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A spike immunity method of digital integrating radiometer signals

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Abstract. A spike immunity method of digital integrating radiometer signals in the jamming environment is described. The certain integrating algorithm selection is adaptively made. The purpose of the method is real–time signal processing, and the basic is an alternative selection of the least offset signal estimation using nonparametric "Nearest Neighbour" rule. It is assumed that the signal has a single mode probability distribution, close to normal. The additive spike–like jam makes the "tails" of the distribution "heavier", which leads to different offsets for linear and rank mean estimation on the integrating interval. The integrating interval is chosen significantly less than double bandwidth of antenna system and radiometer. For the given assumption of the sorts of signal and jam the method works faster and delivers better efficiency as compared to the well known rank estimations. The extra correlation of the subsequent samples does not exceed 16%. The results of the numerical modeling and experimental method testing are given. The results show the improvement of the radiometer sensitivity by about 20–25%.

Key words: digital integrating — correlation — distribution — robust

1. Introduction

The fast real–time processing of radiometer signals can be successfully implemented because of the existence of modern high performance ADC and data acquisition systems. One can successfully fight therewith the powerful spike jams, using a sampling frequency 100–1000 times that required by the sampling theorem. In this case the powerful spikes could be easily discarded by threshold processing. However things become complicated if the spikes power gets comparable to the noise signal variance. Erukhimov et al. (1988; 1990) have shown the reasons for using robust methods for raw radiometer data compression. These algorithms are effective also in fighting not very powerful spikes as mentioned above. Analyzing algorithms considered in those articles one can see that we are dealing with some alternative aspects, which are typical for most statistical estimating tasks. On the one hand, the trivial meaning average allows us to have the minimum variance of mean estimation for the normally distributed noise - like signal. But it is absolutely non–robust and the mean estimation gets senseless if even a single spike appears. On the other hand, the median–like rank estimation is very robust to spike–type contamination (up to 50%), but there is loss in efficiency in case of normally distributed, spike–free signal. The worst case is the median estimation upon the infinite sampling: the efficiency drops to 0.637. The compromise Hodges–Lehmann (Hodges and Lehmann, 1957) estimation, which is used for post data processing at the RATAN–600, has 0.95-0.98 efficiency, but it is robust just in the case of no more than 25% contamination. Moreover, the calculation of this estimation is quite time consuming, because the sorting of $n \cdot n/2$ values, where n is sampling amount, is involved. It presents some difficulties for using such an estimation in real–time procedures.

However, there is a very promising way of solving this problem if one can formalize some rules to choose different algorithm on–the–fly, during raw data processing. It can be done, based on some general features of signal and spikes. There are hardware dynamic "spike–depression" devices, which are still used in some radiometers at the RATAN–600. But because of the analog type of these devices, only some sorts of analog threshold criteria could be used. Those criteria are completely unrobust and always need the frequently applied fine tuning, which is very difficult and undesirable for a long–term observation cycle.

The digital integration method with adaptive selection of the optimal algorithm is given in this article. The method is quite robust and based on some general prior information about the signal and spikes.

2. Description of algorithm

The procedure of radiometer signal integration can be considered as a sort of reducing dimension of the initial sampling space, where the samples are the result of analog–to–digital conversion. As a result of this procedure the sampling space within the integrating interval gets reduced to a single sample, which reflects the signal mean estimation.

A variety of circumstances when one needs to select some optimal procedure of the signal estimation is usually splitted into three classical cases.

1. The probability distribution of the signal and spikes is completely known.
2. The probability distribution of the signal and spikes is known only as a function, the parameters are unknown.
3. The probability distribution of the signal and spikes is unknown, however some general features are known.

These cases are well described in the classical statistics literature and lead correspondingly to Bayes, parametric and nonparametric algorithm of the estimation obtaining. The third case is the most frequent if we are interested in getting reliable robust estimation.

Despite the variety of effects, which are responsible for building the radiometer signal statistic (Christiansen and Högbom, 1988), the standard radiometer signal processing, low bandwidth filtration, leads to the "normalization" of the end signal statistics (Levin, 1974). However the spikes influence disturbs the signal distribution making the "tails" heavier, comparing to normal distribution function.

The model of realization of such a process as a mixture of normal and Poisson processes is considered in Erukhimov (1988). Given calculations show that the estimation offset strongly depends on the jam intensity and could be very different depending on the used estimation algorithm. Thus, there is a way to depress jams having a few sorts of estimation all together and choosing the best one (with the least offset) using some available prior information.

For the given model it seems to be enough to have the mean average and median estimation. The first one is the optimum for the normally distributed noise signal, the second one practically does not have an offset for a reasonable level of spikes contamination.

Thus, the optimal mean estimating procedure makes us to choose one of the two previously obtained estimations, which could be done by testing two hypotheses:

- H_0 – no spikes in the estimation interval,
- H_1 – the sample is contaminated with spikes.

The mentioned estimation upon the n–dimensional sample could be obtained like this:

$$\hat{m}_{H_o} = \frac{1}{n}\sum_{i=1}^{n} x_i\,, \qquad \hat{m}_{H_1} = med_n(X).$$

Before choosing the classification algorithm let us make some reasonable assumptions:

- The sampling period is significantly less than the integrating window interval which itself is significantly less than typical non–stationary time period for sky objects and atmospheric trend signals. In such a case we can neglect the non–stationary behaviour of the mean in the integrating interval;
- The multidimensional probability distribution of the process is close to the symmetrical one and monotonously falls as it gets away from the means;
- The offset of the mean estimation is caused by short spikes and the average time between these spikes is significantly greater than the integrating window.

Only the first condition is the main one, the others just lead to some limitation on using the considered algorithm.

Analyzing the above assumptions one can choose the suitable classification algorithm based on p–state measure, such as "Nearest Neighbour" one (Patrick, 1972), which, in particular, has been effectively used in real time feedback system (Ulyanov and Chernenkov, 1983)

In our particular case the classification algorithm sounds like this: when processing the window number k we choose from alternative[1] mean estimations that one which is closest to one chosen for window k-1.

Applying the mentioned algorithm the following recursive formula can be written:

$$\hat{m}_0 = med_n(X_0), \hat{m}_k = \begin{cases} \frac{1}{n}\sum_{i=1}^{n} x_i & , \quad |d'_k| \le |d''_k| \\ med_n(X_k) & , \quad |d'_k| > |d''_k| , \end{cases}$$

where:

$$\begin{aligned} d'_k &= \tfrac{1}{n}\textstyle\sum_{i=1}^{n} x_i - \hat{m}_{k-1}, \\ d''_k &= med_n(X_k) - \hat{m}_{k-1}. \end{aligned}$$

The estimation is robust, because there is no dependency neither on signal distribution parameters, nor on spikes power involved. Because there is no need to increase the sample amount for estimation calculation, in contrast to Hodges–Lehmann algorithm, the meaning average and the median can be obtained fast enough.

Let us write down the steps of the algorithm

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[1] If we are talking about non real–time processing, one can move through the record in reverse direction too. In this case the number of alternatives to choose from is doubled.

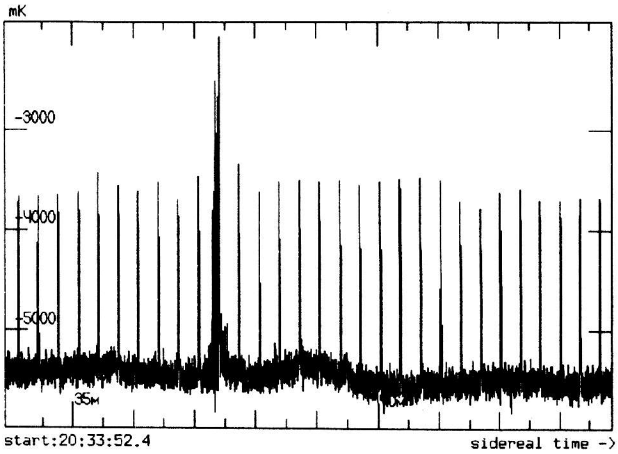

Figure 1: *The record, processed by different algorithms.*

1. Calculation of the median estimation for the initial window and holding it.
2. Calculation of the median estimation and meaning average for the next (moved) window.
3. Calculation of the absolute deviations between the previous estimation and the following two.
4. Taking as true the estimation which has minimum of the mentioned deviation.
5. Go to step 2.

Because of the obvious justifiability of the considered estimation and also the continuity of the data acquisition process, for the real–time case one could take off the first step, using the zero estimation mean instead.

Tabl.1 contains the comparison of the processing results, obtained by the described method on the first cabin, "Continuous" data acquisition complex, with the previous ones. The significant performance benefit as compared to the best rank estimations can be seen. There is also variance benefit as compared to the other algorithm despite the greater spikes power level. The table contains the results of 60000 samples records processing. One of these records is shown in Fig. 2.

The quality of the considered algorithm can be also illustrated by Fig. 1. At the top of the figure the record containing the source and spike jams is drawn. The results of different sorts of 5–time compression of this record, meaning average, Hodges–Lehmann procedure, considered algorithm, are drawn at the bottom. One can see the considered adaptive algorithm is preferable even by the low degree of compression, since all the spikes have been depressed.

A disadvantage of the considered algorithm is the appearance of some extra correlation between subsequent samples in the output process. This effect is typical for any feedback algorithm acting as a low bandwidth filter. The dependence of the mentioned extra correlation on the compression factor, which is obtained by numerical modeling, is drawn in Fig. 3.

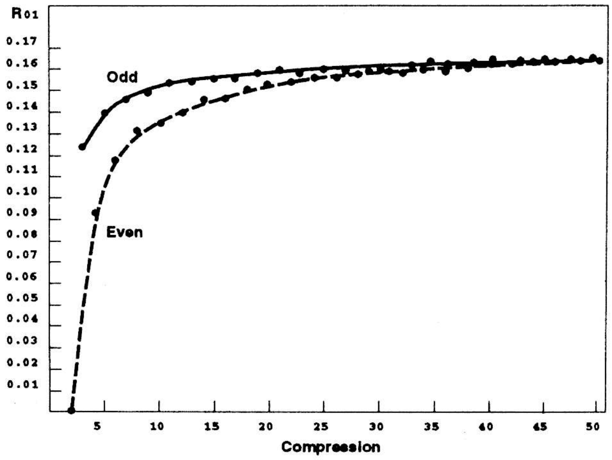

Figure 3: *The dependency of subsequent samples correlation coefficient in compression ratio.*

The odd and even compression factor points are drawn as different curves. It can be seen that there is a slight increasing of correlation with increasing of the compression ratio up to asymptotic value about 0.16. This may be due to the well known effect of dropping the efficiency of the median estimation to the asymptotic value $2/\pi$ with increasing the amount of samples (Hodges and Lehmann, 1967). Such a kind of relation to the features of the median estimation could be also confirmed by different values of the correlation coefficient for the odd and even compression factor values.

Despite the fact the graph is obtained for the initial Gauss distribution of the noise process, it actually does not have a strong dependence on the type of initial distribution, if the above mentioned assumptions are justified. That is because the output process gets normalized starting even from small averaging windows.

Thus, if the above mentioned condition are true, the extra correlation effect can be neglected in practical use of the considered algorithm.

3. Observational data

In April 1996 the described method was included in the software of the automatic data acquisition complex "Continuous". The software was changed after a week–long observation to the common astrophysical program, SAI and SAO. Konnikova V. K. (SAI) observed some discrete sources at the Western sector of RATAN–600. She acquired the data on the six wide–band radiometers of centimeter wavelength. The acquisition frequency was 100 samples per second for each channel with hardware filtering by RC–chain

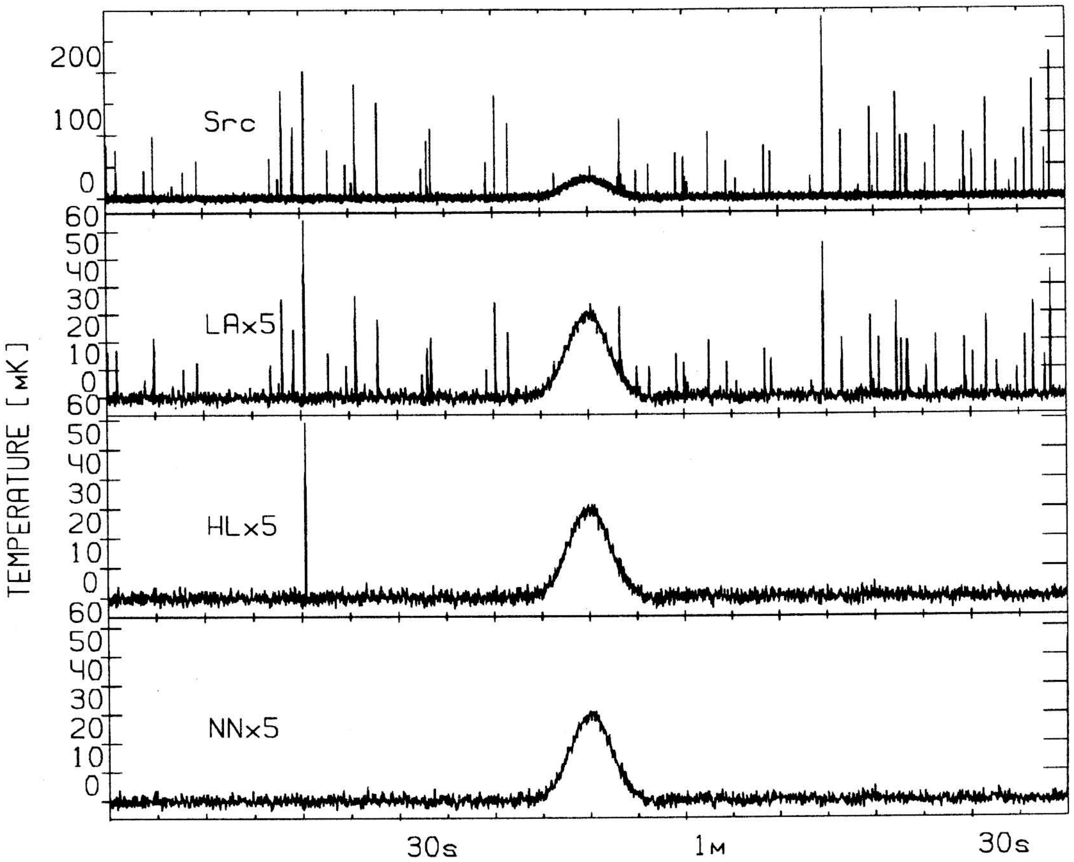

Figure 2: *The results of the 5-fold compression of the model record by meaning average, Hodges–Lehmann procedure and the considered algorithm.*

Table 1: *The comparison of the processing results, obtained by the described method.*

Compression	10			25			50			100		
	t c.	σ	σ_3	t c.	σ	σ_3	t c.	σ	σ_3	t c.	σ	σ_3
Meaning aver.	1.46	26.5	16.4	1.44	22.9	14.6	1.51	20.6	18.0	1.51	17.4	17.2
Median	1.82	27.3	19.0	2.35	21.7	15.3	3.36	18.3	18.3	5.04	13.1	12.3
HL-algorithm	10.1	26.7	17.1	90.1	22.7	15.0	675	19.7	18.7	5556	15.5	16.1
NN-algorithm	1.88	26.4	17.2	2.37	21.4	13.5	3.31	18.4	16.8	5.03	13.3	10.4

with the value 0.01 s. At the next step the system made digital integration in real time using data compression with the factor of 10. And the value of the median was calculated as the estimation of medium before change of algorithm. The results of data processing of observation records on the 4–13th of April with appropriate radiometers are shown in Figs. 4 – 6. Records of discrete sources (up to 53) were made, and we did not clean records from interferences and sources. More than 400 multifrequency recordings are used in data reduction. Histograms of computed estimates of sensitivities are shown in the figures for each wavelength. A shift of histogram picks shows improvement of the real sensitivity of 20–25%. This corresponds to the theoretical expectation.

It should be noted that the relatively strong effect of sensitivity improvement for the radiometer of 13 cm is due to its engineering tuning and spike de-

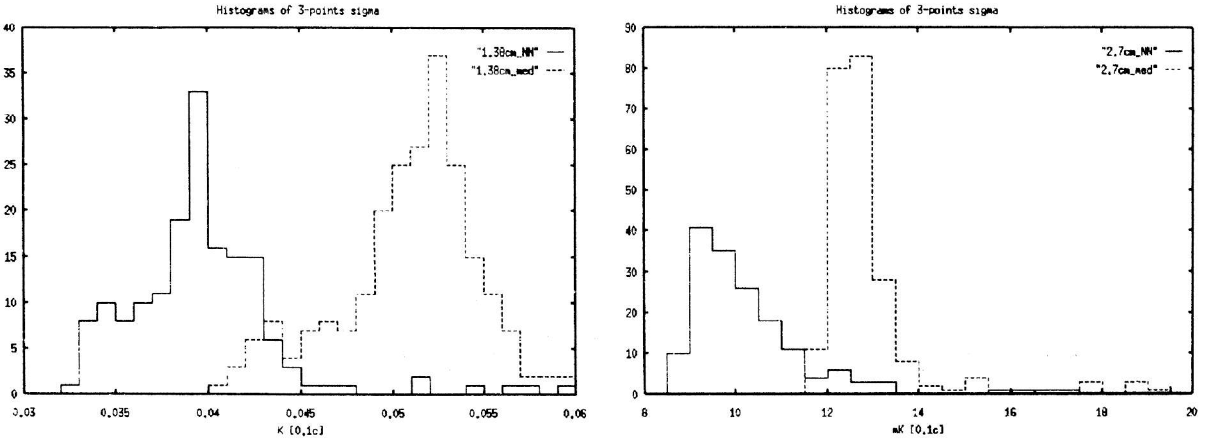

Figure 4: *Measurement of sensibility by observing at the wavelengths 1.38 cm and 2.7 cm.*

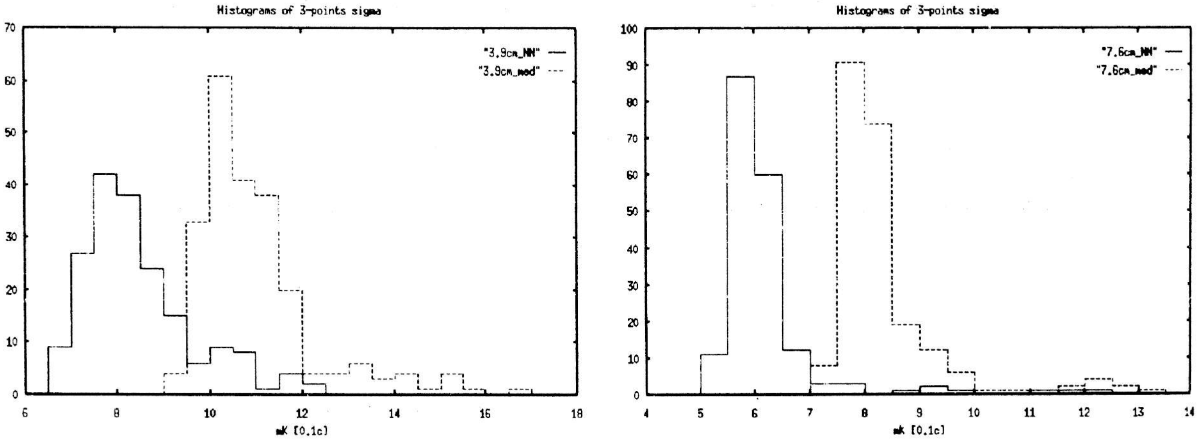

Figure 5: *Measurement of sensibility by observing at the wavelengths 3.9 cm and 7.6 cm.*

pression devices also, which was done on the day of algorithm substitution. This figure shows also that the effect is not visible so obviously at the wavelength of 31 cm, polluted by industrial interferences, apparently caused by low percentage of the general interval of the operation of the linear part of the algorithm.

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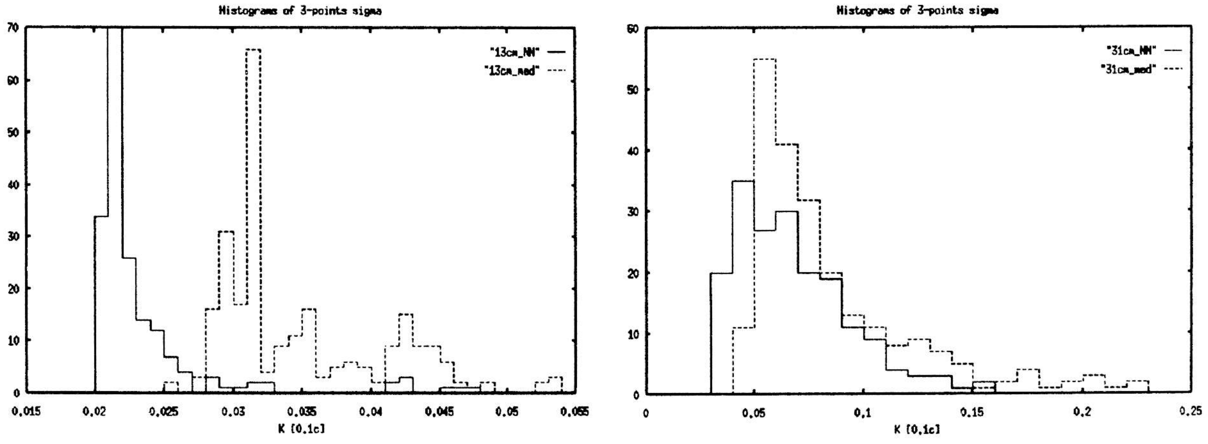

Figure 6: *Measurement of sensibility by observing at the wavelengths 13.0 cm and 31 cm.*