# A Data Reduction Concept For FIRST/PACS

Horst Bischof[a], A. Nabil Belbachir[a], Dieter Hönigmann[a], and Franz Kerschbaum[b]

[a]Vienna University of Technology
Pattern Recognition and Image Processing Group
Favoritenstr. 9/1832, A-1040 Vienna, Austria
[b]Institut für Astronomie der Universität Wien
Türkenschanzstr. 17, A-1180 Vienna, Austria

## ABSTRACT

This paper describes a novel On-Board data compression concept for the FIRST/PACS mission of the European Space Agency (ESA). Using the lossy and lossless compression, the presented method offers a high compression rate with a minimal loss of potentially useful scientific data. It also provides higher signal to noise ratio than that for standard compression techniques. The various modules of the data compression concept are discussed in detail. We demonstrate the method on synthetic data.

**Keywords:** FIRST, PACS, Data Compression, On-board Software, Infrared Astronomy

## 1. INTRODUCTION

Data compression is becoming increasingly important for economical storage and transmission in several applications. In fact, this is most demanding in Science, Earth and Space Observation missions where images are generated in different domains with higher resolution and therefore larger dimensions. This yields to an important increase in terms of data volume and bit rate. Furthermore, telemetry capabilities did not follow the same performance increase. Therefore, compression becomes a requirement for communication systems in charge of storage and/or transmission of the data.

Basically, data compression is a matter of modeling. The more information can be derived from it the less information has to be transmitted. There are many data compression algorithms which the output quality and the algorithmic complexity depend on the chosen application. Each application requires its own modeling. Differential Pulse-Code Modulation (DPCM) is a spatial or temporal compression technique that gives good results in many cases. However, DPCM is less suited for very noisy data or data with jump-type behavior.[1,2]

The adaptive Run-Length Coding technique has proven to be efficient for lossless data compression, especially for images which contain an uniform background. However, when this condition is not fulfilled the storage capacity might even raise.

The FIRST Photoconductor Array Camera & Spectrometer (PACS)[3] is one of the three instruments operating on board the Far InfraRed Space Telescope (FIRST)[4] foreseen to be launched on 2007.

Our task in the framework of the PACS consortium is to implement a robust On-Board Data Compression Software on its DSP yielding a high signal to noise ratio and a commandable compression rate. This task is of special importance because of the extreme compression ratio (depending on the instrumental mode up to 70!) dictated by the combination of a high raw data rate with a relatively low telemetry rate available for a L2-orbit space mission.

We present in this paper a new data Compression/Reduction Concept which provides such a high compression ratio. This is achieved by a combination of On-board data reduction with lossless compression algorithms.

This paper is structured as follows. In section 2, we present the problem statements and the characteristics of the astronomical data. In section 3, the descriptions of the proposed data compression concept and its modules. The experimental results on the application of this reduction concept on synthetic data are given in section 4. We conclude with a short summary.

Further author information: (Send correspondence to H.B.)
H.B.: E-mail: bis@prip.tuwien.ac.at
F.K.: E-mail: kerschbaum@astro.univie.ac.at

## 2. PROBLEM STATEMENT

The FIRST-PACS detector arrays are realized by two extrinsic Ge:Ga photoconductor filled pixel arrays of format $25 \times 16$ including integrated crygenic readout electronics (CRE). The two arrays are specialized for two wavelength regimes (40–120 $\mu$m and 100–210 $\mu$m, respectively) by applying physical stress to the longer wavelength module.

When such detectors are receiving Infrared photons from an astronomical or internal source, the voltage V at its output will increase as a function of time. The incoming photons excite charge carriers into the conduction or valence band. The voltage increase is proportional to the current through the detector which is in turn proportional to the number of photons falling on the detector. In the case of the PACS instrument the Cold Readout Electronics pre-amplifies and samples the photo-currents generated in the detector. Since the output voltage should stay within a quite limited range, a voltage reset pulse is applied in addition to a sample pulse after a number of desired voltages has been sampled. For PACS there will be typically only 4 samples on each ramp.

The main challenge is the high data rate of the instrument. The raw data stream consists of $2 \times 25 \times 18$ CRE channels, so a total of 900 channels. With maximum readout rate of 256 Hz we get a sampling rate of 230400 samples/s. Conversion of this analog data stream by means of a 16 bit ADC yields the maximum data rate of the raw data stream of 3600 Kbits/s. For transmission of science data different transmission modes are foreseen. In Science PACS Prime Mode maximum data rate is limited to 100 Kbit/s, while in Science PACS Partner Mode it is limited to 50 Kbit/s. In Science BURST Mode, the maximum data rate is 400 Kbit/s. Therefore for the prime mode, a minimum compression ratio of 36 is required*. In addition to that, the detectors are continuously exposed to high energy cosmic particles inducing a disturbance (glitches) of the readout voltage which decrease the signal to-noise ratio and hence the data accuracy level. In the sequel we assume the characteristics as depicted in Tab. 1 of the detector and the signals.

| | |
|---|---|
| Signal/Noise ratio | $\approx 6000$ |
| Glitch rate | 10s/pixel |
| Glitch tails | $< 0.5$s |
| Detector output | 16bit |
| Significant bits | 14bit |

**Table 1.** Assumed data characteristics

The maximum possible compression rate we could obtain by a lossless compression (i.e., the original measurements can be recovered) can be computed as follows: A compression ratio of 16/14 is obtained by eliminating non-significant bits via spatial and temporal redundancy reduction. An additional compression factor of 4 is obtained by calculating the slope of the ramp, which has to be given at least with the accuracy of the S/N. Therefore, 16 bit for the slope are sufficient. A further lossless compression of the signal is not possible because it contains basically the noise of the telescope, which is by definition, incompressible. This noise cannot be eliminated because we would loose the astronomical signal. Therefore we can achieve a lossless compression factor of 4.57. Since lossless compression is impossible at such rate we have to perform on-board processing.

In the next section we describe our compression concept in detail.

## 3. DATA COMPRESSION CONCEPT

This section reviews the basic concept for PACS data reduction / compression software to achieve the desired downlink data rates. Figure 1 presents the different software modules. First, the data packet received from the Focal Plane Unit, will be grouped into a set of reset interval measurements (useful time). Each one is called Ramp. It contains a measurement samples during one reset interval†.

The compression concept can be coarsely divided into three modules:

*This is for the PACS prime photometry mode, in what follows will only consider this mode, because for the other modes the requirements for the compression are less demanding

†In what follows we will consider only one array. The processing for the other array is similar

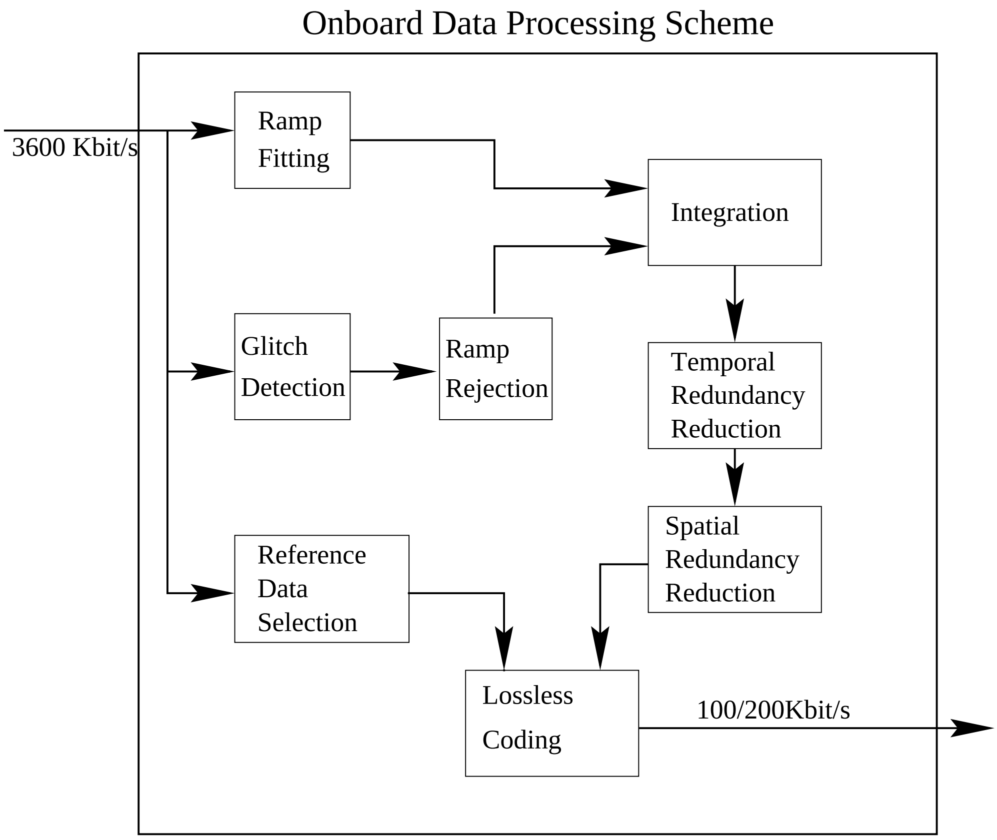



**Figure 1.** A schematic diagram outlining the data compression software.

1. Integration: The integration part of the software performs the on-board data reduction. The basic idea is that in order to achieve the high compression ratio we have to integrate several ramps on-board. Since, a ramp maybe effected by glitches, we have to ensure that we do not integrate over this ramps. This is done in the glitch detection and ramp rejection module.

2. Loss-less coding: The loss-less coding part of the software consists of the temporal and spatial redundancy reduction and the loss-less coder.

3. Reference data selection: This module is responsible for transmitting selected ramps without compressing them. The main reason for this module is to check the performance of the compression software on ground. In what follows we will not describe this module further.

In the following subsections we describe the individual modules in detail, with special emphasize on the integration and glitch detection part.

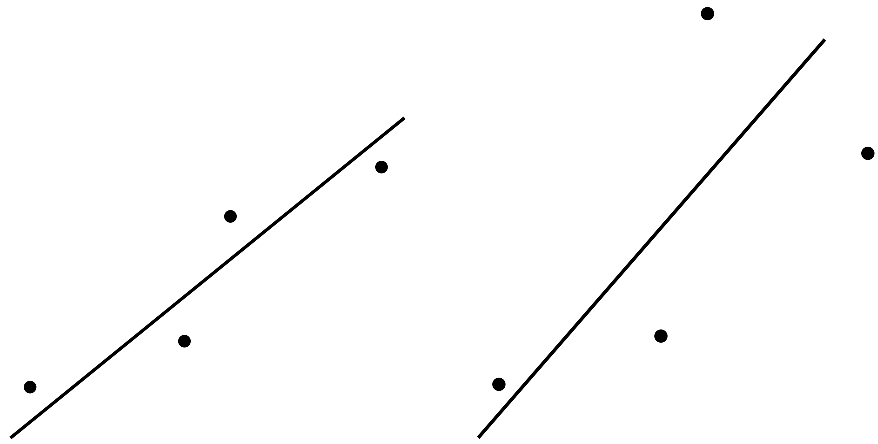
### 3.1. Ramp Fitting

Ramp fitting is one of the crucial steps of the proposed data reduction concept. In this paper, we only will consider linear ramps. We can show that an extension to the non-linear ramps could be easily done when analytic model of the ramp is available. The ramps are fitted to the sensor readings in order to obtain the flux. Let us consider the samples belonging to a ramp given by a vector $\mathbf{x} = [x_1, \dots x_n]^T$. A linear ramp is given by

$$\mathbf{x} = s\mathbf{t} + o + \eta$$

where $s$ is the unknown slope, $\mathbf{t}$ are the known instants of sampling $o$ is the unknown offset and $\eta$ is a vector of random variables with distribution of every element assumed to be $N(0, \sigma)$, characterizing the noise process. In order to obtain the parameters of interest this equation has to be solved in a robust manner. We have following options:

**Least squares solution:** The least squares solution can be easily calculated in analytic form, and is optimal with respect to the Gaussian noise process. However, in case of gross outliers (i.e., glitches) it performs very poor. Fig. 2(a) shows an example where least squares is performing very well. Whereas Fig. 2(b) shows the least squares solution on the same data as in Fig. 2(a) where one sample is an outlier. One can clearly see that the obtained ramp is far from being perfect.



(a) (b)

**Figure 2.** Least squares fitting.

**Robust solution:** Since we have to find the solution in a robust manner we are looking for a robust fitting procedure. There have been many proposals how to obtain a solution to the above equation in the presence of outliers (e.g. see[5,6]). Since we are dealing with only a few samples per ramp we have chosen the RANSAC (Random Sample Consensus) algorithm[7] for robust fitting. The basic idea of RANSAC (for line fitting) is the following (see also Fig. 3):

1. Take randomly two samples and calculate the line which passes exactly through these samples.
2. All samples which are within a pre-specified distance $\Theta$ to the line are put into the support set.
3. Repeat this process many times.
4. Select the line with the largest support set (if there is more than one take the one with the smallest residual error).

In our case we are dealing with just 4 samples per line, therefore we can calculate all 6 lines. If we are dealing with ramps containing more samples (e.g. like for ISO) we will take only a subset of points to speed up the processing. The threshold $\Theta$ required can be set according to the noise level e.g. $\Theta = 2\sigma$. It can be shown that RANSAC obtains the theoretically optimal breakdown point of 50%, i.e. it still can fit ramps if not more than 50% of the points are outliers. Fig. 4(a) shows the same example like in Fig. 2(b) but fitted using RANSAC. One can clearly see that in this case the outlier is ignored and we obtain a perfect fit. Fig. 4(b) demonstrates the drawback of RANSAC, namely its low efficiency in removing Gaussian noise. Since the RANSAC solution is based only on two points we have no possibility of reducing the Gaussian noise. To alleviate this problem we combine the robustness of RANSAC with the optimality of the Least squares method.

**RANSAC and Least Squares:** The idea is very simple. We first perform RANSAC on the ramp, then we take all points in the support set to calculate the least squares solution. Thereby we have the robustness of RANSAC and in addition the efficiency of the least squares solution. Fig. 5 demonstrates this on the example of Fig. 4(b). One can clearly see that the solution obtained ignores the outlier and smoothes the Gaussian noise.

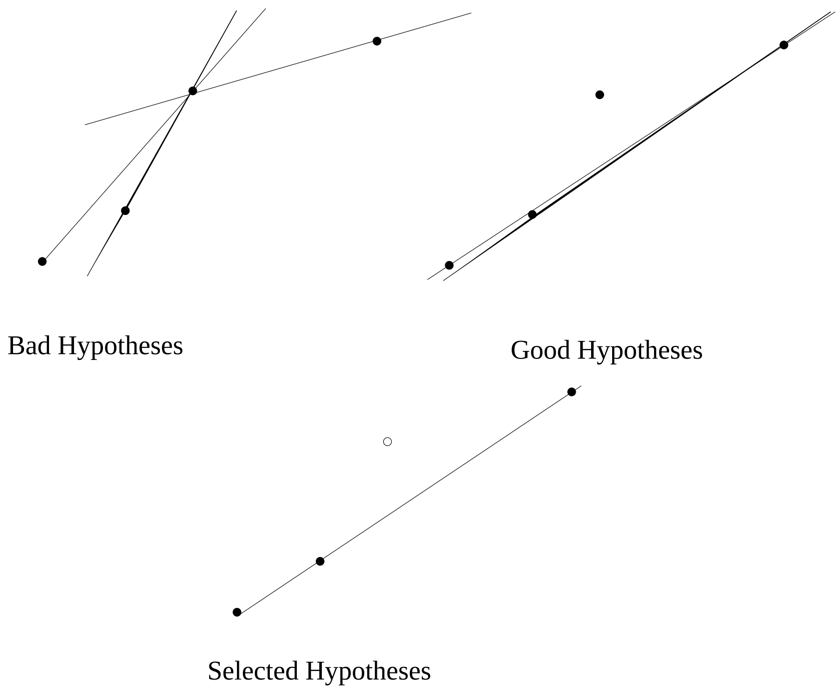



**Figure 3.** Illustration of RANSAC.

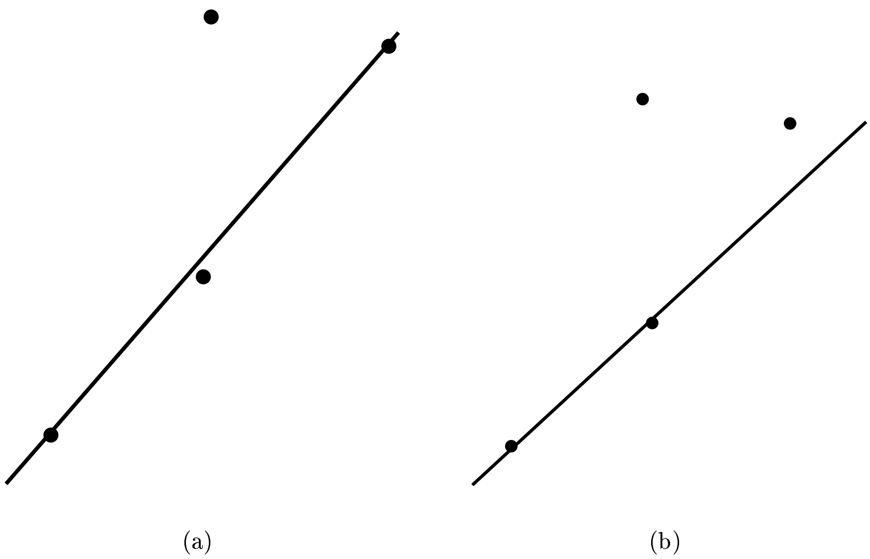



**Figure 4.** RANSAC Fitting.

The result of the ramp fitting are the slope and the offset of the ramps, and for each sample on the ramp we have a flag if it is an outlier or not. If it is not an outlier we have in addition a residual value. This is the input to the glitch detection module.

### 3.2. Glitch detection

Since we will perform on-board integration we have to ensure that we do not integrate over invalid sensor readings (i.e. glitches). The detection of such events will be performed in the glitch detection module. The glitch detection

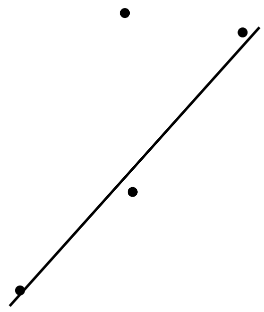


**Figure 5.** Illustration of RANSAC and Least squares.

will be done at the individual sample level "Intrinsic Deglitching" as well as at ramp level "Extrinsic Deglitching" and by considering subsequent ramps.

**Intrinsic Deglitching:** This is done by the residual and offset information calculated by the ramp-fitting module. All ramps where an outlier has been detected will be discarded.

**Extrinsic Deglitching:** In this case we have to take into account the difference in slope between two subsequent ramps. If two subsequent slopes differ more than $2\sigma$ we have an indication of a glitch.

All ramps which are effected by glitches are discarded. Since we have only four points per ramp it does not make sense to take those parts of the ramp into account which are not effected by glitches.

Another critical issue is detection of glitch tails. Since the behavior of the detector might change for some time after it has been hit by a glitch, this is a critical issue. At the moment the concept foresees to discard all samples within a fixed time interval when a glitch has been detected. However, in the future we will investigate also methods such that this can be detected automatically.

### 3.3. Integration

The integration module will perform on-board integration of the sensor readings in order to achieve the desired compression ratio. This is the lossy compression part of the software. Special emphasis has to be paid in order to guarantee integration over the right readings - synchronized with the positions of the chopper - and not to integrate over ramps affected by glitches. Thus, the integration process first determines whether to discard all data of a CRE integration block if there is a lack of confidence in at least some of the samples. Then slope data of a number of successive ramps within the same chopper position will be added, if they are free of glitches.

### 3.4. Spatial and Temporal Redundancy Reduction

The previous modules represent the lossy, i.e. reduction, part of the PACS data reduction/compression system. The further modules constitute the lossless, i.e. compression, part. To perform the high compression rate required, many iterated compression should be applied. After the integration we have a sequence of arrays we call it frames (i.e., $\mathbf{A}^t$, where $\mathbf{A} \in \mathbb{R}^{16\times 25}$ is an array of integrates slopes at time $t$). Since temporarily and spatially adjacent measurements will be similar we can use this fact for further data reduction.

**Temporal Redundancy Reduction:** Let us calculate $\Delta^{t+1} = \mathbf{A}^t - \mathbf{A}^{t+1} \ldots \Delta^{t+n} = \mathbf{A}^t - \mathbf{A}^{t+n}$. If subsequent frames are similar $|\Delta^{t+i}| << |\mathbf{A}^{t+i}|, 1 \leq i \leq n$, therefore we can gain in the compression ratio encoding $\mathbf{A}^t$ and $\Delta^{t+i}, 1 \leq i \leq n$.

**Spatial Redundancy Reduction:** After the temporal redundancy reduction spatially neighboring values in $\Delta^{t+i}$ should be similar (in the ideal case they are zero), therefore we can gain additional compression by encoding the difference of neighboring pixels.

### 3.5. Loss-less Coding

Redundancy reduction as outlined above should have reduced the magnitude of pixels values as much as possible. This fact makes it possible to make assumptions about the distribution of the data, what is a prerequisite for efficient lossless compression. Generally, the astronomical images have uniform background stray-light "Dark Current". Therefore, the data packet related will contain many identical sample values. The redundancy reduction is suitable to optimize the data packet size. The Run-Length Encoding is a well-suited method for the redundancy reduction. Data compression is obtained by specifying only the data value, the data position and the number of time is repeated. This module finds its performance for data packets of 900 detectors. Since this is a standard technique used in data compression we will not describe it further.

## 4. EVALUATION OF THE COMPRESSION CONCEPT

This section we evaluate the compression concept on a theoretical basis. In addition, we will illustrate the key concepts (i.e. ramp fitting and glitch detection) on simulated data. For a more detailed experimental evaluation on realistic data see the accompanying paper.[8]

Let us first consider how many ramps have to be integrated in order to achieve the desired compression ratio of 36. As we have explained in section 2 with lossless compression we can achieve only a compression ratio of 4.57. The additional compression factor of 7.8 has to be gained by integration of ramps. Therefore, we have to integrate over 8 ramps[‡].

The next thing to consider is the potential loss of scientific data. Of course, the glitch detection will not be 100% correct. We can quantify the potential loss of scientifically valid data by the glitch detection rate and the number of ramps that will be integrated. Assuming a glitch rate of every 10s/pixel, with a glitch tail of 0.5s we get a probability of $p_{glitch} = 1/20$ that a ramp is effected by a glitch. Then we can calculate the potential loss of scientific data $p_{loss}$ by

$$p_{loss} = 1 - (1 - p_{glitch}(1 - p_{det}))^n$$

where $n$ is the number of integrated ramps and $p_{det}$ is the glitch detection efficiency.

Table 2 lists the potential data loss for various numbers of integrated ramps for different glitch detection rates.

| # ramps | no glitch detection | 50% | 90% | 99% |
|---|---|---|---|---|
| 2 | 9.75% | 4.94% | 0.99% | 0.1% |
| 4 | 18.55% | 9.63% | 1.99% | 0.19% |
| 8 | 33.66% | 18.33% | 3.93% | 0.39% |
| 14 | 51.23% | 29.84% | 6.77% | 0.67% |

**Table 2.** Potential loss of scientific data

A glitch detection rate of more than 95% seems feasible, therefore the potential data loss will be around 1%-3%. In fact it will be lower because in the above calculations we have assumed for simplicity that a glitch and its tail are independent events, which is not true. In fact, if the glitch is detected we have also detected its tail. In addition we have assumed that when we do not detect a glitch all integrated measurements will be lost. In fact if we miss a small glitch and integrate over it, this just decreases the signal to noise ratio. Another thing we have not considered is false negative rate, i.e. we discard a ramp even if it is not affected by a glitch, this will of course also lead to a loss of scientific data. But this can be directly estimated. In addition, this has no effect on the other data. From these considerations one can see that the desired compression ratio can be achieved with minimal loss of scientifically valuable data.

‡In fact, integration over 7 ramps should be sufficient because due to the decrease in signal to noise ratio we could gain the rest by temporal and spatial redundancy reduction

### 4.1. Synthetic Data

Fig. 6 shows a demonstration of ramp fitting and glitch detection part of the compression concept. The upper part of the figure shows the original data. The other plots show the various fitting and glitch detection procedures. Since standard least squares gives very bad results we used a robust method called iterative reweighted least squares. From this plots one can see that all glitches are successfully removed. Some additional ramps not affected by glitches get removed because we always remove the ramp which follows a glitch. For a more detailed experimental evaluation on synthetic and ISO data see the accompanying paper.[8]

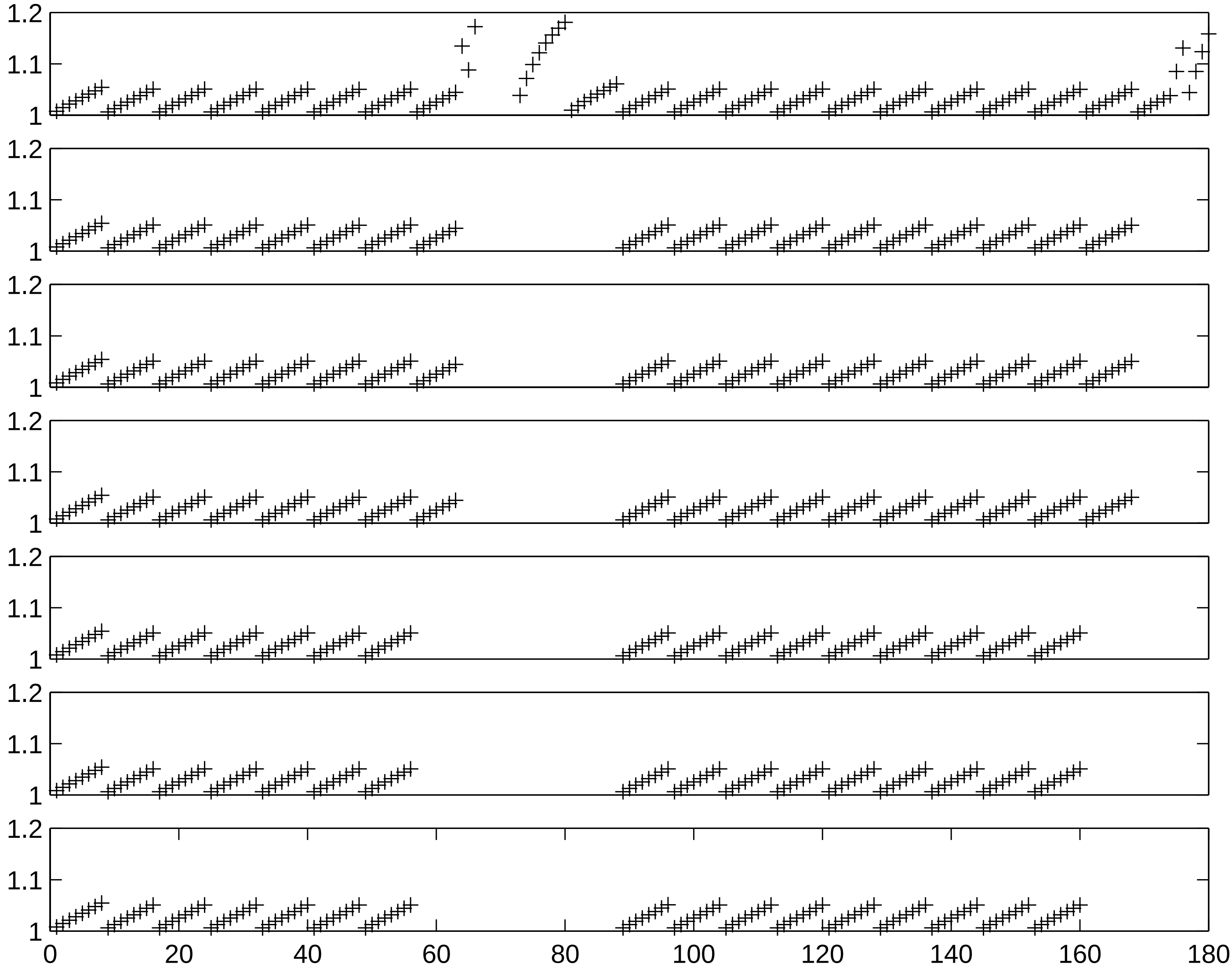



**Figure 6.** Illustration of various fitting and glitch detection methods. From top to bottom: Original synthetic data, iterated reweighted least squares fitting, RANSAC and RANSAC + Least squares fitting, glitch detection with iterated reweighted least squares, RANSAC and RANSAC+Least squares.

## 5. CONCLUSION

In this paper we have described a novel On-Board data compression concept for the FIRST/PACS mission of the European Space Agency (ESA). We have described the key-modules like ramp-fitting and glitch detection in detail. Our concept combines lossy and lossless compression, the presented method offers a high compression rate with a minimal loss of potentially useful scientific data. It also provides higher signal to noise ratio than that for standard compression techniques. In an accompanying paper[8] we illustrate the method presented in this paper on on synthetic data and data from ISO.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## REFERENCES


1. F. Kordes, R. Hogendoorn, and J. Marchand, "Handbook of data compression algorithms." Spacecraft Control and Data Systems Division, ESA TM-06, 1990.
2. "Round table on data compression techniques for space application." ESTEC/WSP, Noordwijk, The Netherlands, 2-3 Oct, 1996.
3. A. Poglitsch, N. Geis, and C. Waelkens, "Photoconductor array camera and spectrometer (pacs) for first," in *UV, Optical, and IR Space Telescopes and Instruments VI*, J. B. Breckinridge and P. Jakobsen, eds., SPIE, 2000.
4. G. L. Pilbratt, "FIRST ESA cornerstone mission," in *UV, Optical, and IR Space Telescopes and Instruments VI*, J. B. Breckinridge and P. Jakobsen, eds., SPIE, 2000.
5. F. R. Hampel, E. M. Ronchetti, P. J. Rousseeuw, and W. A. Stahel, *Robust Statistics - The Approach Based on Influence Functions*, John Wiley & Sons, 1986.
6. P. J. Rousseuw and A. M. Leroy, *Robust Regression and Outlier Detection*, Wiley, New York, 1987.
7. M. A. Fischler and R. C. Bolles, "Random sample consensus: A paradigm for model fitting with applications to image analysis and automated cartography," *Communications ACM* **24**, pp. 381–395, June 1981.
8. F. Kerschbaum, H. Bischof, N. Belbachir, T. Lebzelter, and D. Hönigmann, "Evaluation of FIRST/PACS data compression on ISO data," in *UV, Optical, and IR Space Telescopes and Instruments VI*, J. B. Breckinridge and P. Jakobsen, eds., SPIE, 2000.