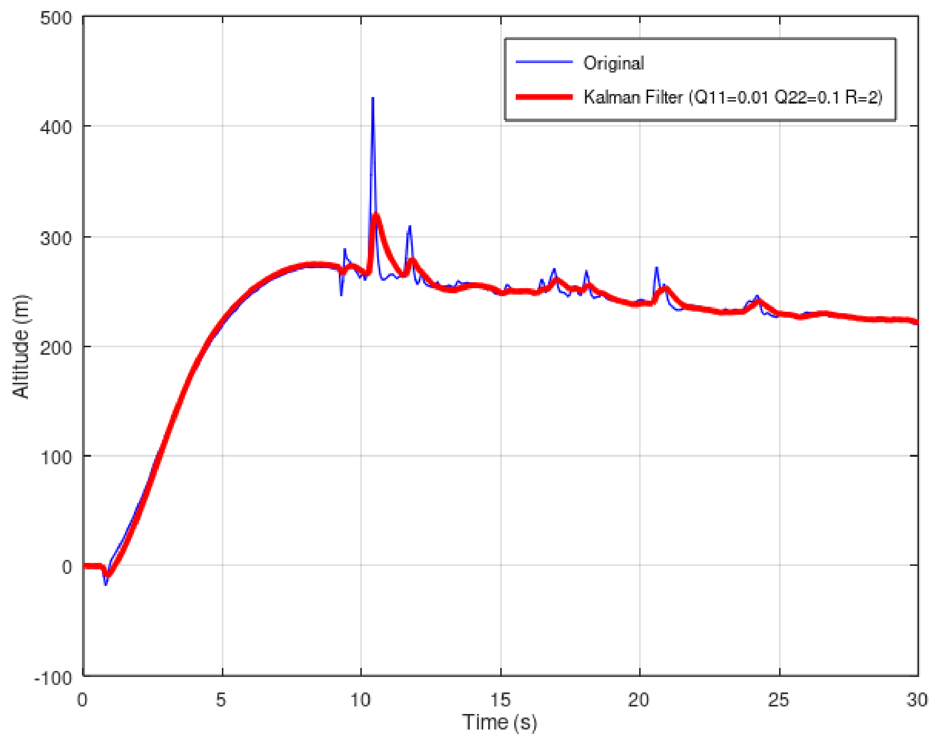

Figure 5.4-1. The 1-D constant velocity Kalman filter reduced but did not eliminate the primary noise spike.

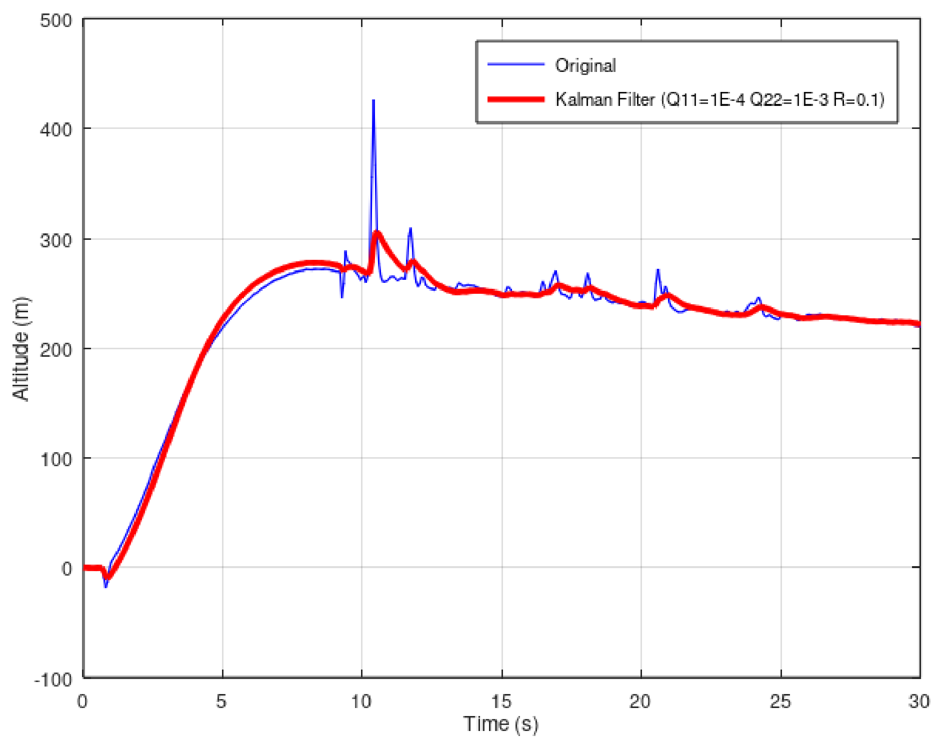

Figure 5.4-2. Using "AI tuned" coefficients for the Kalman filter caused the filtered values to drift from actual data.

5.5 ITERATIVE STRUCTURAL SPLINE

There are many types of smoothing splines that are used to smooth data.[7] However, these methods can be limited by mathematical formulation (polynomial, B-spline, etc.) and equation order.

A novel approach was developed using the structural finite element method (FEM).[8] A beam FE model was developed with one node (2 DOF) for each data point in the altitude history. Beam elements connected the data points. A pictorial of the undeformed shape of the FE model is shown in Figure 5.5-1.

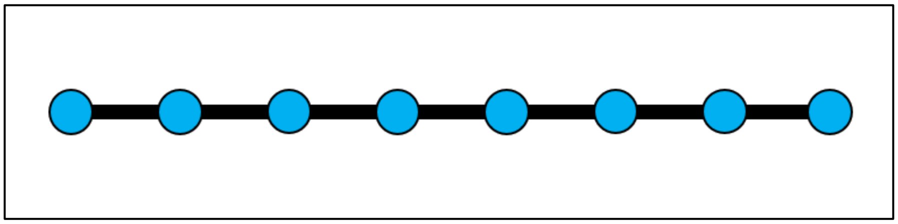

Figure 5.5-1. A beam FE model was created with one node per altitude point.

The nodes in the beam model were enforced to move to the points in the altitude history. The constraint forces were calculated. This is illustrated in Figure 5.5-2.

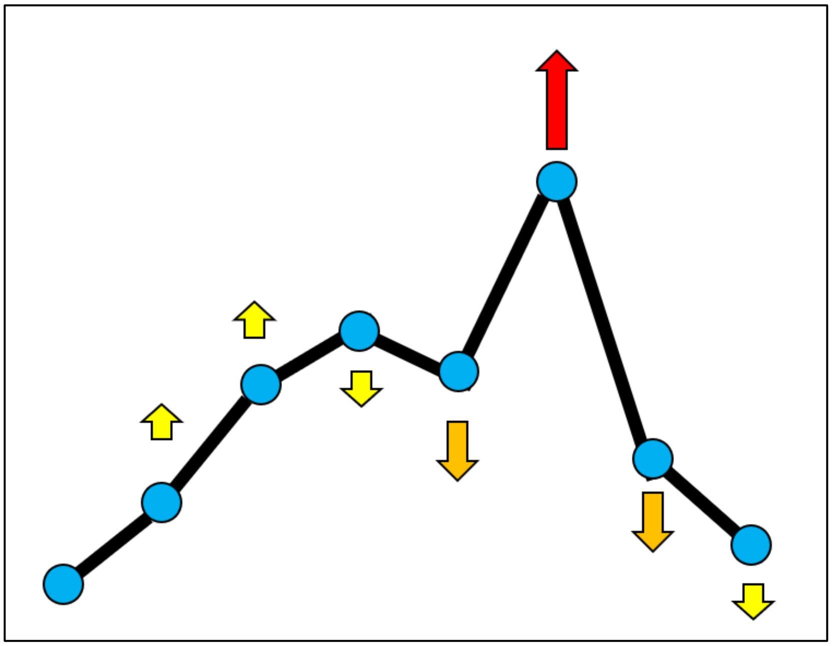

Figure 5.5-2. Forces to move the nodes to the altitude values are calculated.

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[7] https://en.wikipedia.org/wiki/Smoothing_spline
[8] https://en.wikipedia.org/wiki/Finite_element_method

Where the altitude changes smoothly (such as during ascent), the forces required to deform the beam are small. Where the altitude changes suddenly (ejection, noise spikes, etc.) and the beam has to bend sharply, the forces are very large.

The iterative structural spline method works as follows:

- Develop the finite element model and active constraints
- Deform the beam to the active constraint values (altitude data)
- Calculate the forces required to deform the beam
- Identify the largest force
- Release the node at that location (i.e., deactivate the altitude constraint)
- Repeat the process until the apogee doesn't significantly change or the constraint forces decrease to an acceptable value

The iterative structural spline was applied to the example altitude history. Overall results including the iteration process are shown in Figure 5.5-1. A detailed view of the primary noise spike is shown in Figure 5.5-2. The iterative structural spline did well at identifying and eliminating the noise spikes. The final altitude history is shown in Figure 5.5-3.

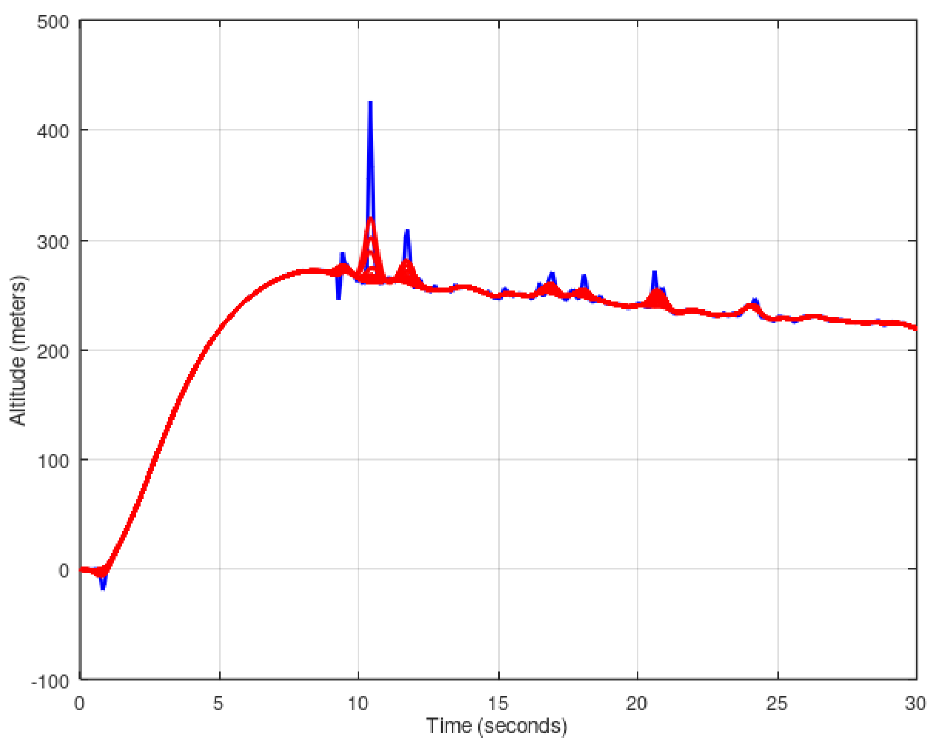

Figure 5.5-1. The iterative structural spline did well on the example flight history.

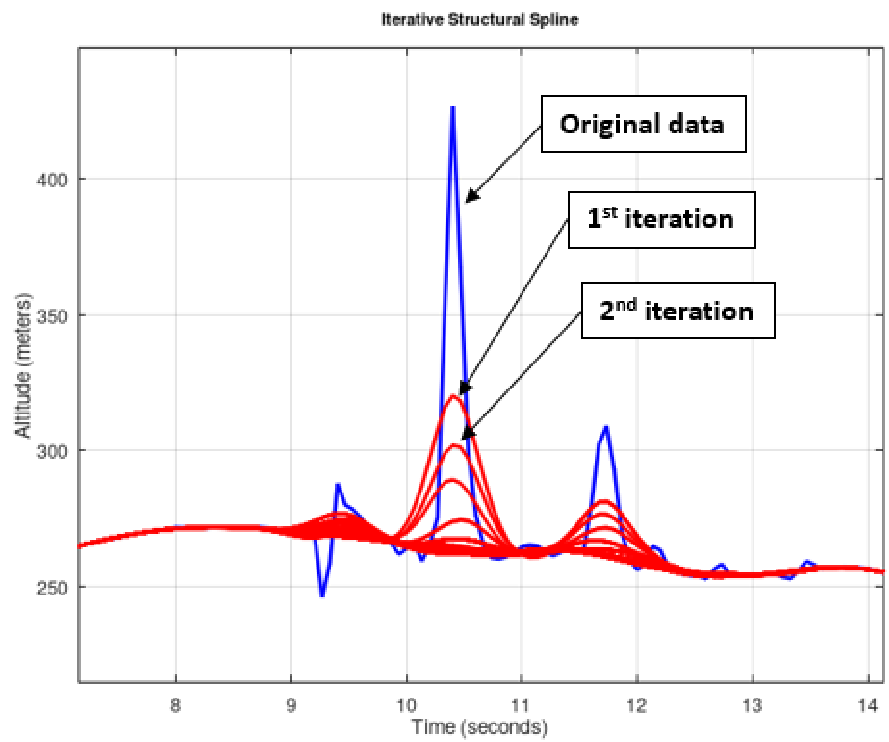

Figure 5.5-2. The iterative structural spline identified and smoothed noise spikes over several iterations.

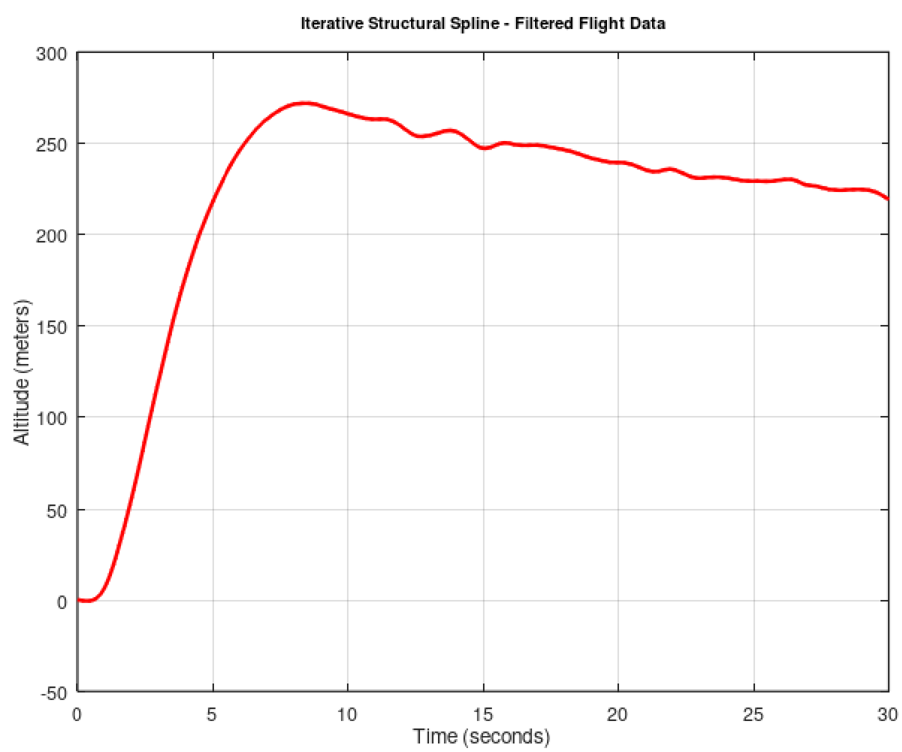

Figure 5.5-3. The iterative structural spline did well on the example flight history.

One disadvantage of the iterative structural spline method is that it can be numerically intensive. That may be acceptable for solutions performed postflight on a computer. The method might not be feasible for flight software inside an altimeter.

5.6 MEDIAN FILTER

"A median filter is a non-linear digital filtering technique used to remove noise from images, signals, and videos while preserving edges. It works by replacing each value in a dataset with the median of its neighboring values within a defined window."[9]

"The standard median filter is one of the most commonly used and effective methods for removing spike (impulsive) noise from signals and images."[10]

A median filter (MF) is a windowed approach somewhat similar to the Simple Moving Average. The SMA uses the **average** of the values within the window, while a median filter uses the **median** value of the values within the window.

The results from a median filter depend on the window size relative to the duration of a noise spike. The window should be an odd number and be large enough such that the number of points in the noise spike is less than half the window. For example, if the noise spike is five samples long, the median filter window size should be 11 or greater. However, using an overly large window may affect real data.

The median filter can be used in an adaptive mode. Start with a baseline window size (perhaps 11 points), then increase the window size by two points per pass until the results stabilize (i.e., no significant change in apogee).

Two examples of using a Median Filter are shown in Figures 5.6-1 and 5.6-2. In the first example, a fixed window of 25 points was used. In the second example, In Figure 5.6-2, an Adaptive Median Filter (AMF) was used. The filter had a starting window size of 5 points. Converged results were obtained after reaching a window size of 15 points.

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[9] https://en.wikipedia.org/wiki/Median_filter
[10] https://www.sciencedirect.com/science/article/abs/pii/S0926985112001474

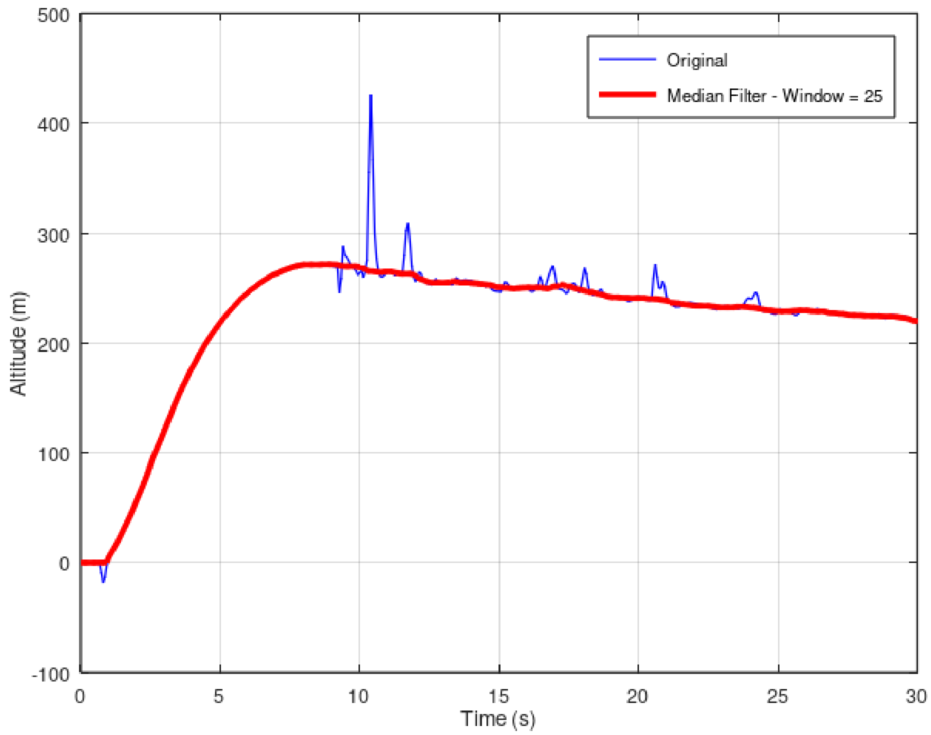

Figure 5.6-1. The median filter with a fixed window size of 25 points worked well on the example flight history.

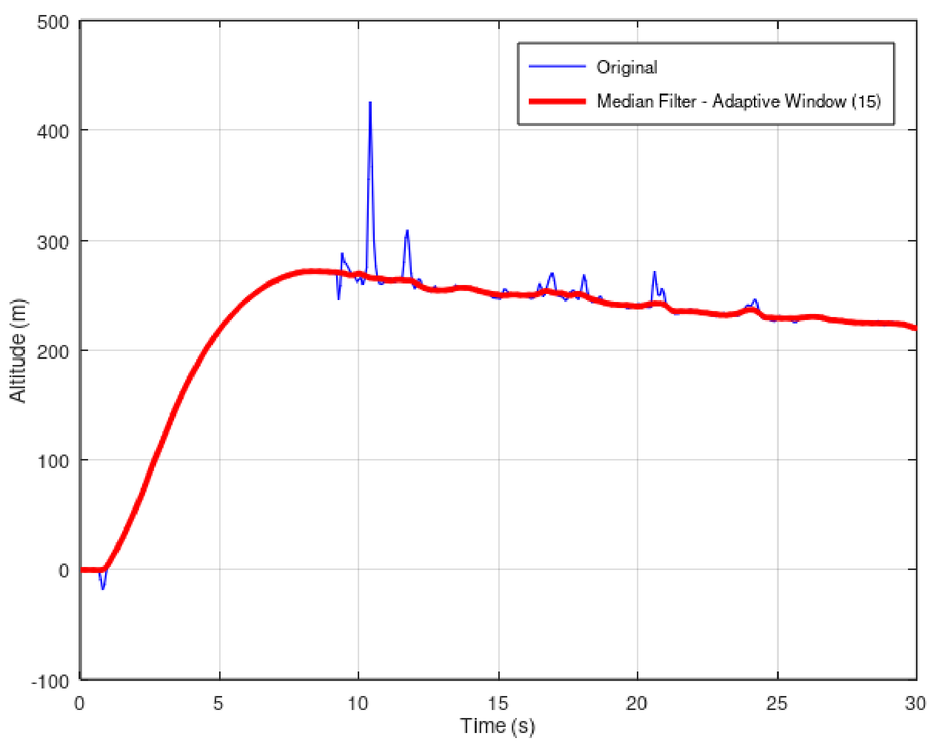

Figure 5.6-2. The adaptive median filter converged using a window size of 15.

5.7 SAVITZKY–GOLAY FILTER

A median filter can be very effective at removing spike noise. However, it isn't overly effective at fine smoothing of the output values.

An additional smoothing step can be performed following the application of a median filter. Standard smoothing methods such as SMA or EWMA could be used. However, an interesting smoothing technique is the Savitzky–Golay (SG) filter.[11] The SG filter uses a windowed approach similar to SMA and MF. While SMA calculates the **average** value and MF returns the **median** value, the SG filter fits a **polynomial** of a specified order to the points within the window. The polynomial approach returns the filtered value. In addition, the polynomial coefficients can be easily used to calculate accurate derivatives. For altimeter processing, this allows for calculation of more accurate velocities from altitude data. Accurate velocity data is valuable for altitude checking algorithms such as the Estimated Maximum Altitude method (discussed in Section 6.2).

An example of SG smoothing is shown in Figure 5.7-1.

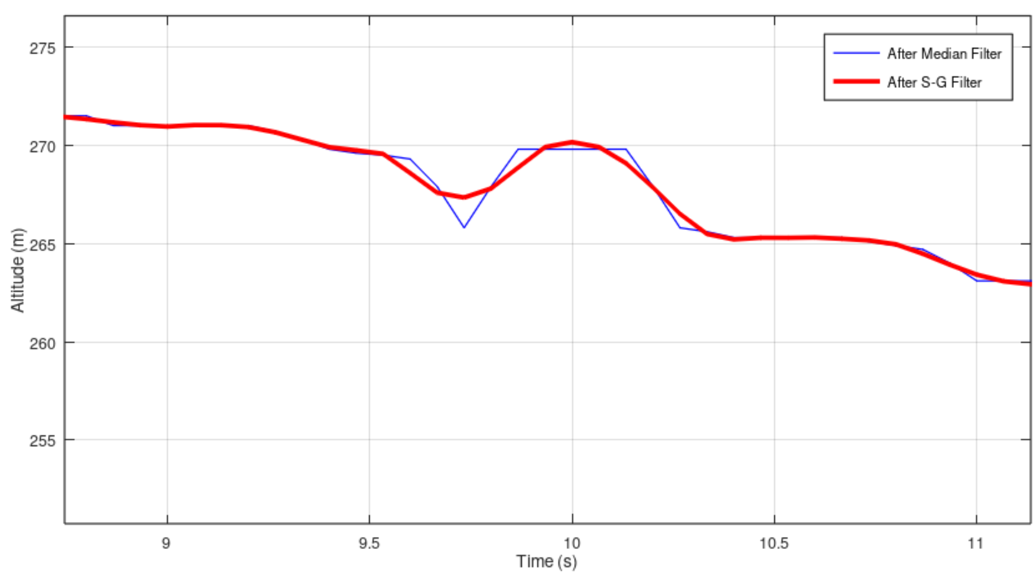

Figure 5.7-1. The Savitzky-Golay filter can smooth data and provide accurate derivatives.

[11] https://en.wikipedia.org/wiki/Savitzky%E2%80%93Golay_filter

5.8 ADAPTIVE MEDIAN / SAVITZKY–GOLAY

A robust approach for altimeter processing is to use a two-step approach:
1) Adaptive Median filter to remove spikes and other noise artifacts; and
2) Savitsky-Golay filter for smoothing of altitude values and calculation of velocities.

The AM/SG filter process was applied to the four cases shown in Section 4. The results are shown in Figures 5.8-1 through 5.8-4. In all cases, the AM/SG filter process worked well to provide realistic apogee values.

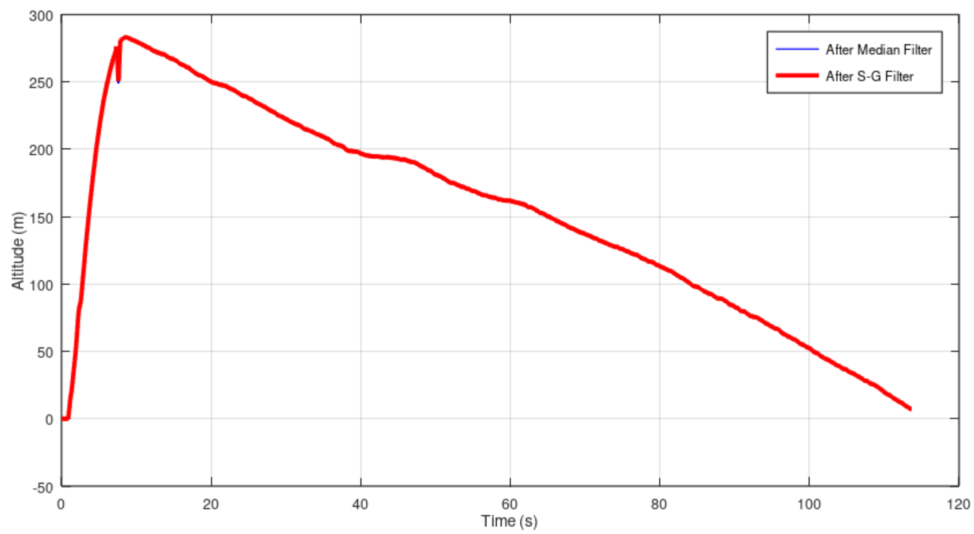

Figure 5.8-1. The AM/SG filter easily handled the "single dip" flight history.

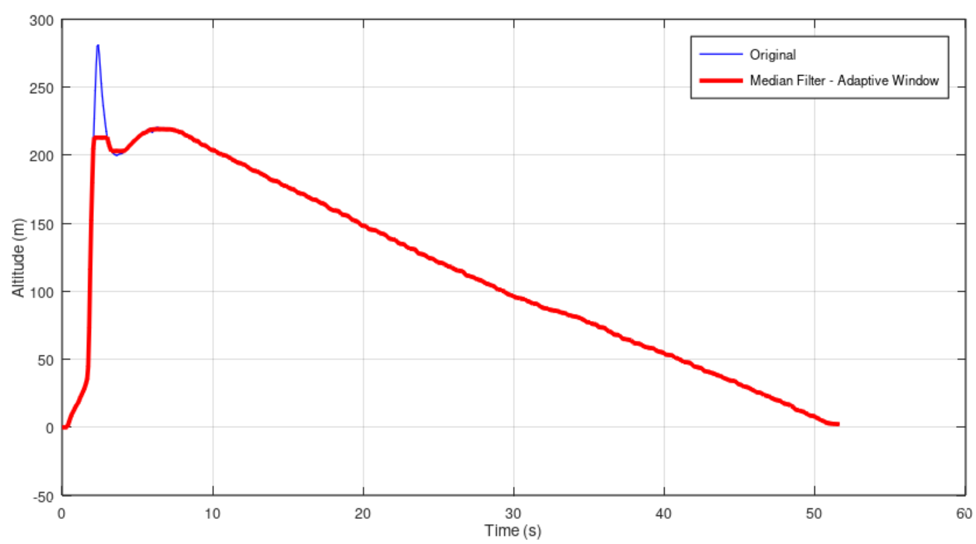

Figure 5.8-2. The AM/SG filter removed enough of the anomalous spike so that the apogee was reasonable.

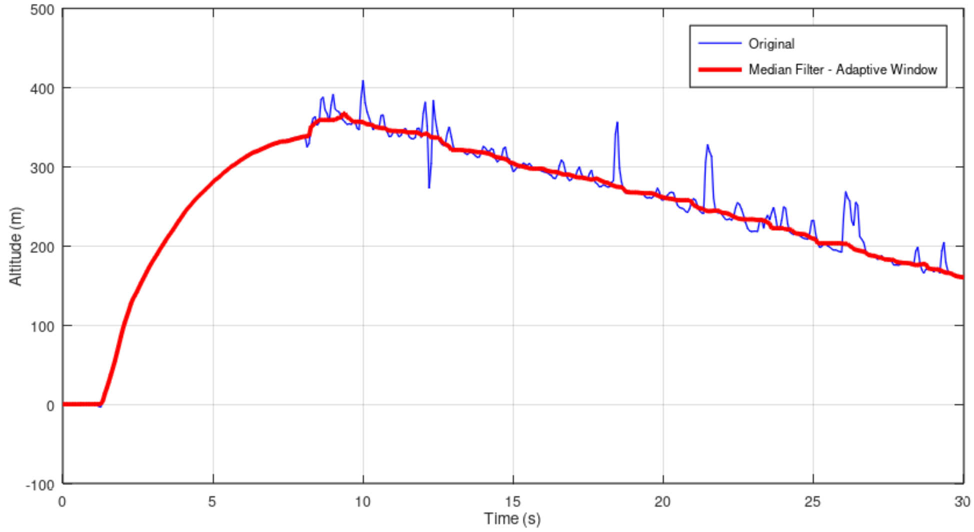

Figure 5.8-3. The AM/SG filter gave a reasonable answer for the "higher after ejection" case.

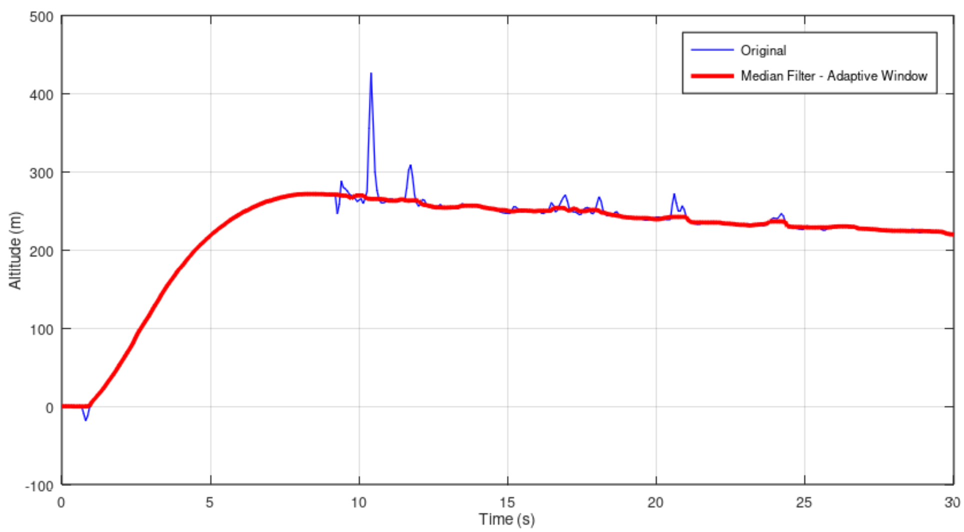

Figure 5.8-4. The AM/SG filter did well on Flight History #4.

6 ALTITUDE CHECKING METHODS

6.1 ESTIMATED MAXIMUM ALTITUDE

A rocket's maximum altitude can be estimated at any point in flight given its current altitude and velocity. This process is illustrated in a graphic[12] developed by the NASA Glenn Research Center (see Figure 6.1-1).

Inputs and assumptions for the Estimated Maximum Altitude (EMA) calculation:

- Rocket's Cd, A, and mass (ballistic coefficient)
- Constant gravity
- Constant air density
- Coasting after burnout

(Note: if the EMA is calculated while the motor is burning, the EMA value will increase until burnout. The EMA should remain ~constant after burnout.)

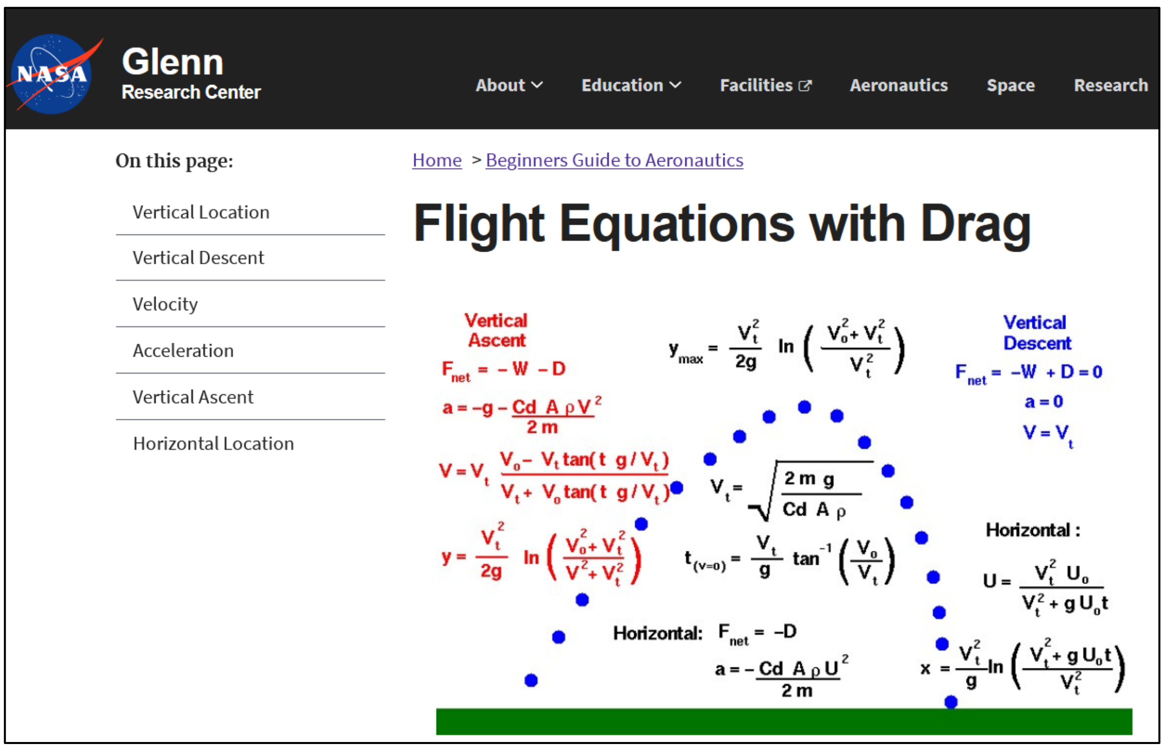

Figure 6.1-1. A rocket's maximum altitude can be estimated given its ballistic coefficient and current altitude & velocity.

[12] https://www1.grc.nasa.gov/beginners-guide-to-aeronautics/flight-equations-with-drag/

The equations for the Estimated Maximum Altitude are:

$$H_{max} = H_0 + \frac{V_t^2}{2\,g} \ln\left(\frac{V_0^2 + V_t^2}{V_t^2}\right)$$

$$V_t = \sqrt{\frac{2\,m\,g}{C_d\,A\,\rho}}$$

$$BC = \frac{m}{C_d\,A}$$

$$V_t = \sqrt{\frac{2\,g\,BC}{\rho}}$$

where:

H_{max}	= estimated maximum altitude
H_0	= current altitude
V_0	= current velocity
V_t	= terminal velocity
g	= acceleration due to gravity
ρ	= air density
m	= mass of the rocket
C_d	= drag coefficient
A	= cross-section area
BC	= ballistic coefficient

An example of an EMA calculation is shown in Figure 6.1-2. The EMA value should approximately match the rocket's apogee. This is especially true as the rocket approaches apogee and the velocity effect in the EMA equation approaches zero. Any significant difference between the EMA and actual apogee warrants detailed examination of the flight data.

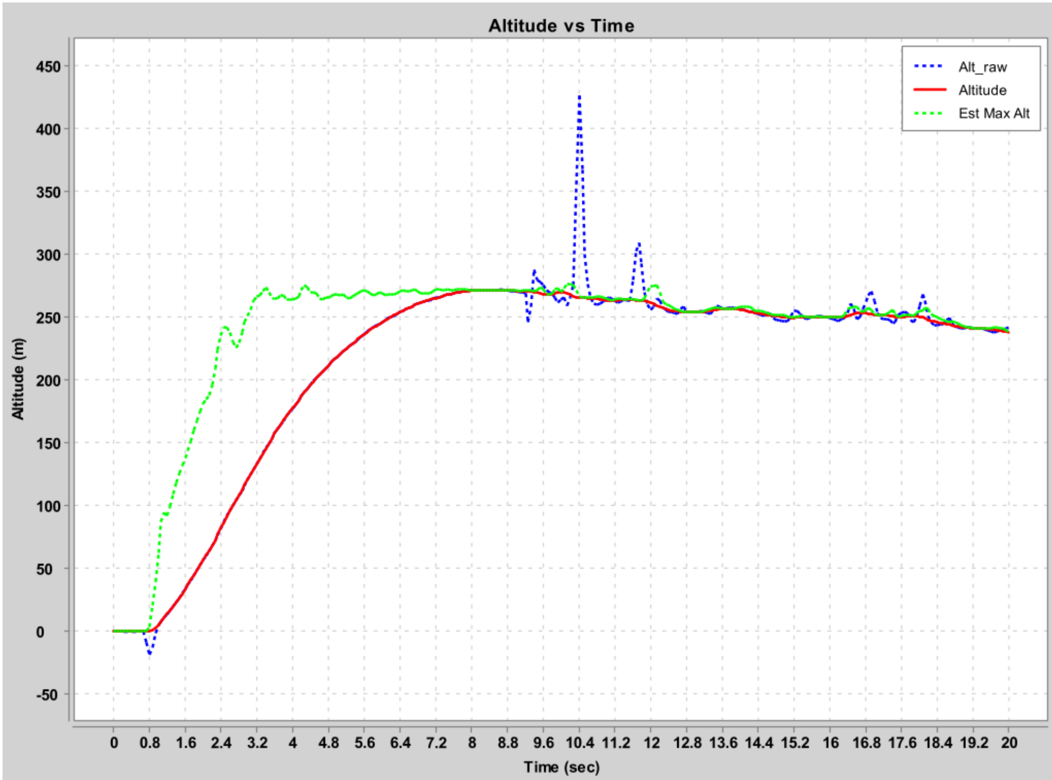

Figure 6.1-2. Any significant difference between the EMA and actual apogee warrants detailed examination of the flight data.

The rocket's ballistic coefficient is an important term in the EMA equation. Some typical ballistic coefficients for selected events are shown below in Table 6.1-1.

Table 6.1-1. Ballistic coefficients for selected events.

	S1B - FAI Altitude					S5C - FAI Scale Altitude					S2/P - Precision Fragile Payload			
Diameter	**25**	mm	0.025	m		**30**	mm	0.03	m		**66.04**	mm	0.0660	m
Radius	12.5	mm	0.0125	m		15	mm	0.015	m		33.02	mm	0.0330	m
X-Sect Area	490.9	mm^2	0.000491	m^2		706.9	mm^2	0.000707	m^2		3425.3	mm^2	0.00343	m^2
Mass	**9**	grams	0.009	kg		**25**	grams	0.025	kg		**350**	grams	0.35	kg
CD	**0.4**					**0.6**					**0.5**			
Ballistic Coef (BC)			**45.8**	kg/m^2				**58.9**	kg/m^2				**204.4**	kg/m^2
BC = M / (Cd A)														

6.2 ACCELERATION-BASED ALTITUDE

If the altimeter has an accelerometer, the altitude of the rocket can be calculated by double-integrating the longitudinal acceleration data. The accuracy of this calculation depends on 1) the accuracy of the acceleration sensor; and 2) whether the rocket ascended vertically or at an angle.

An example is shown in Figure 6.2-1. The acceleration-based altitude should approximately match the barometric-based apogee if the rocket ascended vertically. Any significant difference between the acceleration-based altitude and barometer-based apogee warrants detailed examination of the flight data.

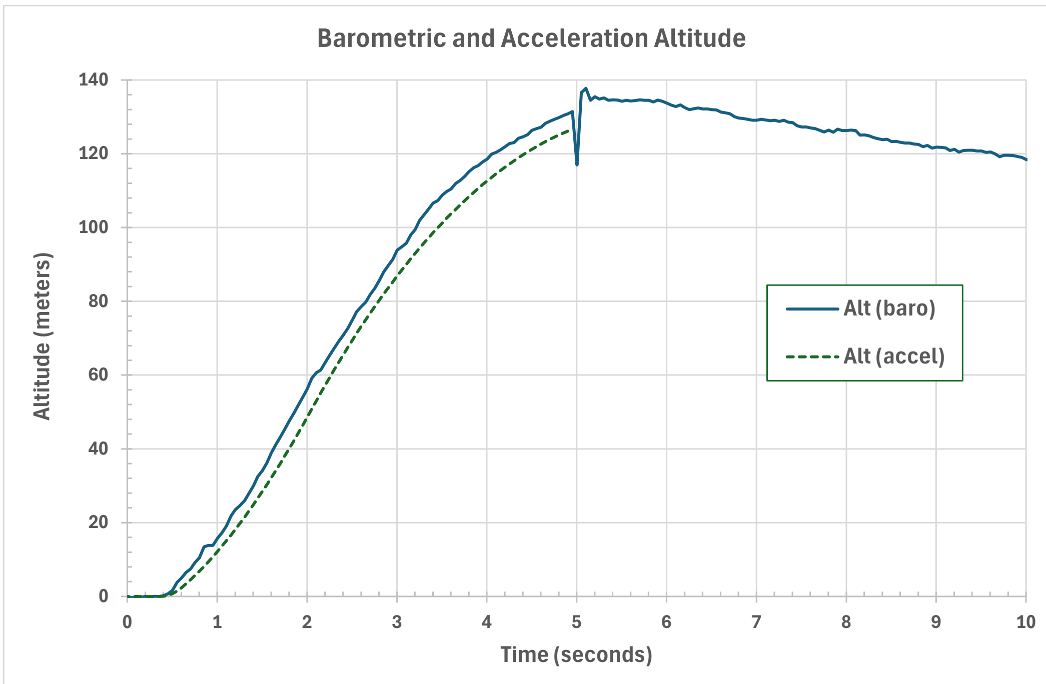

Figure 6.2-1. Acceleration-based altitude should agree reasonably well with barometer-based results if the rocket's trajectory was vertical.

7 FUTURE OPPORTUNITIES

The field of signal processing is enormous. There are many, many methods for filtering and processing data to improve quality. Some additional methods that could potentially be applied to altimeter data are described in this section.

7.1 DIRECT NOISE REMOVAL

Fourier Transform. The Fourier transform converts a time domain signal into a series of sine and cosine functions. For noise reduction of altimeter data, it might be possible to retain the low frequency terms and eliminate the high frequency content (noise). The retained information could be converted back to the time domain by an inverse Fourier transform.

There are several challenges for this approach. Fourier transform/inverse Fourier transform works best with a stationary signal with zero mean and Gaussian noise. Altimeter histories do not satisfy these conditions, so some preliminary data processing would be needed. Also, the inverse Fourier transform is not necessarily a unique transformation. Checks would be needed to make sure the transform/inverse transform process does not affect actual flight data.

Wavelets. Wavelets are somewhat similar to the Fourier transform A time domain signal is converted to a series of wavelets instead of sine/cosine functions. There are many wavelet families (Haar, Daubechies, Symlets, Coiflets, etc.) that could be evaluated. However, the use of wavelets faces many of the same challenges as the Fourier transform.

Median Absolute Deviation. The Median Absolute Deviation (MAD) method is a technique used primarily for identifying outliers in datasets, especially in cases where traditional "mean and standard deviation" methods cannot be easily applied. The MAD approach does the following:

- Determine the median of the dataset or window
- For each data point, compute the absolute deviation from the median
- Calculate MAD (the median of the absolute deviations)
- Decide on a threshold to classify points as outliers. A common approach is to set a threshold as a multiple of the MAD, usually 2- or 3-times MAD.

- Eliminate any data points if their absolute deviation from the median exceeds the calculated threshold, creating a cleaner version of the data for further analysis.

The MAD approach might provide the benefit of a Median filter for handling “spike” noise while allowing other traditional filter methods (SMA, EWMA, etc.) to provide smoothing.

7.2 ADVANCED FILTERS

There are a variety of advanced filters that may provide more robust operation in the presence of altimeter noise. Some possibilities are briefly listed below.

Hempel filter. Robust filter designed to address issues like outliers and non-Gaussian noise. Builds upon the principles of the Kalman filter but enhances the algorithm to provide better performance in challenging environments.

Robust Kalman filter. Designed to handle outliers and non-Gaussian noise. “M-estimators” reduce the effect of outliers by adjusting the weights assigned to measurements. Adaptive filtering techniques allow for real-time adjustments to the filter parameters.

Particle filter. Handle nonlinear and non-Gaussian dynamics effectively. Represent the state with a set of weighted samples (particles) and can adapt to sudden changes, making them robust against spike noise.

H-infinity filter. “Its robust nature allows it to perform well in environments with significant disturbances, including spike noise”.

AI/ML. It may be possible to use Artificial Intelligence/Machine Learning (AI/ML) to train an agent to accurately recognize relevant altitude data while ignoring noise spikes and other artifacts. This would likely require a substantial dataset of altitude histories.

8 SUMMARY AND RECOMMENDATIONS

This R&D project investigated filters and related methods for processing altimeter results to provide realistic apogee values for altitude contests. Seven filters were examined:

- Simple Moving Average (SMA)
- Exponentially Weighted Moving Average (EWMA)
- 2nd order Low Pass (Butterworth) filter
- Kalman filter
- Median filter
- Structural spline filter
- Savitzky–Golay filter

The results indicated that the Structural Spline filter and the Median filter did well on several challenging example flight histories that had significant "spike" noise and other anomalies. The Structural Spline filter was computationally intensive but could be studied further. The best computationally efficient approach was to use a Median filter (to remove noise) followed by a Savitzky-Golay filter (to smooth the data).

Much more work can be done in this field. Using the AM/SG approach, more flight histories should be examined to see if there are cases that challenge the robustness of this approach. Additional methodology work can be done including looking at noise/outlier elimination and advanced robust filters.

9 EQUIPMENT, FACILITIES, AND BUDGET

I would like to acknowledge the following contributors of flight data:

- Bernard and Avis Cawley
- Taras Tartaryn
- Alan Stokker
- Many TARC/ARC teams

9.1 EQUIPMENT

The following equipment and programs were used in this project:

- Laptop computer
- GNU Octave software (https://octave.org/)

9.2 FACILITIES

No special facilities were used for this project.

9.3 PROJECT BUDGET

All work was performed on a computer using altimeter data from prior flights. The budget for this project was $0.

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