Deglitching SPIRE Interferograms

Peter Davis-Imhof, Trevor Fulton, Joshua Litven

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1. Background

Early in 2009, the European Space Agency will launch the Herschel Space Observatory to make astronomical observations in the far-infrared and submillimeter (see http://sci.esa.int/herschel/) to help understand the formation of stars and galaxies. Among the three instruments on board is SPIRE, the Spectral and Photometric Imaging Receiver. The SPIRE imaging photometer and spectrometer both employ bolometric detector arrays.

The SPIRE instrument team aims to provide astronomers with an accurate measurement of the astronomical object of interest. Data processing has to take care to remove instrumental artifacts before presenting data to the astronomer. Cosmic rays are a significant source of data contamination. Cosmic ray particles can strike the detection system of the SPIRE instrument and cause transient alterations to the signal, commonly referred to as "glitches". The cosmic rays deposit their energy in the detection system essentially instantaneously. Subsequent filtering of the detector signal gives these glitches a characteristic shape determined by the filter characteristics of the read-out electronics and the thermal inertia of the detector material (see Illustration 1).

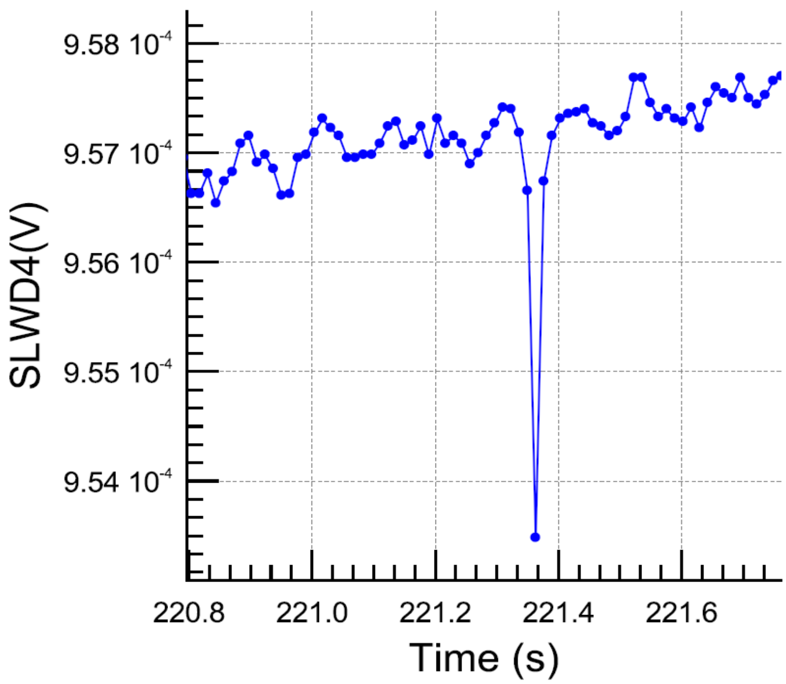

Illustration 1: Sample glitch recorded by a SPIRE detector during ground-based flight model testing

The SPIRE spectrometer is a Fourier transform spectrometer (FTS) and the instrument records interference patterns. For any given observation, the SPIRE FTS will make n redundant measurements. During data processing, the raw data from the SPIRE instrument are turned into interferograms I as a function of optical path difference (OPD) x. The i'th interferogram will contain signal contributions from the sources in the two input ports, noise, and glitches

$$I(x) = I^{source}(x) + I^{noise}(x) + I^{glitch}(x)$$

One of the final steps in the data processing pipeline computes the average interferogram for the n

measured interferograms:

$$\bar{I}(x) \equiv \frac{1}{n}\sum_i^n I_i(x)$$

$$\bar{I}(x) = \frac{1}{n}\sum_i^n \left(I_i^{source}(x) + I_i^{noise}(x) + I_i^{glitch}(x)\right)$$

If the noise is randomly distributed then the average of the noise contribution the interferogram will go to zero: $\overline{I^{noise}}(x) \rightarrow 0$

$$\bar{I}(x) = \frac{1}{n}\sum_i^n \left(I_i^{source}(x) + I_i^{noise}(x) + I_i^{glitch}(x)\right)$$

$$\bar{I}(x) \rightarrow \frac{1}{n}\sum_i^n \left(I_i^{source}(x) + I_i^{glitch}(x)\right)$$

Glitches, however, will still contaminate the signal from the source. The goal is to remove the glitch signature from the individual interferograms: $I_i^{glitch}(x) \rightarrow 0$. Only then will the average interferogram reflect the radiation from the source only.

$$\bar{I}(x) \rightarrow \frac{1}{n}\sum_i^n \left(I_i^{source}(x) + I_i^{glitch}(x)\right)$$

$$\bar{I}(x) \rightarrow \frac{1}{n}\sum_i^n I_i^{source}(x)$$

An effective and robust algorithm is required to automatically identify and remove glitches in each interferogram.

2. Glitches as outliers

Thee deglitching scheme described here relies on statistical analysis and the mathematical notion of an “outlier”. There is no broad consensus as to the precise definition of an outlier in the mathematical literature. Intuitively, an outlier can be understood as an element in a set of numbers which derives from a distribution different than the distribution from which most of the elements in that set derive (cf. Thode 2002, p. 123; Davies & Gather 1993, p. 782). This characterization applies to a glitch when comparing the glitch signal at a certain OPD to redundant measurements without the energy added from a cosmic ray hit. Outlier detection for an observation of the SPIRE FTS is a nontrivial process for a number of reasons:

- Commonly, outlier detection is performed by setting a threshold above which a data point is flagged. However, within an interferogram, there is strong modulation around a central burst. Thus, one cannot create a static threshold for the whole interferogram.
- The interferograms vary significantly when different sources are observed. A single threshold, even if it depends on OPD, will only be of limited effectiveness when detecting outliers.

3. Small number statistics

Another aspect of the usage of the SPIRE FTS further complicates matters: Astronomers are limited by the observation time available to them and are frugal in their use of this time. When using the SPIRE spectrometer for the key science programs, which accounts for about 50% of the nominal mission time, they have often chosen to make only a small number of repeated measurements on a given source (see Illustration 2). An outlier detection algorithm for the SPIRE spectrometer is therefore required to operate on data with sample sizes as low as 2 in more than 30% of all observations. In more than 50%

of all observations there are less than 10 iterations. Measurements are repeated 17 times or fewer in about 75% of all observations. This leaves sample sizes of 20 and higher for only 25% of all observations.

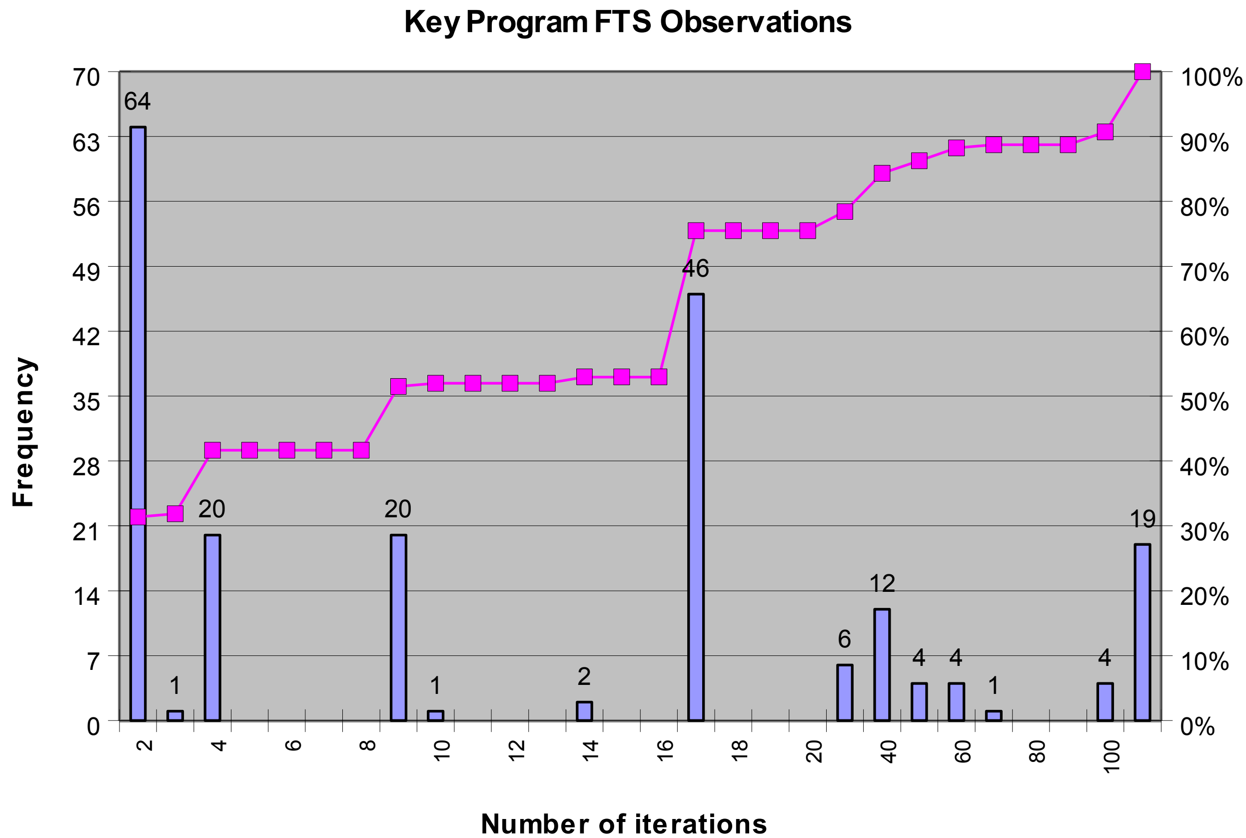

Illustration 2: FTS observations during the Guaranteed and Open Time Key Programs

An algorithm to identify outliers will depend on various parameters. A suitable parameter choice has to be made. There are two conflicting requirements for a glitch detection algorithm:

(1) Flag as few as possible false positives, i.e. data samples which are not glitches.

(2) Identify as many as possible glitches correctly.

This study takes the following approach: Each considered set of parameters is evaluated on the basis of how many false positives an algorithm will find. A parameter set is accepted as a feasible choice for the data processing pipeline if fewer than 0.1% of data samples are flagged as false positives. Of the parameter sets which satisfy this condition, those parameter are identified which correctly identify an acceptable number of glitches in data from the SPIRE ground-based test campaign PFM4.44

4. Outlier detection

A wide range of methods is available for the statistical identification of outliers. Many practitioners have used a simple “3-sigma clipping” approach. It has become more common to use outlier detection methods based on the median rather than the mean. Both algorithms are studied below.

a) Two basic algorithms

First, the terminology is defined to describe the studied algorithms.

Definitions:

$I_i(x)$: Interferogram signal as a function of optical path difference x for scan i, where $i=1,\ldots,n$

$I(x)=(I_1(x), I_2(x), \ldots, I_n(x))$: The interferogram signal vector as a function of OPD x

Standard Deviation Clipping

A simple outlier identification relies on the standard deviation as a measure of the variability of the data around the average value:

$$I_i(x) \text{ is an outlier } \textit{iff}$$
$$|I_i(x)-\bar{I}(x)| \geq k \cdot \sigma_I(x) \; \textit{with} \; k>0$$
$$\sigma_I^2(x) \equiv \frac{1}{n-1}\sum_i^n (I_i(x)-\bar{I}(x))^2 \text{: Standard deviation interferogram}$$

MAD Clipping

Alternatively, one could use an equivalent criterion using the median instead of the mean and median absolute deviation (MAD) instead of the standard deviation:

$$I_i(x) \text{ is an outlier } \textit{iff}$$
$$|I_i(x)-MEDIAN(I(x))| \geq 1.4826 \cdot k \cdot MAD(I(x)) \; \textit{with} \; k>0$$
$$MEDIAN(I(x)) \equiv \frac{1}{2}\left(I_{\left[\frac{n+1}{2}\right]}(x)+I_{\left[\frac{n}{2}\right]}(x)\right)$$
$$\textit{where} \; I_{[j]} \text{ denotes the j'th element of the ordered set } \{I_i\}$$
$$[X] \text{ denotes the first integer lower than or equal a real number}$$
$$MAD(I_i) \equiv MEDIAN\left(|I_1-MEDIAN(I)|, \ldots, |I_n-MEDIAN(I)|\right)$$

The factor of 1.4826 ensures that the MAD and the standard deviation can be compared on an equal footing when it comes to specifying the expectation for the proportion of randomly distributed points that fall within a certain range around the average for normally distributed data.

b) Performance limitations of the two algorithms

Both algorithms suffer different shortcomings for small sample sizes. “Small” here is taken to be fewer than 18 elements (cf. Illustration 2).

The standard deviation clipping suffers from the well-known Masking Effect (cf. Davies and Gather 1993, p. 784). Consider the data in Illustration 3, which shows ten elements from five normally distributed datasets (average = 0, standard deviation = 1) except for a single point in the second dataset which was set to a value of 30, simulating a glitch.

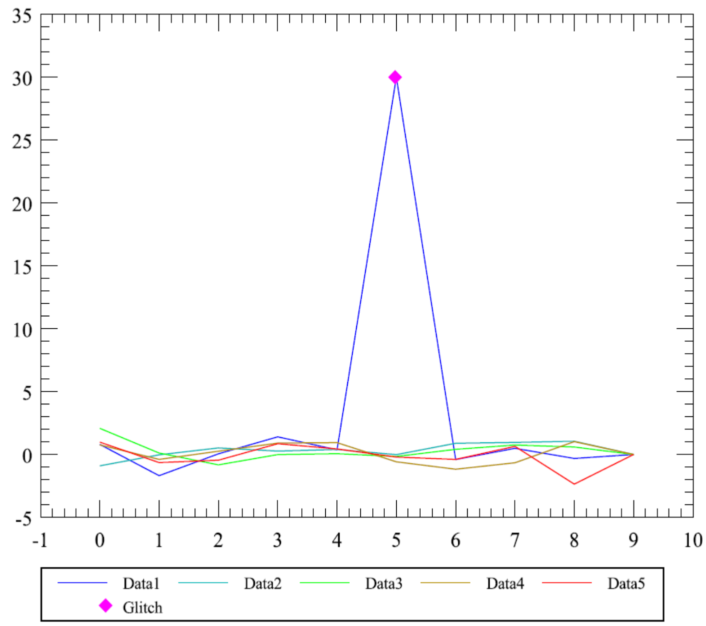

Illustration 3: A single glitch at a value of 30 (arbitrary units) in five datasets of ten elements which are otherwise created with a Gaussian random number generator

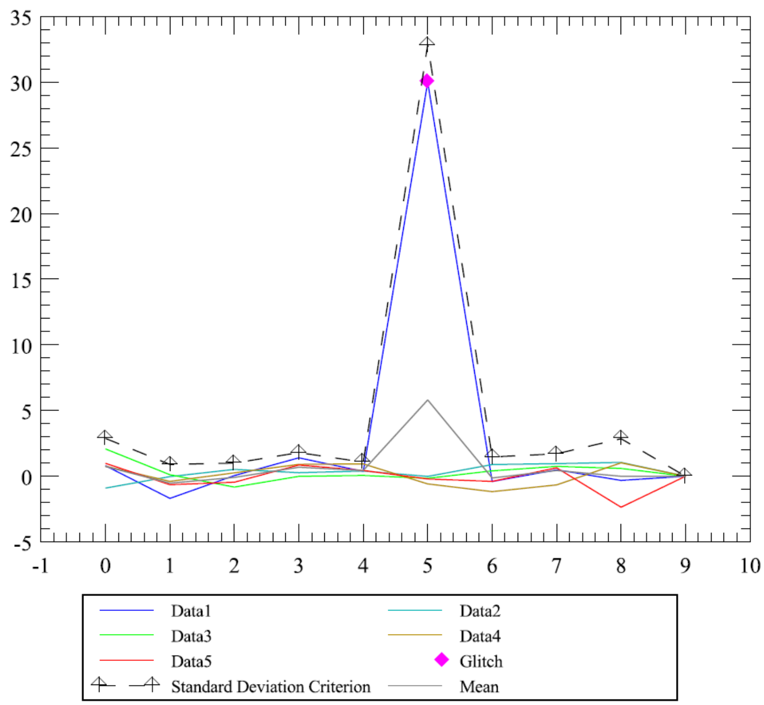

Illustration 4: Standard Deviation Clipping applied to the data

The standard deviation clipping with a threshold factor of $k=2$ does not identify the glitch as an outlier because not only is the glitch value exceedingly large but so is the mean plus the threshold factor times the standard deviation. The latter increases quadratically and because of the small sample size, the envelope defined by the standard deviation around the average is not violated.

The MAD clipping with a threshold factor of *k=2* easily identifies the glitch as an outlier, as is shown in Illustration 5.

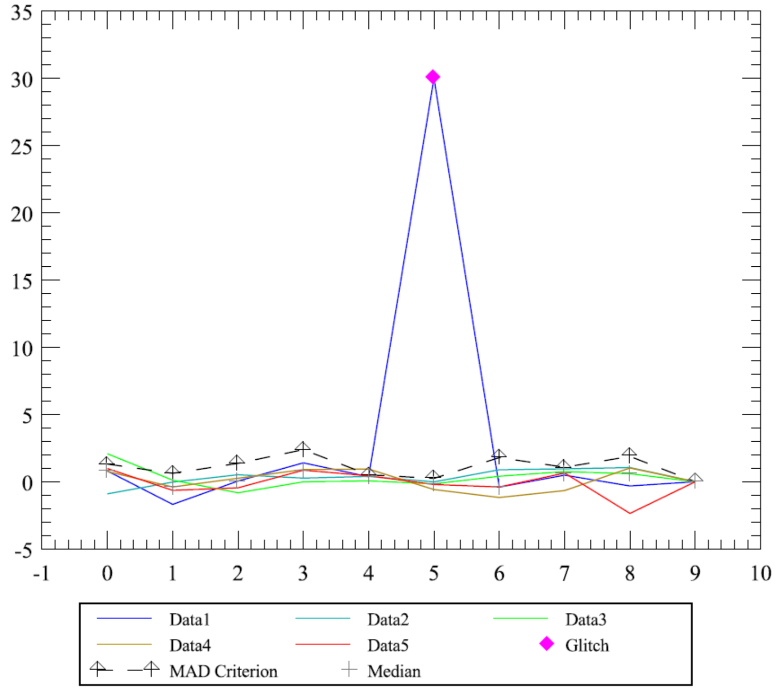

Illustration 5: MAD clipping applied to the data

MAD clipping suffers from an effect which may be called “accidental grouping”. It is documented in the following figures. Consider five normally distributed datasets with ten data points each (mean = 0, standard deviation = 1) as in Illustration 6.

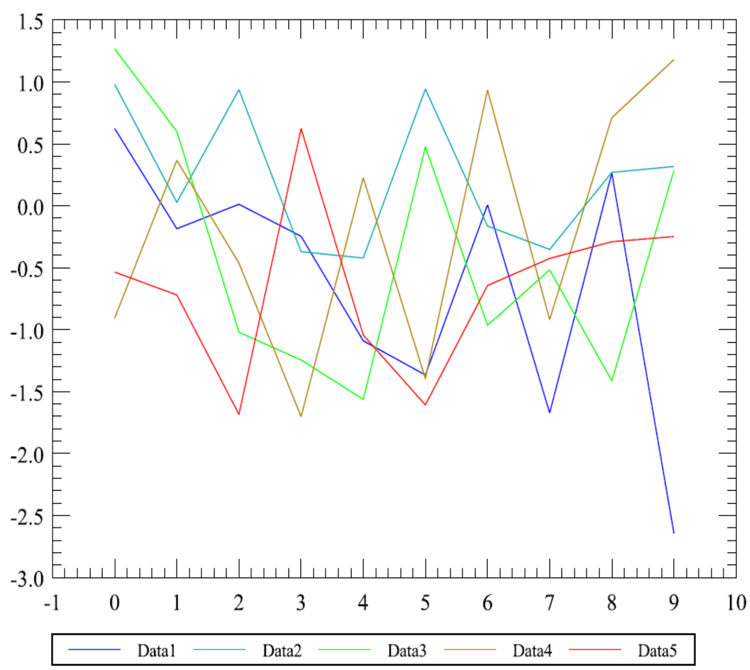

Illustration 6: Five datasets created with a Gaussian random number generator

Even though there are, by construction, no glitches present in the data, MAD clipping identifies two outliers at index 5. The data are not examples for infrequent but large values in a Gaussian distribution as one might expect. Instead, three out of the five data points at index 5 lie closely together, leading to a very small MAD, i.e. a very strict condition for outlier detection which is then violated by the remaining two data points.

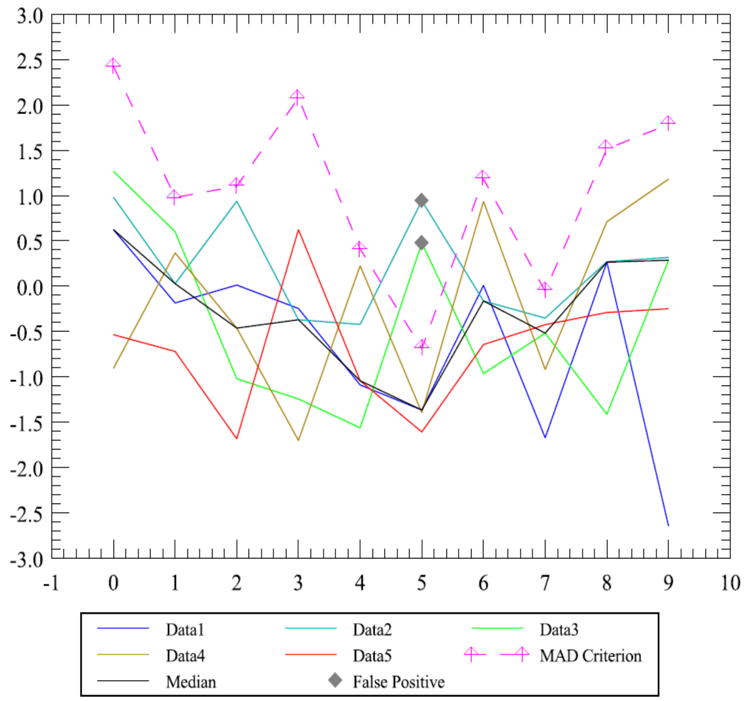

Illustration 7: MAD clipping applied to white noise

Applied to the same data, the standard deviation clipping has no trouble recognizing the white noise as what it is and not flagging an outlier (see Illustration 8).

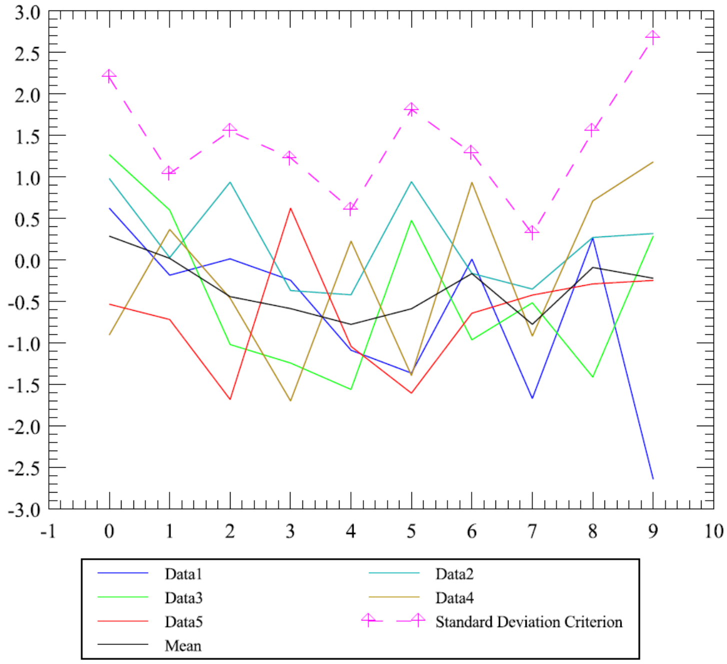

Illustration 8: Standard deviation clipping applied to white noise

If the sample size is small, identifying glitches correctly and avoiding false positives is difficult for standard deviation and MAD clipping respectively. As the sample size increases, these problems are less likely to occur:

- For **standard deviation clipping**, each normally distributed dataset decreases the standard deviation by a factor of $\sqrt{N/N+1}$, making the outlier identification more sensitive. For example, increasing the sample size from 3 to 6 reduces the standard deviation by ~25%. Simply by adding one more normally distributed dataset would lead to the identification of the glitch in Illustration 3 in almost all cases.
- The **MAD clipping** is less likely to suffer from accidental grouping as it is less likely to occur for larger samples sizes. Illustration 9 shows how the mean percentage of false positives decreases as the number of scans increases and converges towards the value of ~4.55% expected for a Gaussian distribution.

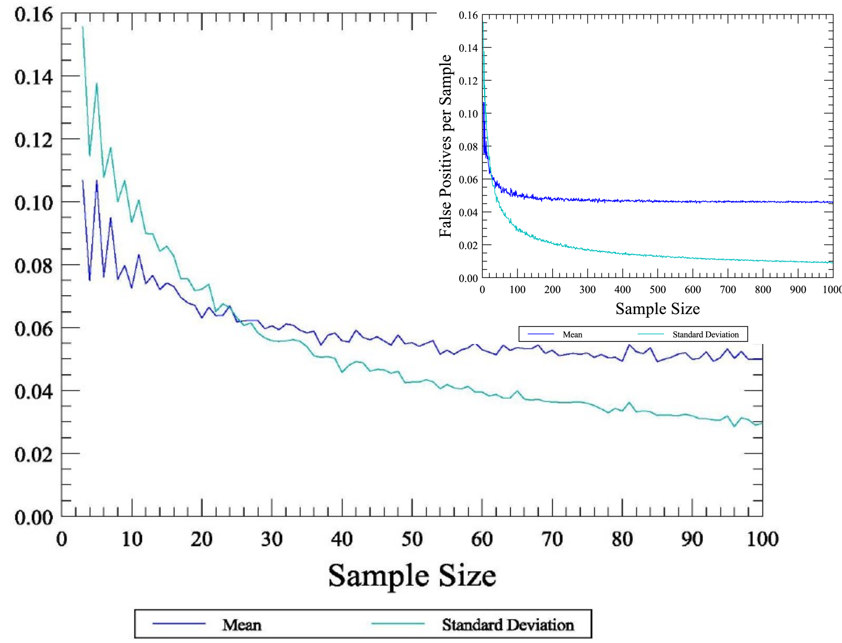

Illustration 9: The mean percentage of false positives from MAD clipping (k=2) as a function of sample size for simulated data up to 100 and 1,000 trials. The standard deviation of the mean is also given.

The comprehensive evaluation of the two algorithms must quantify the proportion of randomly distributed samples wrongly flagged as outliers and the number of glitches correctly identified. The latter has to rely on an external judgement whether an element is a glitch or not.

Simulations with 5,000 data samples created by a Gaussian random number generator (mean = 0, standard deviation = 1) show two clear trends concerning false positives (see Illustration 10):

- An increase in the threshold factor *k* will decrease the proportion of flagged false positives in a sample for both, standard deviation and MAD clipping.
- An increase in the number of scans *n* will increase the proportion of false positives identified in a sample by standard deviation clipping.
- There is a lower threshold for standard deviation clipping below which no false positives are identified. The regime of not finding any false positives starts at increasingly higher numbers of scans as the threshold factor increases.
- An increase in the number of scans *n* tends to decrease the proportion of false positives in a sample for the MAD clipping.

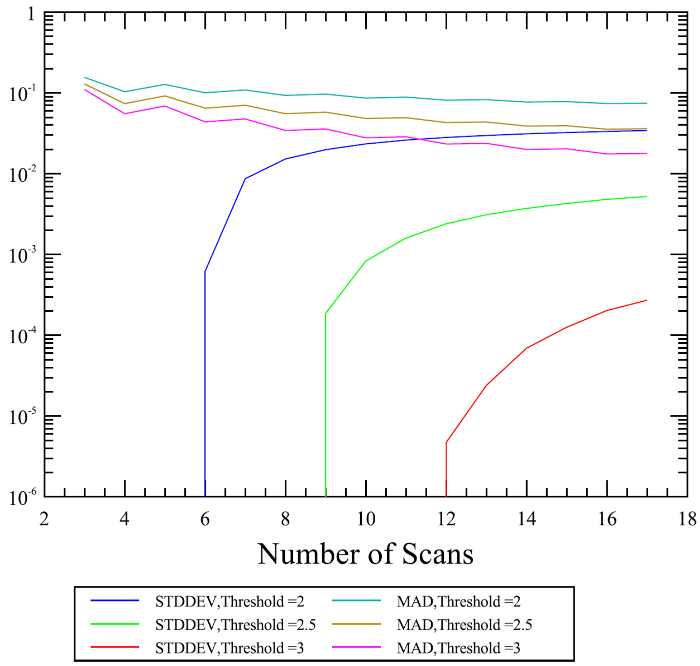

Illustration 10: Ratio of false positives over data elements after 1,000 trials

Using data from the SPIRE ground-based test campaign PFM4 (see 27 Appendix) the standard deviation clipping algorithm was tested for n = 6, 8, 16 scans with a total number of glitches of 89, 87, 11 respectively. The algorithm was applied to PFM4 data, but only for those parameter sets where the expected ratio of false positives was less than 0.1% (see Table 1).

n	Threshold factors where the expected false positive ratio is less than 0.1%
6	2 – 6 in steps of 0.5
8	2 – 6 in steps of 0.5
16	2.5 – 6 in steps of 0.5

Table 1: Parameter sets for standard deviation clipping

In all cases listed in Table 1, the standard deviation clipping did not identify a single outlier. Therefore, not a single glitch was flagged correctly. MAD clipping was not applied to PFM4, because the expected ratio of false positives was significantly higher than the required 0.1% for up to 16 scans (see Illustration 11). These results show that neither of the algorithms is useful to detect glitches when the scan numbers are 16 or less.

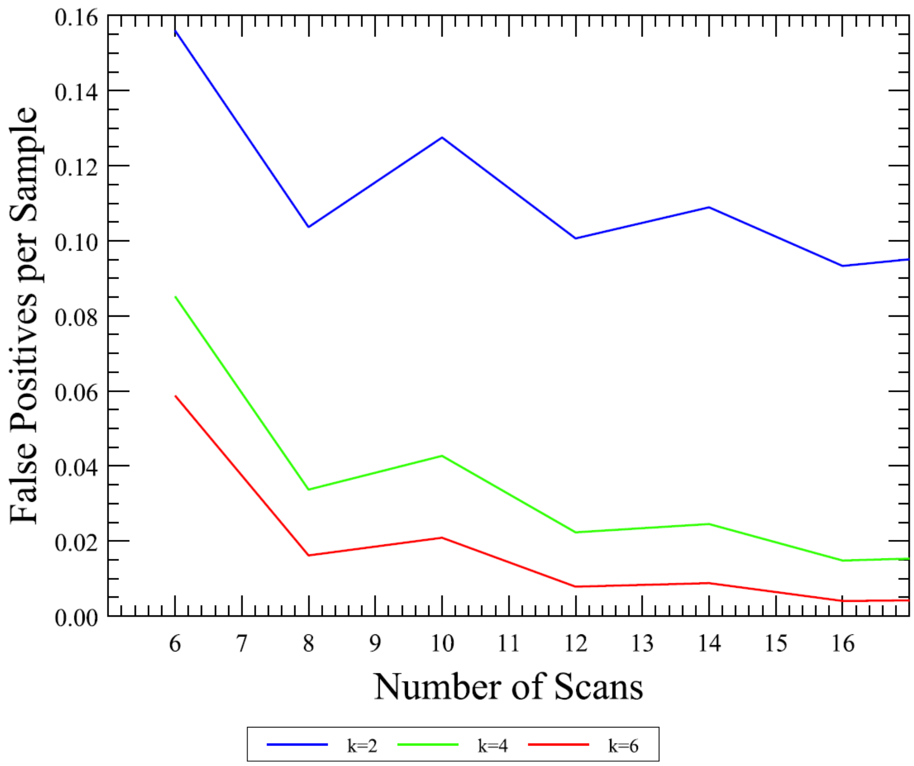

Illustration 11: Expected false positive ratios for the MAD clipping algorithm

5. Outlier detection for SPIRE interferograms

One solution for the problem of not being able to effectively detect outliers is to increase the sample size. Unfortunately, the number of repeated measurements is not negotiable as it is selected by the astronomer and limited by a very scarce resource: observation time. However, alternate means to increase the sample size for the identification of outliers do exist: $\sigma_I(x)$, the standard deviation interferogram, measures the square root of the variance in the averaged interferogram. The variance depends on the performance of the detectors, the electronics, and the amount of change in the signal modulation due to moving the linear translation stage in SPIRE's interferometer. Outside of the central burst region, the variance should be mainly due to the noise introduced by the detectors and the electronics as the changes in modulation are relatively small. This means that the variance should be approximately constant away from the central burst region. The ground-based data confirm this expectation (see e.g. Illustration 12).

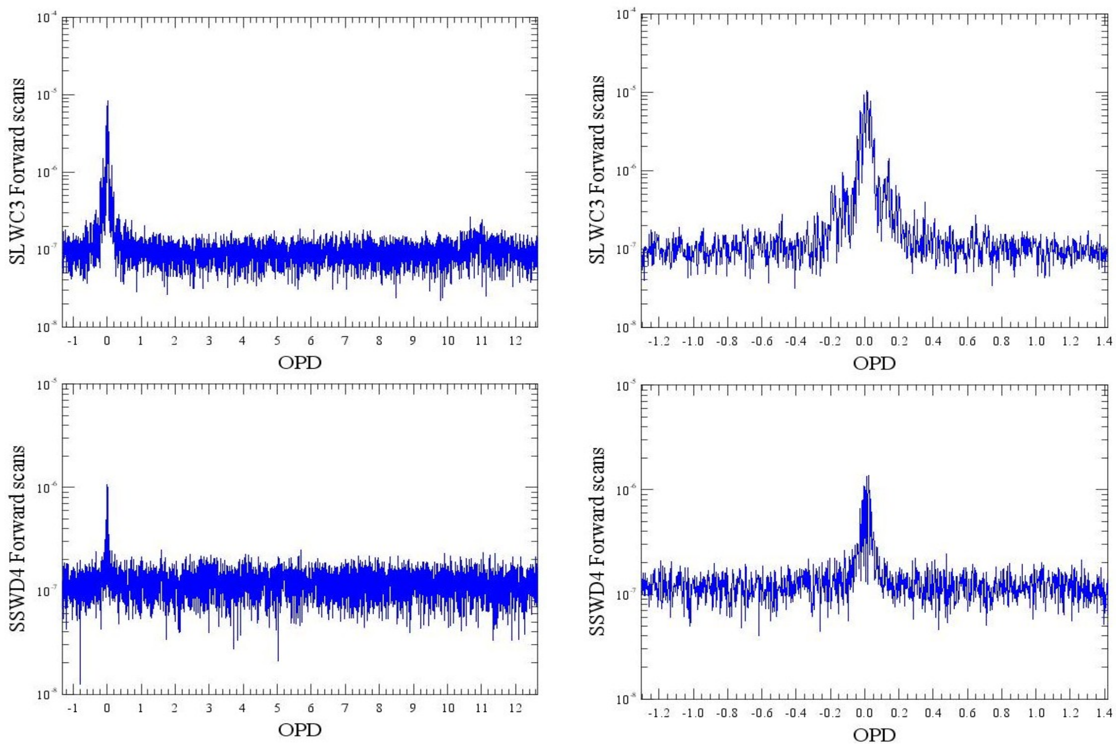

Illustration 12: Standard deviation interferograms of a high (left) and medium (right) resolution observation during PFM4 testing, obsid: 300113C8 and 300114CA, forward scans

A glitch, however, will lead to a significantly increased standard deviation at the OPD where it occurred. The problem of identifying an outlier in a small set of interferograms of commonly fewer than ten can therefore be translated into identifying an outlier within a portion of the standard deviation interferogram. Introducing second-order statistics has an important advantage over the the glitch identification algorithms described earlier: An outlier in the standard deviation interferogram can be identified within a portion of the standard deviation interferogram whose size can be selected independently of the number of scans. The sample size can be set to numbers high enough to avoid the problems associated with identifying outliers in very small sample sizes of less than ten elements. The remaining problem is that the standard deviation interferogram is not flat for the whole OPD range but does reflect significant changes in modulation, i.e. the central burst region. Outlier detection has to take these variations in the standard deviation into account.

a) Algorithm descriptions

The outlier detection algorithms employ second order statistics and operate on a subsection ("window") of the standard deviation interferograms measured during an observation. The proposed algorithms use the mean, standard deviation, median, and median absolute deviation from the median within such a given window:

<u>Windowed Standard Deviation Clipping:</u>

$$I(x) \text{ contains a glitch at position } x \textit{ iff}$$
$$\sigma_I(x) - MEAN_w(\sigma_I(x)) \geq k \cdot STDDEV_w(\sigma_I(x))$$
$$\text{with } MEAN_w(\sigma_I(x)) = \frac{1}{w} \sum_{i=-\frac{w-1}{2}}^{\frac{w-1}{2}} \sigma_I(x + i\,\Delta x)$$
$$STDDEV_w^2(\sigma_I(x)) = \frac{1}{w-1} \sum_{i=-\frac{w-1}{2}}^{\frac{w-1}{2}} \left(\sigma_I(x + i\,\Delta x) - MEAN_w(\sigma_I(x))\right)^2$$
With an odd integer $w \geq 3$ and the OPD interval Δx

Windowed MAD Clipping:

The windowed clipping algorithm with the median absolute deviation is defined equivalently:

$$I(x) \text{ contains a glitch at position } x \textit{ iff}$$
$$\sigma_I(x) - MEDIAN_w(\sigma_I(x)) \geq k \cdot 1.4826 \cdot MAD_w(\sigma_I(x))$$
$$MEDIAN_w(\sigma_I(x)) = \frac{1}{2}\left(\sigma_I^w(x)_{\left[\frac{w+1}{2}\right]} + \sigma_I^w(x)_{\left[\frac{w}{2}\right]}\right)$$
$\sigma_I^w(x)_{[j]}$ as the j'th element of the set $\{\sigma_I(x - \Delta x \frac{w+1}{2}), \ldots, \sigma_I(x + \Delta x \frac{w+1}{2})\}$

after sorting the set in the order of the values of its elements.

$$MAD_w(\sigma_I(x)) = MAD(\sigma_I(x - \Delta x \frac{w+1}{2}), \ldots, \sigma_I(x + \Delta x \frac{w+1}{2}))$$

Once a specific position x is flagged, the following criterion identifies the specific scan with a glitch:

$$\text{If } x \text{ has been identified as the location of a glitch, } I_i(x) \text{ is a glitch } \textit{iff}$$
$$I_i(x) = Max(|MEDIAN(I(x)) - I_j(x)|,\ j = 1, \ldots, n)$$

The algorithm is then applied again to the data without the flagged samples.

It should be noted, that this criterion would, in the case of n=2, flag samples in both interferograms as glitches. This is not a satisfactory solution and a special rule has to be introduced to deal with this special case. Three possible solutions have been proposed to deal with this special case:

1.Calculate the three-point difference $TPD(x) = I(x) - \frac{1}{2} \cdot (I(x - \Delta x) + I(x + \Delta x))$ for the sample in each interferogram and flag that sample as a glitch which has the higher absolute three-point difference. It is not possible to make this calculation for the very first and last element of the interferogram.

2.Use the median of the surrounding data points as reference to determine which interferogram deviates the most from the typical value:

$$\text{If } x \text{ has been identified as the location of a glitch, } I_i(x) \text{ is a glitch } \textit{iff}$$
$$I_i(x) = Max(|MEDIAN(I(x - \Delta x), I(x + \Delta x)) - I_j(x)|,\ j = 1, \ldots, n)$$

This criterion can also be used for the very first and the very last element of the interferogram. In these two cases, the median will be calculated on only one side of the glitch.

3.Instead of applying this algorithm to only the forward or only the reverse scans, it is possible to identify glitches across all scans, irrespective of their direction. This will increase the sample size to four. The main risk for this option derives from some detectors showing systematic differences for forward and reverse scans.

a) False Positives

There are three parameters for the windowed algorithms: Number of scans *n*, window size *w*, and threshold factor *k*. As *n* is determined by the astronomer, the goal is to find a pair of *w* and *k* that optimize the requirements for a glitch finding algorithm for a given *n*.

The first requirement, to find a small number of false positives only, can be verified with data simulated by a standard Gaussian random number generator. We created noise 'interferograms' with 5,000 data samples with an average value of 0 and a standard deviation of 1. We created the normally distributed data and applied the windowed glitch identification algorithms to these data 100 times for each combination of parameters. The following parameter sets were chosen:

Number of Scans *n*	6, ... , 34 in steps of 2
Window Size *w*	5, 11, 17, 23, 25, 27, 29, 31, 33, 35, 41, 47, 53
Threshold factor *k*	2.0, ... , 6.0 in steps of 0.5

The results for the expected false positives show consistent trends:

When increasing the number of scans from 6 to 34, the number of false positives is reduced for both algorithms (see Illustration 13). Both algorithms work better with larger sample sizes.

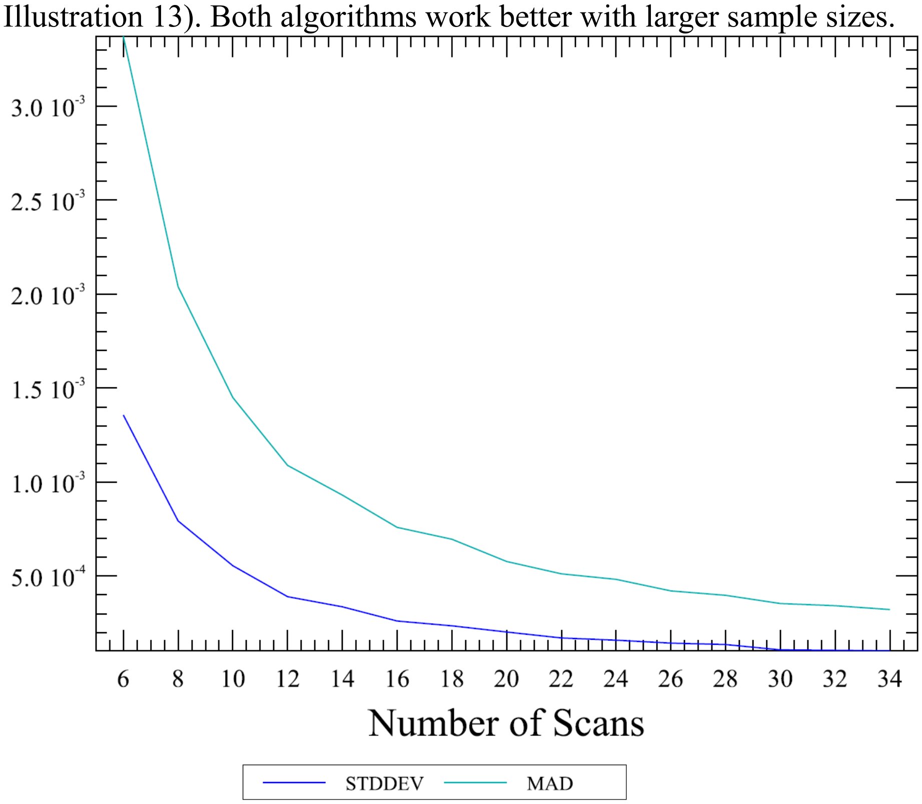

Illustration 13: Expected ratio of false positives as a function of scan number n; k=3, w=53

When increasing the window size from 5 to 53 (see Illustration 14), the two algorithms show different behavior due to the problems discussed in section 45 Performance limitations of the two algorithms. The windowed standard deviation clipping does not flag any samples as outliers for very small windows and the number of false positives increases with increasing window size. The windowed MAD clipping shows the opposite trend: Fewer false positives are identified as the window size increases.

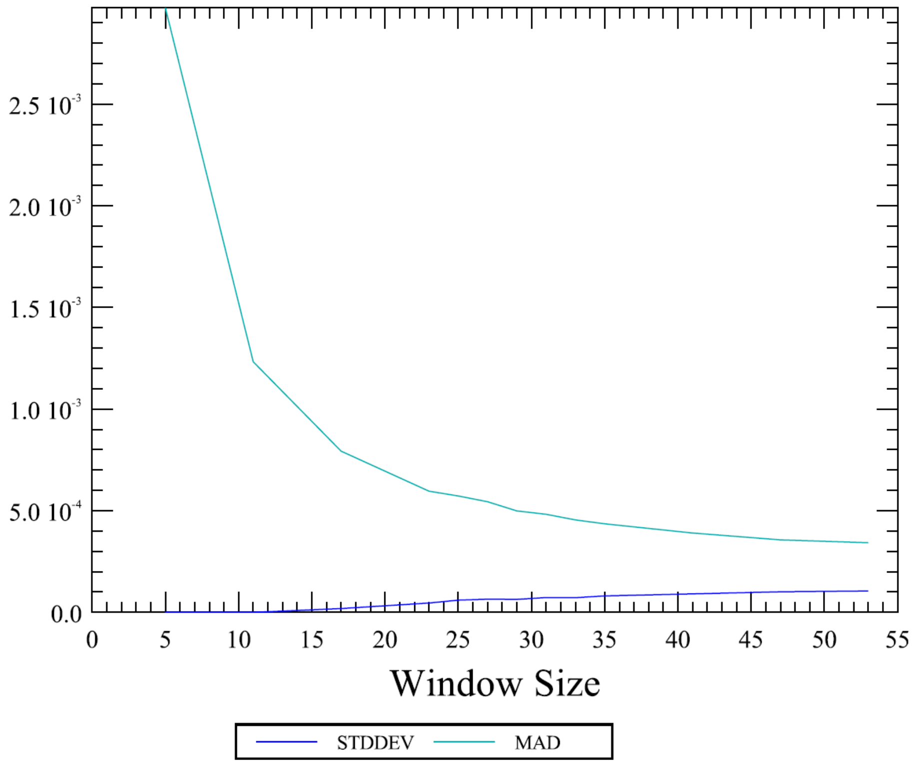

Illustration 14: Expected ratio of false positives as a function of window size w; k=3, N=32

When increasing the threshold factor from 2 to 6, the number of false positives is reduced for both algorithms (see Illustration 15). The threshold outside of which a data sample is flagged becomes wider and fewer outliers are identified in the randomly distributed data.

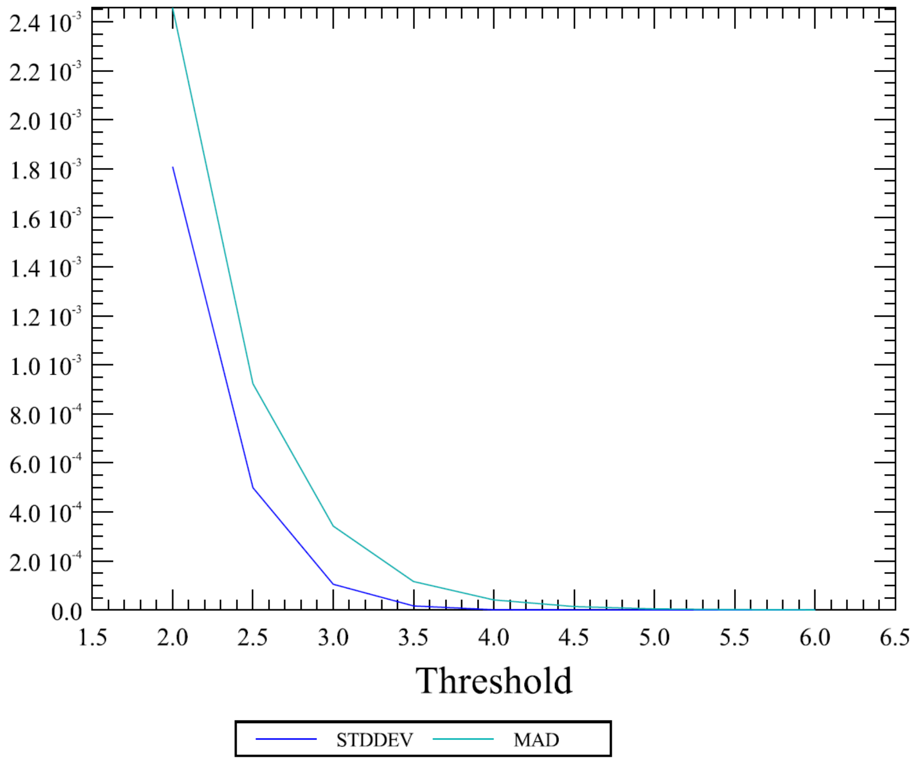

Illustration 15: Expected ratio of false positives as a function of the threshold factor k; N=32, w=53

An interferogram from SPIRE taken with an Astronomical Observation Template in high resolution will contain about 6,000 independent samples. A level of 0.1% glitches was set as an upper bound, leading to less than 6 false positives identified in a typical high resolution interferogram. The expected levels of false positives from a simulation based on a Gaussian random number generator were checked against the level of false positives measured in data collected during the SPIRE ground-based test campaign PFM4 (see 27 Appendix). The windowed glitch identification algorithms were tested for n = 16, 8, 6 scans with a total number of glitches of 11, 87, 89 respectively. Tables 2 to 4 detail the actual (experimental) false positives, expected (theoretical) false positives for all those parameter sets which satisfied the criterion to yield fewer than 0.1% expected false positives. The tables show that those parameter sets that find no false positives whatsoever also identify no or very few glitches correctly. In other words: A certain level of false positives has to be accepted in order to allow for a sensitive detection of glitches.

Windowed Standard Deviation Clipping						Windowed MAD Clipping				
Threshold Factor k	Window Size w	Experimental False Positive Ratio	Theoretical False Positive Ratio	Correct Identifications		Threshold Factor k	Window Size w	Experimental False Positive Ratio	Theoretical False Positive Ratio	Correct Identifications
3.5	17	3.39E-007	1.87E-007	0		6	11	1.95E-004	2.24E-004	4
4	23	1.36E-007	1.87E-007	0		5.5	11	2.71E-004	3.06E-004	5
5	35	6.78E-008	0	0		5	11	3.94E-004	4.43E-004	6
4.5	29	6.78E-008	0	0		6	17	5.54E-005	5.78E-005	6
6	47	0	0	0		4	29	2.80E-004	2.17E-004	7
6	41	0	0	0		4.5	17	2.70E-004	2.71E-004	7
5.5	41	0	0	0		4	33	2.54E-004	1.85E-004	7
6	35	0	0	0		5	17	1.56E-004	1.59E-004	7
5.5	35	0	0	0		4.5	29	1.36E-004	1.07E-004	7
6	33	0	0	0		4.5	31	1.23E-004	8.45E-005	7
5.5	33	0	0	0		4.5	33	1.19E-004	7.69E-005	7
5	33	0	0	0		4.5	35	1.18E-004	7.43E-005	7
6	31	0	0	0		5	53	1.10E-004	1.36E-005	7
5.5	31	0	0	0		4.5	41	9.21E-005	5.62E-005	7
5	31	0	0	0		5.5	17	9.17E-005	9.25E-005	7
6	29	0	0	0		5	29	6.91E-005	4.12E-005	7
5.5	29	0	0	0		5.5	53	6.74E-005	5.04E-006	7
5	29	0	0	0		5	47	6.00E-005	1.87E-005	7
6	27	0	0	0		5	31	5.90E-005	3.90E-005	7
5.5	27	0	0	0		5	33	5.72E-005	3.26E-005	7
5	27	0	0	0		5	35	5.43E-005	3.28E-005	7
4.5	27	0	0	0		5.5	23	5.24E-005	4.14E-005	7
6	25	0	0	0		5.5	25	4.66E-005	4.05E-005	7
5.5	25	0	0	0		5	41	4.23E-005	2.09E-005	7
5	25	0	0	0		5.5	27	4.19E-005	2.72E-005	7
4.5	25	0	0	0		6	53	4.08E-005	1.68E-006	7
6	23	0	0	0		5.5	29	3.51E-005	2.56E-005	7
5.5	23	0	0	0		5.5	47	3.05E-005	6.53E-006	7
5	23	0	0	0		5.5	31	3.00E-005	2.11E-005	7
4.5	23	0	0	0		6	23	2.98E-005	2.07E-005	7
6	17	0	0	0		5.5	33	2.69E-005	1.70E-005	7
5.5	17	0	0	0		5.5	35	2.55E-005	1.38E-005	7
5	17	0	0	0		6	25	2.50E-005	1.87E-005	7
4.5	17	0	0	0		6	27	2.21E-005	1.64E-005	7
4	17	0	0	0		5.5	41	1.93E-005	1.29E-005	7
6	11	0	0	0		6	29	1.77E-005	1.04E-005	7
5.5	11	0	0	0		6	31	1.55E-005	8.40E-006	7
5	11	0	0	0		6	47	1.41E-005	2.80E-006	7
4.5	11	0	0	0		6	33	1.35E-005	8.40E-006	7
4	11	0	0	0		6	35	1.34E-005	7.28E-006	7
3.5	11	0	0	0		6	41	9.57E-006	6.16E-006	7
3	11	0	0	0		4.5	11	5.93E-004	6.50E-004	8
6	5	0	0	0		4	17	4.80E-004	5.04E-004	8
5.5	5	0	0	0		4	27	3.05E-004	2.44E-004	8
5	5	0	0	0		4	31	2.62E-004	1.97E-004	8
4.5	5	0	0	0		4	35	2.50E-004	1.65E-004	8
4	5	0	0	0		4.5	53	1.96E-004	4.07E-005	8
3.5	5	0	0	0		4.5	27	1.52E-004	1.16E-004	8
3	5	0	0	0		5	23	9.49E-005	7.71E-005	8
2.5	5	0	0	0		5	27	7.88E-005	5.86E-005	8
2	5	0	0	0		3.5	31	5.65E-004	4.52E-004	9
4.5	35	2.04E-007	0	1		3.5	33	5.50E-004	4.28E-004	9
4.5	33	1.36E-007	0	1		4	41	2.11E-004	1.51E-004	9
4	25	1.36E-007	1.87E-007	1		4.5	23	1.78E-004	1.61E-004	9
6	53	6.78E-008	0	1		4.5	25	1.67E-004	1.38E-004	9
5.5	53	6.78E-008	0	1		4.5	47	1.25E-004	4.72E-005	9
5.5	47	6.78E-008	0	1		5	25	8.83E-005	6.47E-005	9
5	41	6.78E-008	0	1		3.5	53	6.88E-004	2.93E-004	10
4.5	31	6.78E-008	0	1		3.5	29	5.96E-004	5.09E-004	10
2.5	11	1.54E-004	2.00E-004	2		3.5	47	5.64E-004	3.25E-004	10
4.5	41	2.71E-007	0	2		4	53	3.60E-004	1.09E-004	10
5	53	2.04E-007	0	2		4	47	2.65E-004	1.17E-004	10
4	27	2.04E-007	1.87E-007	2		3	53	0	7.59E-004	11
5	47	1.36E-007	0	2		3	47	0	8.19E-004	11
3	17	3.89E-005	4.83E-005	3		3	35	0	9.55E-004	11
3.5	23	6.04E-006	6.16E-006	3		3	41	0	8.49E-004	11
4	33	1.36E-006	1.12E-006	3		3.5	17	8.76E-004	9.07E-004	11
4	31	1.02E-006	9.33E-007	3		3.5	23	6.84E-004	6.41E-004	11
4	29	6.11E-007	3.73E-007	3		3.5	25	6.57E-004	5.71E-004	11
3.5	27	1.23E-005	1.23E-005	5		3.5	27	6.40E-004	5.43E-004	11
3.5	25	9.30E-006	1.16E-005	5		3.5	35	5.39E-004	4.12E-004	11
4	35	1.90E-006	1.87E-006	5		3.5	41	4.79E-004	3.56E-004	11
4.5	53	1.22E-006	7.46E-007	5		4	23	3.42E-004	3.10E-004	11
4.5	47	6.78E-007	1.87E-007	5		4	25	3.25E-004	2.82E-004	11
3.5	31	1.88E-005	1.60E-005	6						
3.5	29	1.57E-005	1.66E-005	6						
4	47	5.22E-006	6.34E-006	6						
4	41	3.87E-006	2.43E-006	6						
3.5	41	3.56E-005	3.73E-005	7						
3.5	35	2.69E-005	2.72E-005	7						
3.5	33	2.38E-005	2.07E-005	7						
4	53	7.06E-006	4.66E-006	7						
3	27	1.48E-004	1.51E-004	8						
3	23	1.09E-004	1.16E-004	8						
3.5	47	4.61E-005	5.06E-005	8						
2.5	17	5.46E-004	6.21E-004	9						
3	33	2.02E-004	1.94E-004	9						
3	31	1.81E-004	1.82E-004	9						
3	29	1.66E-004	1.69E-004	9						
3	25	1.32E-004	1.43E-004	9						
3.5	53	5.39E-005	4.70E-005	9						
2.5	33	0	9.90E-004	11						
2.5	31	9.76E-004	9.62E-004	11						
2.5	29	9.46E-004	9.32E-004	11						
2.5	27	9.14E-004	9.11E-004	11						
2.5	25	8.58E-004	8.72E-004	11						
2.5	23	7.94E-004	8.22E-004	11						
3	53	3.06E-004	2.61E-004	11						
3	47	2.81E-004	2.58E-004	11						
3	41	2.46E-004	2.22E-004	11						
3	35	2.19E-004	2.04E-004	11						

Table 2: Results for deglitching PFM4 data with 16 scans

Windowed Standard Deviation Clipping						Windowed MAD Clipping				
Threshold Factor k	Window Size w	Experimental False Positive Ratio	Theoretical False Positive Ratio	Correct Identifications		Threshold Factor k	Window Size w	Experimental False Positive Ratio	Theoretical False Positive Ratio	Correct Identifications
6	35	0	0	0		6	11	4.65E-004	5.64E-004	62
6	33	0	0	0		5.5	11	6.48E-004	7.20E-004	64
6	31	0	0	0		6	27	6.82E-005	4.89E-005	66
5.5	31	0	0	0		6	41	3.58E-005	1.31E-005	66
6	29	0	0	0		6	17	1.43E-004	1.81E-004	67
5.5	29	0	0	0		5.5	27	1.20E-004	7.84E-005	67
6	27	0	0	0		6	25	7.43E-005	5.75E-005	67
5.5	27	0	0	0		6	29	5.60E-005	3.77E-005	68
5	27	0	0	0		6	53	5.26E-005	6.34E-006	68
6	25	0	0	0		6	31	4.54E-005	2.54E-005	68
5.5	25	0	0	0		6	33	4.44E-005	2.43E-005	68
5	25	0	0	0		6	35	4.43E-005	2.57E-005	68
6	23	0	0	0		5.5	25	1.29E-004	1.02E-004	69
5.5	23	0	0	0		5.5	29	1.00E-004	6.42E-005	69
5	23	0	0	0		5.5	41	6.51E-005	3.43E-005	69
6	17	0	0	0		6	47	4.00E-005	1.12E-005	69
5.5	17	0	0	0		5.5	17	2.29E-004	2.46E-004	70
5	17	0	0	0		5.5	31	8.45E-005	5.60E-005	70
4.5	17	0	0	0		5.5	33	8.15E-005	5.37E-005	70
4	17	0	0	0		5.5	53	8.75E-005	1.90E-005	71
6	11	0	0	0		5.5	35	8.04E-005	4.07E-005	71
5.5	11	0	0	0		6	23	7.99E-005	6.68E-005	71
5	11	0	0	0		5.5	47	7.00E-005	2.43E-005	71
4.5	11	0	0	0		5	23	2.42E-004	2.43E-004	72
4	11	0	0	0		5	27	2.15E-004	1.67E-004	72
3.5	11	0	0	0		5	31	1.62E-004	1.26E-004	72
3	11	0	0	0		5.5	23	1.39E-004	1.19E-004	72
6	5	0	0	0		5	25	2.29E-004	1.88E-004	73
5.5	5	0	0	0		5	29	1.84E-004	1.52E-004	73
5	5	0	0	0		5	33	1.56E-004	1.04E-004	73
4.5	5	0	0	0		5	35	1.54E-004	1.07E-004	73
4	5	0	0	0		5	17	3.75E-004	4.63E-004	74
3.5	5	0	0	0		5	53	1.57E-004	4.89E-005	74
3	5	0	0	0		4.5	17	6.29E-004	7.52E-004	76
2.5	5	0	0	0		4.5	29	3.54E-004	2.94E-004	76
2	5	0	0	0		5	41	1.26E-004	7.84E-005	76
6	41	0	0	1		4.5	23	4.45E-004	4.22E-004	77
5.5	35	0	0	1		4.5	25	4.21E-004	3.83E-004	77
5.5	33	0	0	1		4.5	27	3.97E-004	3.18E-004	77
5	29	0	0	1		4.5	31	3.18E-004	2.62E-004	77
4.5	23	0	0	1		4.5	33	3.09E-004	2.39E-004	77
4.5	25	2.53E-008	0	5		4.5	35	3.08E-004	2.28E-004	77
5	31	0	0	6		5	47	1.31E-004	4.96E-005	78
6	47	0	0	14		4.5	41	2.59E-004	1.84E-004	80
5	33	5.06E-008	0	16		4	25	8.01E-004	7.56E-004	81
5.5	41	7.59E-008	0	17		4	27	7.68E-004	6.62E-004	81
4.5	27	5.06E-008	0	17		4.5	47	2.66E-004	1.53E-004	82
3.5	17	6.58E-007	1.12E-006	21		4	23	8.36E-004	8.21E-004	83
6	53	1.52E-007	0	24		4	31	6.42E-004	5.68E-004	83
5	35	7.59E-008	0	25		4	33	6.27E-004	5.17E-004	83
4.5	29	2.78E-007	0	28		4.5	53	2.93E-004	1.29E-004	83
4	23	5.06E-007	3.73E-007	30		4	29	7.05E-004	6.24E-004	84
4.5	31	5.06E-007	0	36		4	35	6.23E-004	4.70E-004	84
5.5	47	2.53E-007	0	36		3.5	53	0	8.16E-004	85
4	25	8.61E-007	7.46E-007	40		4	53	5.83E-004	3.50E-004	85
5	41	4.30E-007	0	41		4	47	5.46E-004	3.82E-004	85
4.5	33	6.58E-007	0	44		4	41	5.40E-004	4.16E-004	85
5.5	53	4.05E-007	0	44		3.5	47	0	8.90E-004	86
4	27	1.80E-006	1.87E-006	46		3.5	41	0	9.76E-004	86
4.5	35	8.61E-007	0	47						
4	29	2.78E-006	1.12E-006	50						
5	47	7.34E-007	0	50						
4	31	3.59E-006	4.85E-006	51						
4.5	41	1.59E-006	1.12E-006	53						
3.5	23	1.78E-005	2.46E-005	54						
2.5	11	3.68E-004	5.70E-004	55						
5	53	9.87E-007	0	55						
3	17	9.96E-005	1.61E-004	57						
4	33	5.39E-006	5.97E-006	57						
3.5	25	2.71E-005	4.07E-005	58						
4.5	47	2.43E-006	2.24E-006	62						
4.5	53	3.70E-006	2.24E-006	64						
4	35	7.16E-006	7.46E-006	65						
3.5	27	3.77E-005	4.03E-005	69						
4	41	1.29E-005	1.46E-005	69						
3.5	29	4.81E-005	7.69E-005	72						
4	47	2.08E-005	2.24E-005	72						
4	53	2.67E-005	2.84E-005	75						
3.5	33	7.09E-005	8.51E-005	76						
3.5	35	8.32E-005	9.40E-005	77						
3.5	31	5.80E-005	7.87E-005	77						
3	23	2.79E-004	3.88E-004	78						
3	25	3.41E-004	4.26E-004	79						
3.5	53	1.63E-004	1.88E-004	79						
3.5	41	1.09E-004	1.21E-004	79						
3	27	3.94E-004	4.90E-004	81						
3.5	47	1.36E-004	1.38E-004	81						
3	33	5.18E-004	5.50E-004	82						
3	31	4.71E-004	5.52E-004	82						
3	29	4.38E-004	5.02E-004	82						
3	41	6.24E-004	6.84E-004	83						
3	35	5.63E-004	6.06E-004	83						
3	53	7.68E-004	7.94E-004	84						
3	47	7.02E-004	7.60E-004	84						

Table 3: Results for deglitching PFM4 data with 8 scans

Windowed Standard Deviation Clipping

Threshold Factor k	Window Size w	Experimental False Positive Ratio	Theoretical False Positive Ratio	Correct Identifications
6	35	0	0	0
6	33	0	0	0
6	31	0	0	0
5.5	31	0	0	0
6	29	0	0	0
5.5	29	0	0	0
6	27	0	0	0
5.5	27	0	0	0
5	27	0	0	0
6	25	0	0	0
5.5	25	0	0	0
5	25	0	0	0
6	23	0	0	0
5.5	23	0	0	0
5	23	0	0	0
6	17	0	0	0
5.5	17	0	0	0
5	17	0	0	0
4.5	17	0	0	0
4	17	0	0	0
6	11	0	0	0
5.5	11	0	0	0
5	11	0	0	0
4.5	11	0	0	0
4	11	0	0	0
3.5	11	0	0	0
3	11	0	0	0
6	5	0	0	0
5.5	5	0	0	0
5	5	0	0	0
4.5	5	0	0	0
4	5	0	0	0
3.5	5	0	0	0
3	5	0	0	0
2.5	5	0	0	0
2	5	0	0	0
6	41	0	0	1
5.5	35	0	0	1
5.5	33	0	0	1
5	29	0	0	1
4.5	23	0	0	1
5	31	2.52E-008	0	5
4.5	25	2.52E-008	0	5
6	47	2.52E-008	0	14
5	33	1.01E-007	0	15
4.5	27	1.01E-007	0	16
5.5	41	1.76E-007	0	18
3.5	17	9.33E-007	2.49E-006	20
6	53	2.77E-007	0	25
5	35	1.76E-007	0	26
4.5	29	4.54E-007	0	29
4	23	7.81E-007	4.98E-007	31
4.5	31	8.57E-007	0	37
5.5	47	4.29E-007	0	37
4	25	1.46E-006	2.99E-006	41
5	41	8.07E-007	0	42
4.5	33	1.08E-006	0	45
5.5	53	7.81E-007	0	45
4	27	2.67E-006	2.49E-006	47
4.5	35	1.41E-006	1.49E-006	48
4	29	4.06E-006	6.47E-006	51
5	47	1.36E-006	0	51
4	31	5.50E-006	1.24E-005	52
4.5	41	2.52E-006	9.95E-007	54
2.5	11	4.34E-004	9.89E-004	55
3.5	23	2.31E-005	5.72E-005	55
5	53	1.64E-006	4.98E-007	55
3	17	1.23E-004	3.00E-004	57
4	33	8.04E-006	1.09E-005	58
3.5	25	3.52E-005	7.06E-005	59
4.5	47	3.81E-006	2.49E-006	62
4.5	53	5.57E-006	5.97E-006	64
4	35	1.12E-005	2.14E-005	65
3.5	27	4.88E-005	1.05E-004	69
4	41	1.86E-005	3.03E-005	69
3.5	29	6.20E-005	1.27E-004	72
4	47	2.89E-005	4.93E-005	72
4	53	3.77E-005	6.67E-005	75
3.5	33	9.13E-005	1.69E-004	76
3	23	3.39E-004	6.69E-004	77
3.5	53	2.12E-004	3.42E-004	77
3.5	35	1.08E-004	2.00E-004	77
3.5	31	7.51E-005	1.51E-004	77
3	25	4.12E-004	7.47E-004	78
3.5	41	1.43E-004	2.32E-004	78
3	27	4.78E-004	8.55E-004	79
3.5	47	1.78E-004	3.10E-004	79
3	29	5.31E-004	8.94E-004	80

Windowed MAD Clipping

Threshold Factor k	Window Size w	Experimental False Positive Ratio	Theoretical False Positive Ratio	Correct Identifications
6	11	5.36E-004	8.81E-004	62
6	27	8.50E-005	8.61E-005	66
6	41	4.97E-005	3.13E-005	66
6	17	1.70E-004	2.66E-004	67
5.5	27	1.48E-004	1.68E-004	67
6	25	9.23E-005	1.07E-004	67
6	29	7.17E-005	5.67E-005	68
6	53	6.77E-005	1.69E-005	68
6	31	5.99E-005	5.67E-005	68
6	35	5.85E-005	3.93E-005	68
6	33	5.83E-005	5.27E-005	68
5.5	17	2.72E-004	4.66E-004	69
5.5	25	1.58E-004	1.77E-004	69
5.5	29	1.27E-004	1.48E-004	69
5.5	41	8.91E-005	6.87E-005	69
6	47	5.43E-005	2.14E-005	69
5.5	31	1.08E-004	1.21E-004	70
5.5	33	1.05E-004	1.10E-004	70
5.5	53	1.13E-004	4.28E-005	71
5.5	35	1.04E-004	9.60E-005	71
6	23	9.96E-005	1.15E-004	71
5.5	47	9.54E-005	5.72E-005	71
5	23	2.92E-004	4.28E-004	72
5	27	2.63E-004	3.20E-004	72
5	31	2.04E-004	2.52E-004	72
5.5	23	1.68E-004	2.04E-004	72
5	17	4.39E-004	7.47E-004	73
5	25	2.77E-004	3.86E-004	73
5	29	2.30E-004	2.66E-004	73
5	53	2.03E-004	1.04E-004	73
5	35	1.98E-004	2.08E-004	73
5	33	1.98E-004	2.15E-004	73
4.5	29	4.34E-004	5.41E-004	75
4.5	23	5.30E-004	7.78E-004	76
4.5	25	5.03E-004	6.73E-004	76
4.5	27	4.78E-004	5.83E-004	76
4.5	31	3.94E-004	4.63E-004	76
4.5	35	3.86E-004	4.17E-004	76
4.5	33	3.84E-004	4.45E-004	76
5	47	1.76E-004	1.35E-004	76
5	41	1.70E-004	1.43E-004	76
4.5	47	3.41E-004	2.93E-004	80
4.5	41	3.35E-004	3.30E-004	80
4.5	53	3.75E-004	2.43E-004	81
4	33	7.64E-004	9.22E-004	82
4	35	7.63E-004	8.68E-004	82
4	53	7.30E-004	6.30E-004	83
4	47	6.87E-004	6.79E-004	83
4	41	6.84E-004	7.87E-004	83

Table 4: Results for deglitching PFM4 data with 6 scans (cropped back from 8 scans by removing scans 5 & 6)

Illustrations 16 to 18 directly compare the expected and the actual false positive glitch ratios. In general, the expected and actual false positive ratios are in better agreement for the windowed standard deviation clipping than for the windowed MAD clipping. As the scan number decreases the agreement for both algorithms becomes worse. For the highest scan number of 16, both algorithms show good agreement except for MAD clipping which shows systematic deviations for specific parameter sets. More detailed inspection of the data shows that these outliers employ large window sizes larger than 40. Further analysis has shown that a disproportional number of outliers for these algorithms is found around the center burst region – when compared to smaller window sizes. Once the window size becomes comparable to the width of the center burst, MAD clipping will again run into the problem of accidental grouping and flag significantly more outliers for interferograms than for randomly distributed data.

In addition to the observation that the deglitching algorithms studied here do flag false positives, it is also possible to specify where in the interferograms such false positives are flagged. Overall, both algorithms will flag more outliers in the center burst region than further away from ZPD. Positions that are flagged as containing outliers even though no obvious deviant data sample can be seen, correspond to large values in the standard deviation interferogram. These large standard deviation values, in turn, correspond to a large slope in the original interferograms, i.e. they are close to the zero-crossings of the interferograms. In summary: both algorithms will flag false positives. If they do, it is likely that the false positives are close to the zero-crossings within the center burst of interferograms.

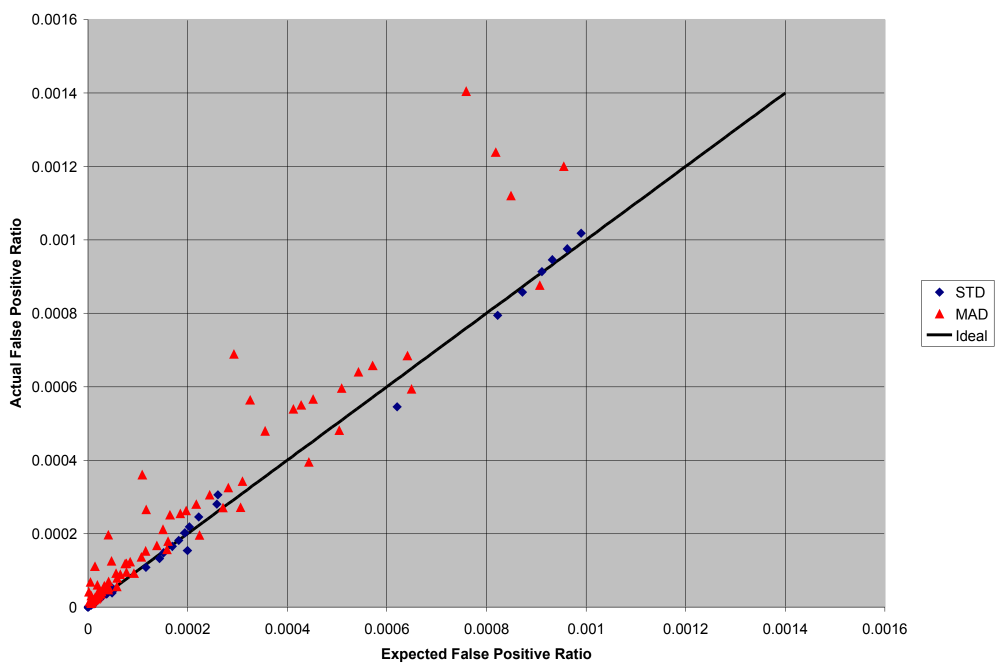

Illustration 16: Comparison of actually identified and expected false positives for windowed standard deviation and MAD clipping; PFM4 - 16 scans

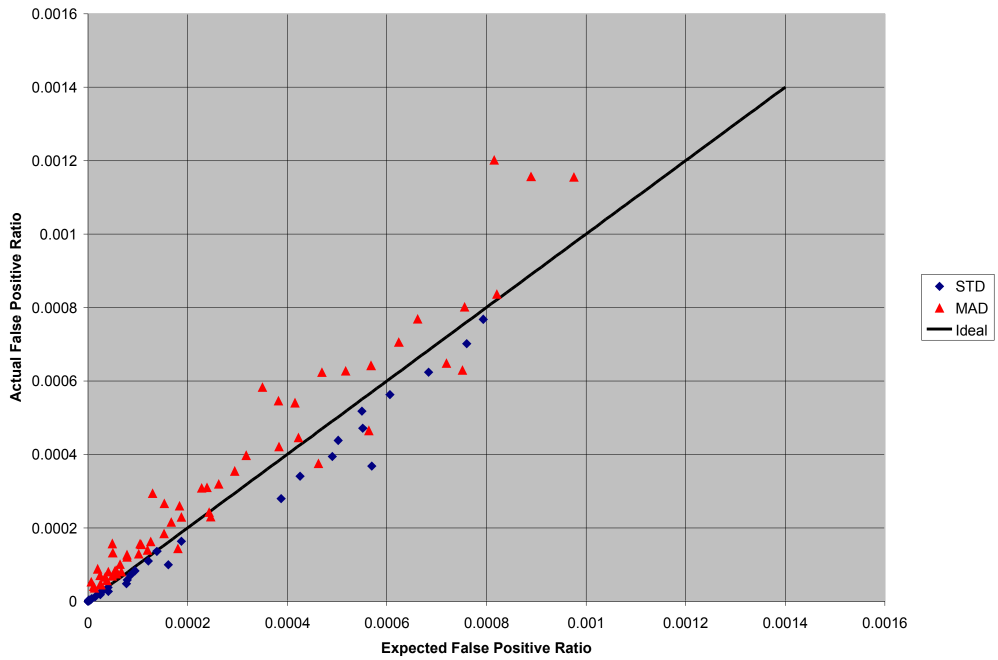

Illustration 17: Comparison of actually identified and expected false positives for windowed standard deviation and MAD clipping; PFM4 - 8 scans

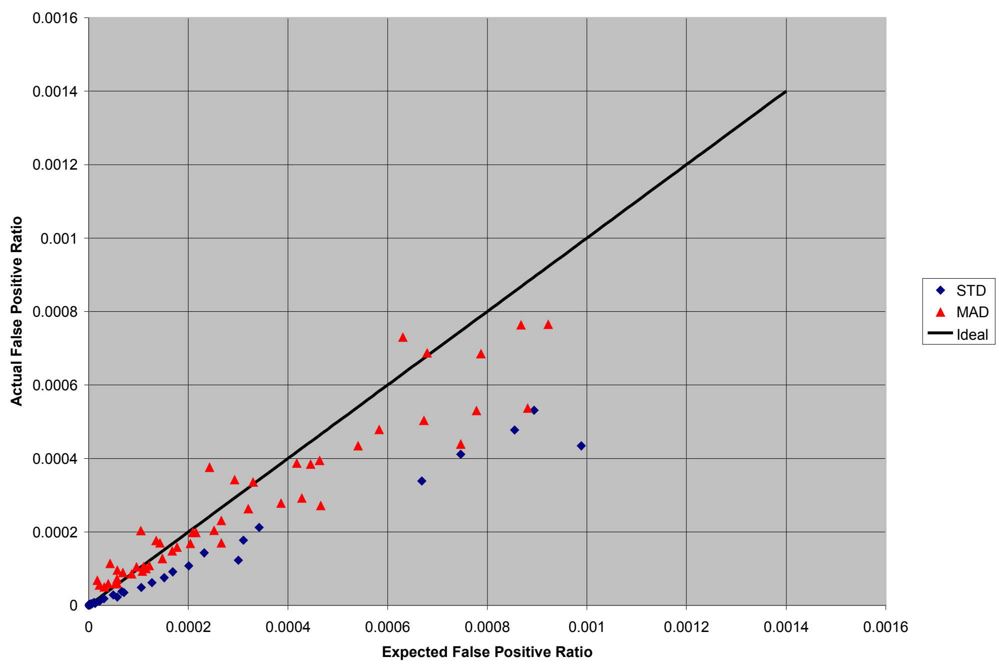

Illustration 18: Comparison of actually identified and expected false positives for windowed standard deviation and MAD clipping; PFM4 - 6 scans

b) Correct Identifications

External information on the location of actual glitches has to be available in order to assess whether an outlier that has been identified by a deglitching algorithm is, in fact, a glitch. It is very time-consuming to manually evaluate hours worth of data. Also, manual evaluation introduces a dependency on the particular person who inspected the data. We therefore decided to make use of the 1st level deglitching module with its default settings (SPIRE builds as of October 16, 2008 until end of November 2008). This resulted in a total of 29 and 129 glitches for observations with 16 and 8 scans respectively. Josh Litven then reviewed these glitches visually and rejected glitches as false positives which do not seem to be due to a transient disturbance in the detector timeline. This reduced the total number of glitches to 16 and 111 glitches for observations with 16 and 8 scans respectively. At that point, the detector timelines were merged with the spectrometer mechanism timeline into spectrometer detector interferograms. The location of the glitch identified by 1st level deglitching within the interferogram is calculated at this point. A number of glitches were not present in the interferograms because they occurred in the detector timelines before or after the stage mechanism was in motion, further reducing the total number of glitches to 11 and 89 for observations with 16 and 8 scans respectively. A glitch is taken to have been correctly identified if 2nd level deglitching identified a glitch within three sample points to either side of the location of a real glitch as vetted by the process described earlier.

The results of this process are shown in the fifth and eleventh column for Standard Deviation and MAD Clipping in the tables 2 to 4 which detail the results for observations with 16, 8, and 6 scans. In order to cover the case of 6 scans we removed scans 5 & 6 from the observations with 8 scans, leaving 87 valid glitches. Note that only those parameter combinations with an expected false positive ratio of less than 0.1% are included. The results are summarized below:

For the case of **16 scans**, unfortunately, only 11 glitches were seen in the data, greatly reducing the reliability of any statistically derived result on the performance of the deglitching algorithms with different parameters.

- **Windowed MAD clipping** yielded fewer than 0.1% false positives for a total of 74 parameter sets. The parameter sets range from k=3 and w=11 to the respective maximum values of k=6 and w=53, correctly identifying 4 to 11 glitches. The best result of identifying all 11 glitches correctly were achieved with threshold factors between 3 and 4 and a wide range of window sizes, w=17 – 53.
- **Windowed Standard Deviation clipping** yielded fewer than 0.1% false positives for a total of 101 parameter sets. However, only for 32 parameter sets did windowed standard deviation clipping identify 4 or more glitches correctly (cf. to the paragraph above). These 32 parameter sets range from k=2.5 to 4.5 and w=17 to 53, correctly identifying up to 11 glitches. The best result of identifying all 11 glitches correctly were achieved with threshold factors of either 2.5 or 3 and window sizes between 25 and 53.

For the case of **8 scans**, 89 glitches were seen in the data, giving a much better basis to evaluate the algorithm performance than for the case of 16 scans.

- **Windowed MAD clipping** yielded fewer than 0.1% false positives for a total of 59 parameter sets. The parameter sets range from k=3.5 and w=11 to the respective maximum values of k=6 and w=53, correctly identifying 62 to 86 glitches. The best results of identifying 85 or 86 glitches correctly were achieved with threshold factors of 3.5 or 4 and window sizes between 41 and 53.
- **Windowed Standard Deviation clipping** yielded fewer than 0.1% false positives for a total of 94 parameter sets. However, only for 24 parameter sets did windowed standard deviation clipping identify 62 or more glitches correctly (cf. to the paragraph above). These 24 parameter sets range from k=3.0 to

4.5 and w=25 to 53, correctly identifying between 62 and 84 glitches. The best result of identifying 83 or 84 glitches correctly were achieved with a threshold factor of 3 and window sizes between 29 and 53.

For the case of **6 scans**, 87 glitches were seen in the data, giving a much better basis to evaluate the algorithm performance than for the case of 16 scans.

•**Windowed MAD clipping** yielded fewer than 0.1% false positives for a total of 49 parameter sets. The parameter sets range from k=4 and w=11 to the respective maximum values of k=6 and w=53, correctly identifying 62 to 83 glitches. The best results of identifying 82 or 83 glitches correctly were achieved with a threshold factor of 4 and window sizes between 33 and 53.

•**Windowed Standard Deviation clipping** yielded fewer than 0.1% false positives for a total of 88 parameter sets. However, only for 18 parameter sets did windowed standard deviation clipping identify 62 or more glitches correctly (cf. to the paragraph above). These 18 parameter sets range from k=3.0 to 4.5 and w=23 to 53, correctly identifying between 62 and 80 glitches. The best result of identifying 80 or 79 glitches correctly were achieved with threshold factors of 3 or 3.5 and window sizes between 27 and 47.

6. Conclusions

Four algorithms have been studied in terms of their suitability to identify glitches in interferograms produced by the SPIRE imaging FTS: Standard Deviation clipping, MAD clipping, windowed standard deviation clipping, and windowed MAD clipping.

The results from the analysis of the false positive ratio and the number of correctly identified glitches provide a good – if not comprehensive – basis to make recommendations for the implementation of 2nd level deglitching module in the data processing environment for the SPIRE spectrometer:

0. A good choice of deglitching parameters depends on the number of scans available in the interferogram data product.
1. Standard Deviation clipping should not be used to identify glitches in interferograms with only 16 scans or fewer. This threshold may actually be higher, but it has not been possible to test it so far. Standard Deviation clipping will tend to be too insensitive, not finding any glitches.
2. MAD clipping should not be used to identify glitches in interferograms with only 16 scans or fewer. This threshold may actually be higher, but it has not been possible to test it so far. MAD clipping will tend to be too sensitive, flagging a large number of false positives.
3. The parameter range for windowed MAD clipping that leads to reasonable glitch identification is more than twice as large as for windowed Standard Deviation clipping. The best parameter combinations for windowed MAD clipping lead to better glitch identification than the best parameter combinations for windowed Standard Deviation clipping. Windowed MAD clipping is therefore recommended as the default algorithm.
4. The window for windowed MAD clipping should be smaller than the central burst region of the interferogram studied. A default value of w=33 elements has been found to be effective when applied to data from the PFM4 test campaign.
5. The windowed clipping algorithms do not depend as strongly on the specific window size as they do on the threshold factor. One default value for windowed Standard Deviation clipping (w=41) and windowed MAD clipping (w=33) can therefore be used in the automated pipeline.
6. The default values for the threshold factor for the windowed clipping algorithms should tend to decrease with increasing scan number. When determining the default parameters, the threshold factor was kept to a minimum while still staying below the 0.1% threshold for the false positive ratio. The following default parameters have been implemented:

N	Win STD	Win MAD
4	4	4.5
6	3.5	4
8	3	4
10	3	3.5
12	3	3.5
14	3	3.5
16	3	3.5
18	2.5	3
>18	2.5	3

Table 5: Recommended default parameters for windowed deglitching algorithms

7.

7. Outlook

A lot of work has already been done verifying the performance of different interferogram deglitching schemes. The following additional work would be useful for further refinement of the processing module:

- Verify the performance of the deglitching algorithms with simulated data (cf. test report by LAM on 1^{st} level deglitching) to improve the statistical validity and characterize systematically the ability to correctly identify glitches for arbitrary scan numbers.
- Quantify the suitability of the proposed methods to deal with the special case of two plus two scans.
- Explore whether the skewness interferogram is more suited than the standard deviation interferogram to feed the windowed clipping algorithms.
-

8. Appendix

The SPIRE ground-based test campaign PFM4 was used to evaluate the efficiency of the deglitching algorithms in identifying glitches correctly. The list of used observations from PFM4 is given below. Note that test data for the case of 6 iterations, i.e. three forward and three reverse scans, were created by removing the scans numbered 5 and 6 from the data with 8 iterations.

Data was available for total time periods of 75 and 208 minutes for scan numbers of 16 and 8 respectively.

#	Date	Time	OBSID	Speed (mm/s)	Iterations	Data Size	Duration [min]	SCAL [K]	SCAL2 [K]	SCAL4 [K]	CBB [K]	Resolution	Laser?	Glitches found by 1st level deglitching	1st level glitches per minute	Glitches after manual verification of 1st level glitches	Glitches that were removed manually	1st level glitches projected to ifgms	Glitches that were removed by the projection	SDI scans
1	Dec 7, 2006	19:17:00	'300117A3	0.5	30	42685	8.9					Medium	laser @ 393	0	0.00	0		0		
2	Dec 8, 2006	19:12:00	'30011800	0.525	20	48496	10.1			70		Medium	room only	23	2.28	1	All Pixels with a glitch at 11	N/A	Incorrect # of scans	19
3	Nov 27, 2006		'300114C8	0.5	16	108403	22.6	4.523	4.67	4.594	6.699	High		16	0.71	6	SSWB1: 4,478, 483,619, 801, 1062, 1208, 1412 SSWC5: 892, SSWE6: 294	4	SSWA1: 1366, SSWF4: 1292	
4	Nov 27, 2006		'300114CA	0.5	16	23954	5.0	4.503	4.653	4.578	6.7	Medium		2	0.40	1	SSWB1: 314	0	SSWF1: 305	
5	Nov 27, 2006		'300114CE	0.5	16	108403	22.6	4.527	4.674	4.5984	9.023	High		6	0.27	5	SSWB1: 313	5		
6	Nov 27, 2006		'300114CF	0.5	16	23420	4.9	4.499	4.648	4.5732	9.023	Medium		0	0.00	0		0		
7	Nov 27, 2006		'300114D7	0.5	16	23439	4.9	4.502	9.191	4.5841	6.704	Medium		4	0.82	4		2	SSWB1: 4, SSWF3: 247	
8	Nov 27, 2006		'300114DD	0.5	16	23420	4.9	4.504	14.24	4.5955	6.7	Medium		1	0.20	0	SSWB1: 56	0		
9	Nov 27, 2006		'300114E3	0.5	16	23439	4.9	4.507	20.23	4.6162	6.7	Medium		0	0.00	0		0		
10	Nov 27, 2006		'300114EC	0.5	16	23418	4.9	4.51	4.697	20.159	6.7	Medium		0	0.00	0		0		
11	Dec 8, 2006	15:47:00	'300117F0	0.5	12	18088	3.8					Medium	laser @ 202	0	0.00	0		0		
12	Nov 21, 2006		'300113D4	0.5	10	68645	14.3	4.505	4.651	4.576	6.684	High	Different Bias	1	0.07	1	SLWC3: All Glitches Removed	1		
13	Nov 21, 2006		'300113BB	0.5	8	55444	11.6	4.491	4.653	14.954	6.684	High		15	1.30	11	SLWC1: 699, SSWB1: 108, SSWD3: 265, SSWD6: 149	N/A	Sdi could not be created	
14	Nov 21, 2006		'300113BE	0.5	8	55453	11.6	4.495	4.674	20.082	6.684	High		18	1.56	17	SSWA4: 508	0	All pixels with a glitch at 653	
15	Nov 21, 2006		'300113CD	0.5	8	55454	11.6	4.506	4.706	24.979	6.687	High	Different Bias	4	0.35	3	SSWC4: 12	2	SLWB1: 635	
16	Nov 21, 2006		'300113D0	0.5	8	55440	11.6	4.521	4.814	40.175	6.687	High	Different Bias	1	0.09	1		1		
17	Nov 27, 2006		'300114D6	0.5	8	55461	11.6	4.529	9.196	4.6032	6.727	High		6	0.52	2	SSWB1: 383, 630, 699, 719	2		
18	Nov 27, 2006		'300114DC	0.5	8	55442	11.6	4.529	14.23	4.6127	6.7	High		12	1.04	5	SLWD1: 545, SSWB1: 12,17,57, 87,490, 690	5		
19	Nov 27, 2006		'300114EB	0.5	8	55439	11.5	4.536	4.719	20.128	6.7	High		39	3.38	37	SSWE6: 493, SSWG4:318	37		
20	Dec 6, 2006	13:15:00	'30011720	0.5	8	55452	11.6	4.526	4.671	4.5926	7.225	High		7	0.61	5	SSWD6:21, SSWE4:462	5		
21	Dec 6, 2006	13:56:00	'30011724	0.5	8	55444	11.6	4.53	4.675	4.5965	7.73	High		31	2.68	31		29	SSWB:1 709, SSWF4: 7	
22	Dec 6, 2006	14:19:00	'30011728	0.5	8	55429	11.5	4.533	4.68	4.6009	8.229	High		7	0.61	7		6	SSWB1: 735	
23	Dec 6, 2006	14:47:00	'3001172B	0.5	8	55441	11.6	4.534	4.681	4.6024	8.733	High		1	0.09	0	SSWB1:577	0		
24	Dec 6, 2006	15:29:00	'3001172F	0.5	8	55437	11.5	4.537	4.683	4.6044	13.05	High		0	0.00	0		0		
25	Dec 6, 2006	15:55:00	'30011733	0.5	8	55430	11.5	4.537	4.683	4.6047	15.07	High		0	0.00	0		N/A	Incorrect # of scans	7
26	Dec 6, 2006	16:25:00	'30011737	0.5	8	55445	11.6	4.537	4.683	4.6045	18.07	High		0	0.00	0		0		
27	Dec 6, 2006	21:28:00	'30011760	0.5	8	55433	11.5	4.547	25.92	4.6677	6.707	High		1	0.09	1		1		
28	Dec 7, 2006	13:05:00	'3001177A	0.5	8	55442	11.6					High	laser @ 393	1	0.09	1		1		
29	Dec 7, 2006	22:21:00	'300117BB	0.5	8	55436	11.5			80		High	room only	1	0.09	1		0	SLWE3: 731	
30	Dec 8, 2006	16:11:00	'300117F2	1.0	8	27983	5.8					High	laser @ 202	see comment		see comment		N/A	Not included	
31	Dec 8, 2006	17:22:00	'300117F9	0.5	8	54880	11.4			70		High	laser @ 202	0	0.00	0		0		
32	Dec 8, 2006	17:36:00	'300117FA	0.5	8	54900	11.4			70		High	laser @ 202	0	0.00	0		0		
33	Dec 14, 2006	20:35:00	'30011940	0.500	6					81		High	SLWC3			2		1	SSWF5: 527	
34	Dec 14, 2006	20:47:00	'30011941	0.500	6					81		High				1	SLWC5:438	0	SSWE3: 12	
35	Dec 14, 2006	22:37:00	'30011943	0.500	6					81		High	SLWE1			1	SSWB5:185	0	SSWB5: 544	
36	Dec 14, 2006	22:49:00	'30011944	0.500	6					81		High				0		0		
37	Dec 14, 2006	23:30:00	'30011947	0.500	6					81		High	SLWE1			0		0		
38	Dec 14, 2006	23:47:00	'3001194B	0.500	6					81		High	SLWE1			1		1		
39	Nov 21, 2006		'300113B4	0.5	4			4.477	4.624	9.0625	6.682	High				0	SSWB2:50	N/A	Incorrect # of scans	3
40	Nov 21, 2006		'300113C3	0.5	4			4.494	4.672	20.096	6.683	High				2	SSWB1: 102	0	SSWB1: 362, 363	
41	Nov 21, 2006		'300113C9	0.5	4			4.497	4.674	20.098	6.685	High				1		1		
42	Nov 21, 2006		'300113D2	0.5	4			4.519	4.808	40.443	6.838	High				0		0		
43	Dec 7, 2006	14:54:00	'30011785	0.5	4							High	SLWD2			1		0	SSWF5: 7	
44	Dec 7, 2006	15:11:00	'30011787	0.5	4							High	SLWE2			0		0		
45	Dec 7, 2006	15:27:00	'30011789	0.5	4							High	SLWE2			0		0		
46	Dec 7, 2006	15:38:00	'3001178A	0.5	4							High				1		1		
47	Dec 7, 2006	16:00:00	'3001178C	0.5	4							High	SLWC5			0		0		
48	Dec 7, 2006	16:15:00	'3001178E	0.5	4							High	SLWC3			0		0		
49	Dec 7, 2006	16:32:00	'30011790	0.5	4							High				0		0		
50	Dec 7, 2006	16:45:00	'30011792	0.5	4							High	SLWC3			0		0		
51	Dec 7, 2006	17:03:00	'30011794	0.5	4							High	SLWC3			0		0		
52	Dec 7, 2006	17:19:00	'30011796	0.5	4							High	SLWC3			0		0		
53	Dec 7, 2006	17:31:00	'30011797	0.5	4							High	SLWC3			0		0		
54	Dec 7, 2006	17:47:00	'30011799	0.5	4							High	SLWC3			0		0		
55	Dec 7, 2006	17:57:00	'3001179B	0.5	4							High	SLWC3			0		0		
56	Dec 7, 2006	18:12:00	'3001179D	0.5	4							High	SLWC3			1		1		
57	Dec 7, 2006	18:24:00	'3001179F	0.5	4							High	SLWC3			0		0		
58	Dec 7, 2006	20:38:00	'300117A9	0.5	4					80		High	SLWC3			0		0		
59	Dec 7, 2006	20:49:00	'300117AB	0.5	4					80		High	SLWC3			0		0		
60	Dec 7, 2006	21:00:00	'300117AD	0.5	4					80		High	SLWC3			0		0		
61	Dec 7, 2006	21:11:00	'300117AF	0.5	4					80		High	SLWC3			1		1		
62	Dec 7, 2006	21:22:00	'300117B1	0.5	4					80		High	SLWC3			0		0		
63	Dec 7, 2006	21:33:00	'300117B3	0.5	4					80		High	SLWC3			0		0		
64	Dec 7, 2006	21:45:00	'300117B5	0.5	4					80		High	SLWC3			1		1		
65	Dec 7, 2006	21:57:00	'300117B7	0.5	4					80		High	SLWC3			1		0	SLWE2 :0	
66	Dec 7, 2006	22:08:00	'300117B9	0.5	4					80		High	SLWC3			1		1		
67	Dec 7, 2006	22:36:00	'300117BC	0.5	4					80		High	SLWC3			0		0		
68	Dec 7, 2006	22:46:00	'300117BD	0.5	4					80		High	SLWC3			0	SSWB1:177	0		
69	Dec 7, 2006	22:54:00	'300117BE	0.5	4					80		High	SLWC3			0		0		
70	Dec 8, 2006	14:41:00	'300117ED	0.5	4							High	SSWD4			1		N/A	Incorrect # of scans	3
71	Dec 8, 2006	14:48:00	'300117EE	0.5	4							High	SSWD4			0		0		
72	Dec 8, 2006	18:44:00	'300117FE	0.525	4	24174	5.0			70		High	laser @ 202	31	6.16	0	All Pixels with a glitch at 11, SSWA4: 12	0		
73	Dec 8, 2006	18:59:00	'300117FF	0.525	4	24170	5.0			70		High	laser @ 202	42	8.34	7	All Pixels with a glitch at 11	N/A	Incorrect # of scans	3
																163		109		
	All results exclusive of the following detectors: SLWB3,SLWC2,SSWD7,SSWD5,DP,T,R																			
	Data were loaded from database, converted via EDP, and then 1st level deglitching was applied (no clipping correction)																			