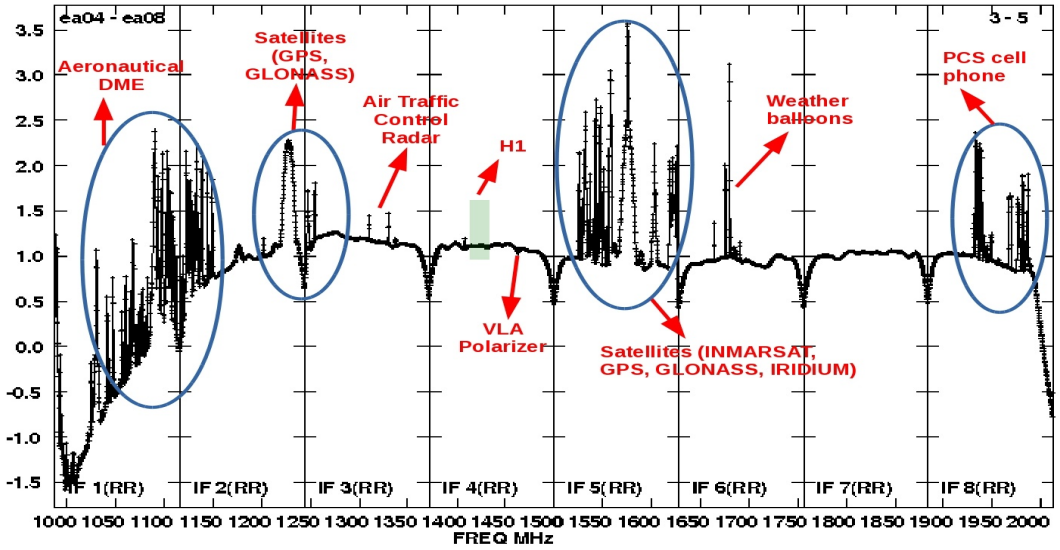
Automated Tuning of RFI Identification and Flagging Algorithms



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UNISUL / UVA
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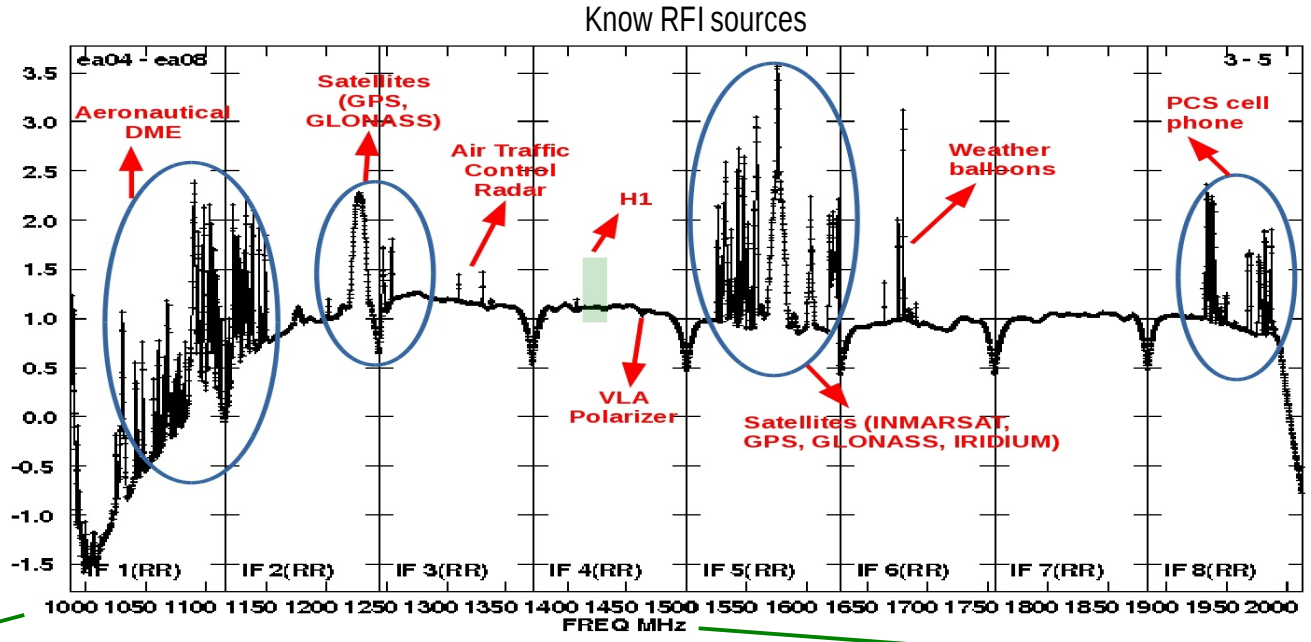
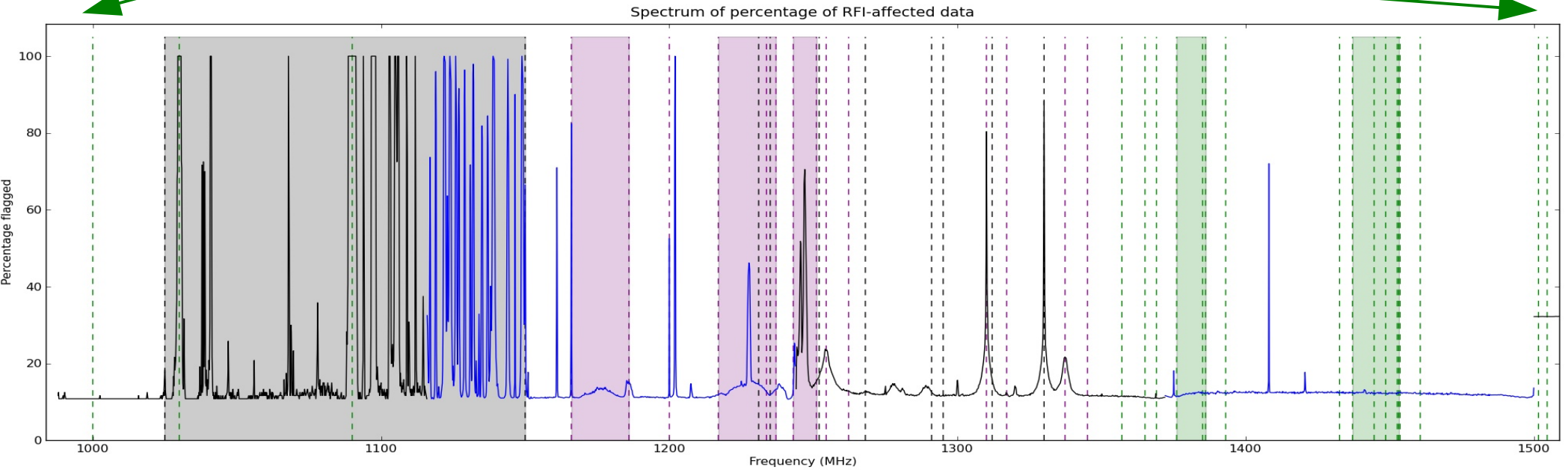
(2016 Summer Intern at NRAO)

URSI – National Radio Science Meeting, Boulder, Colorado, USA
7 Jan 2018

RFI at the VLA





Problem : Autoflag algorithms need manual tuning !

- Autoflag Algorithms Exist

  tfcrop : Outlier detection on 2D time-freq slices [NRAO - CASA]

  rflag : Hierarchical statistical approach [NRAO – AIPS,CASA]

  aoflagger : Outlier detection on 2D time-freq slices [ASTRON]

- They all need tuning for different types of RFI and telescopes

  => This can get tedious even on small fractions of each dataset

  => Not optimal for use in automatic analysis pipelines

- Can we automate the tuning process ?

TFCrop

Adapted from U.Rau, A.P.Rao, GMRT Tech Rep 2003

For each 2D time-freq plane (per antenna pair)

(1) Form an average along one dimension

(2) Calculate a robust piece-wise polynomial fit across the base of RFI spikes

(3) Flag un-averaged values deviating from the fit by > N-sigma

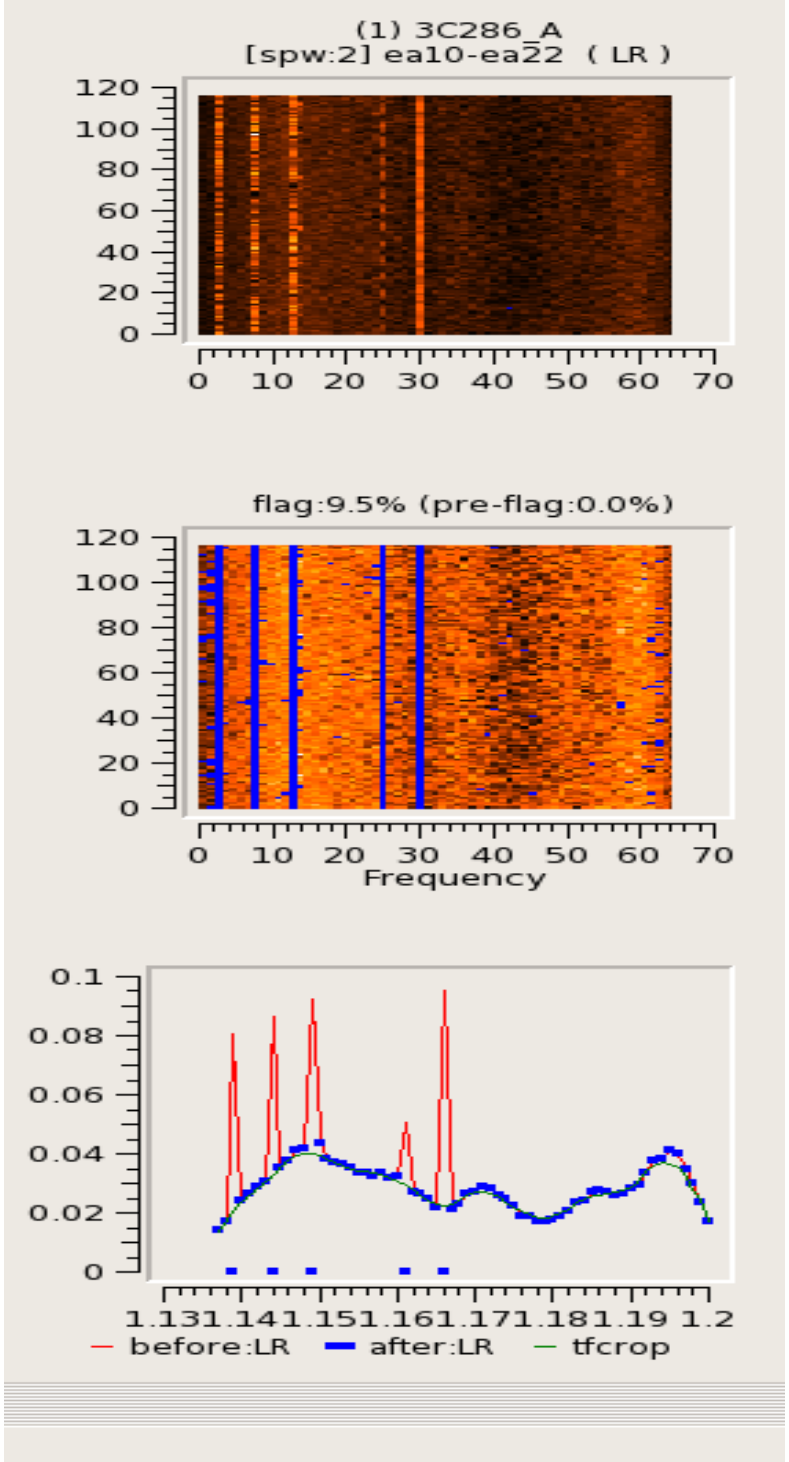
(4) Repeat (1-3) along the other dimension.

Relevant Parameters :

timecutoff, freqcutoff : N-sigma thresholds

usewindowstats : Ways to detect deviation from the fit

maxnpieces : Tuning the robust polynomial fits



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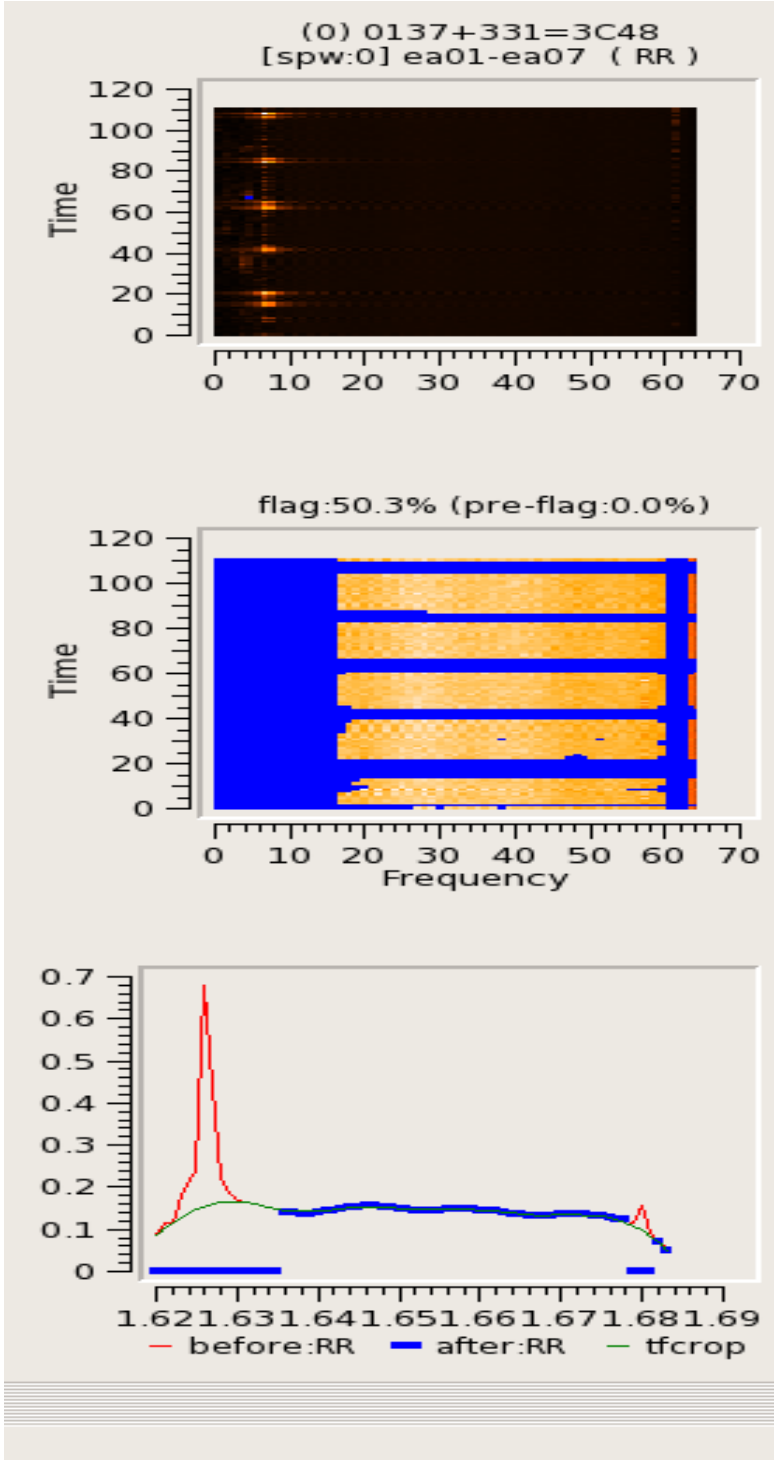


RFlag

A close copy of RFLAG from AIPS
(E.Greisen, 2011)

Repeat* along time and frequency axes :

(1) Calculate local RMS of real and imag parts of visibilities within a sliding window.

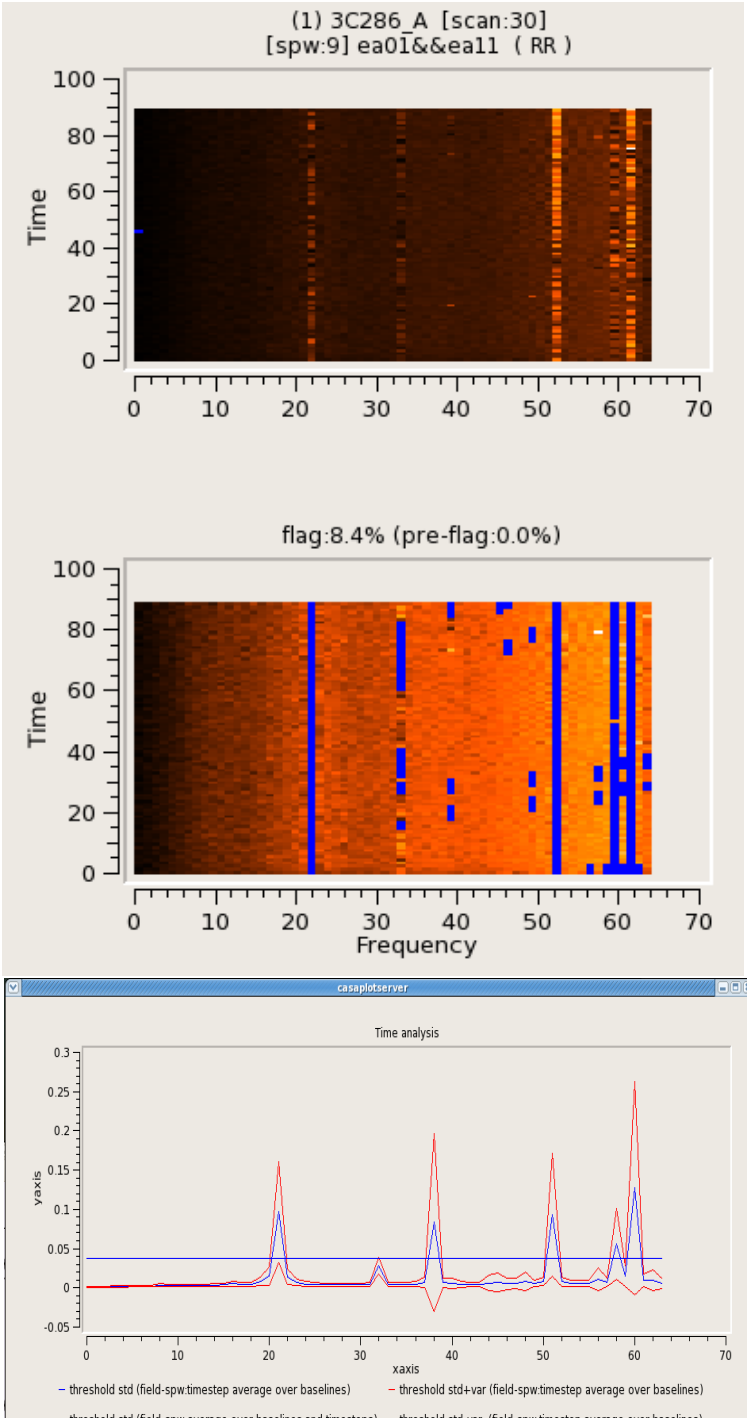
(2) Calculate the median RMS across windows, deviations of local RMS from this median, and the median deviation

(3) Flag if
local RMS > N x (medianRMS + medianDev)

(Most) Relevant Parameters :

timedevscale, freqdevscale : Threshold scale factors

winsize : Sliding window size



Extend Flags

(1) Fill flags if more than X% is already flagged along time(freq)

(2) Merge flags across pols

(3) Flag (based on) surrounding cells

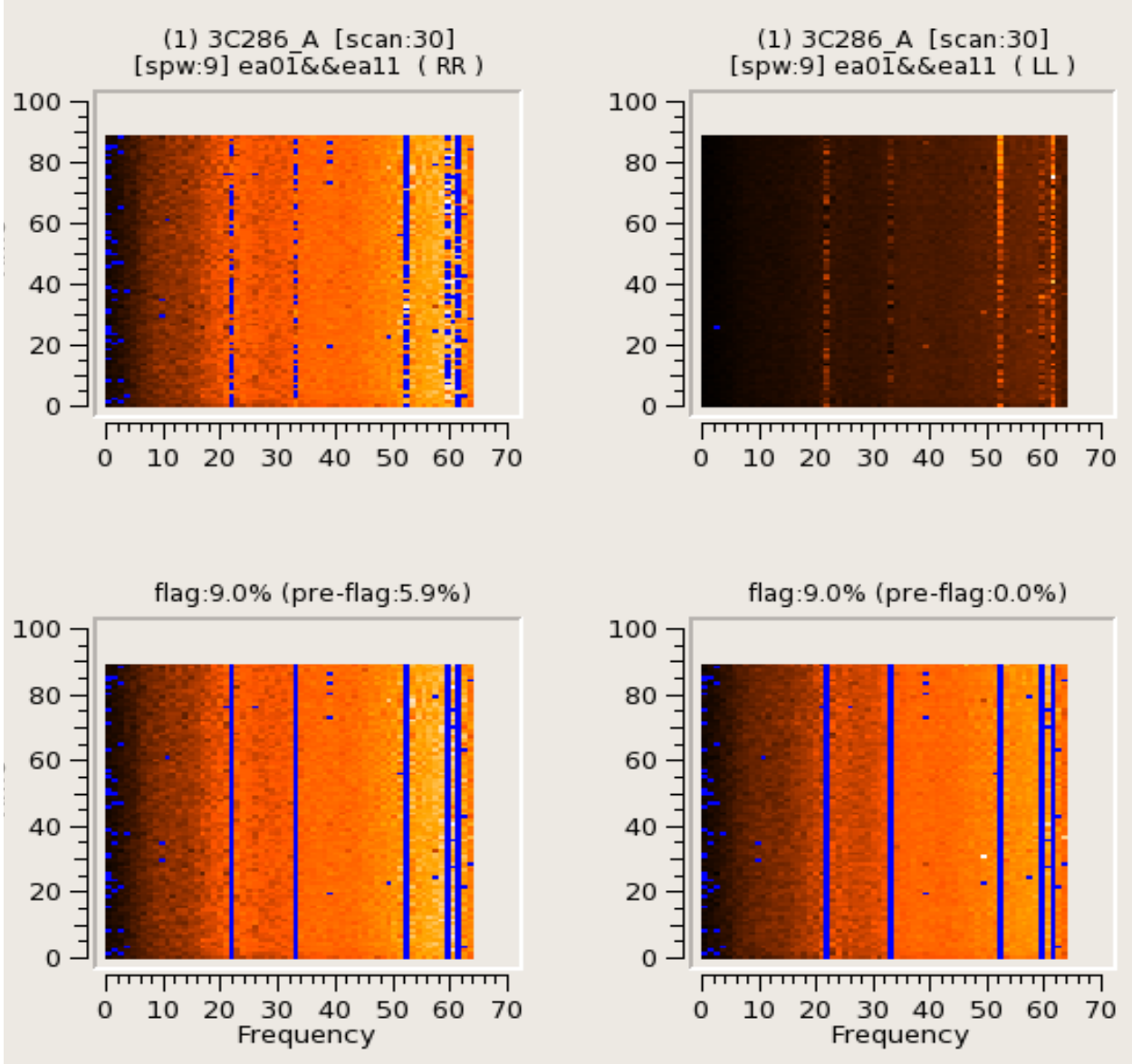
Relevant Parameters :

growtime, growfreq

extendpols

flagneartime, flagnearfreq

growaround

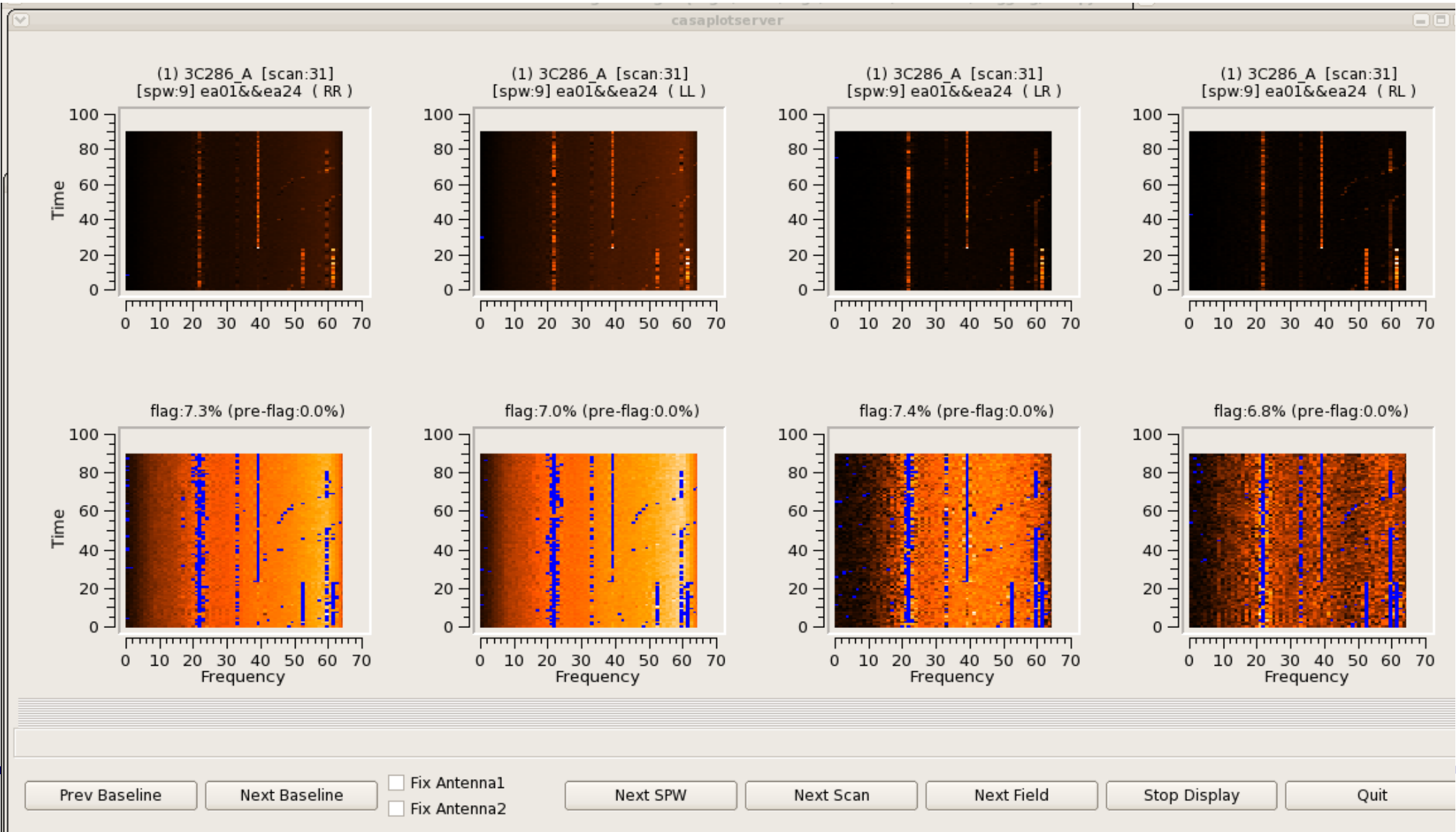


Example : Flag only RR (left panels) + growtime=30.0 + extendpol=True

Examples of Manual Tuning

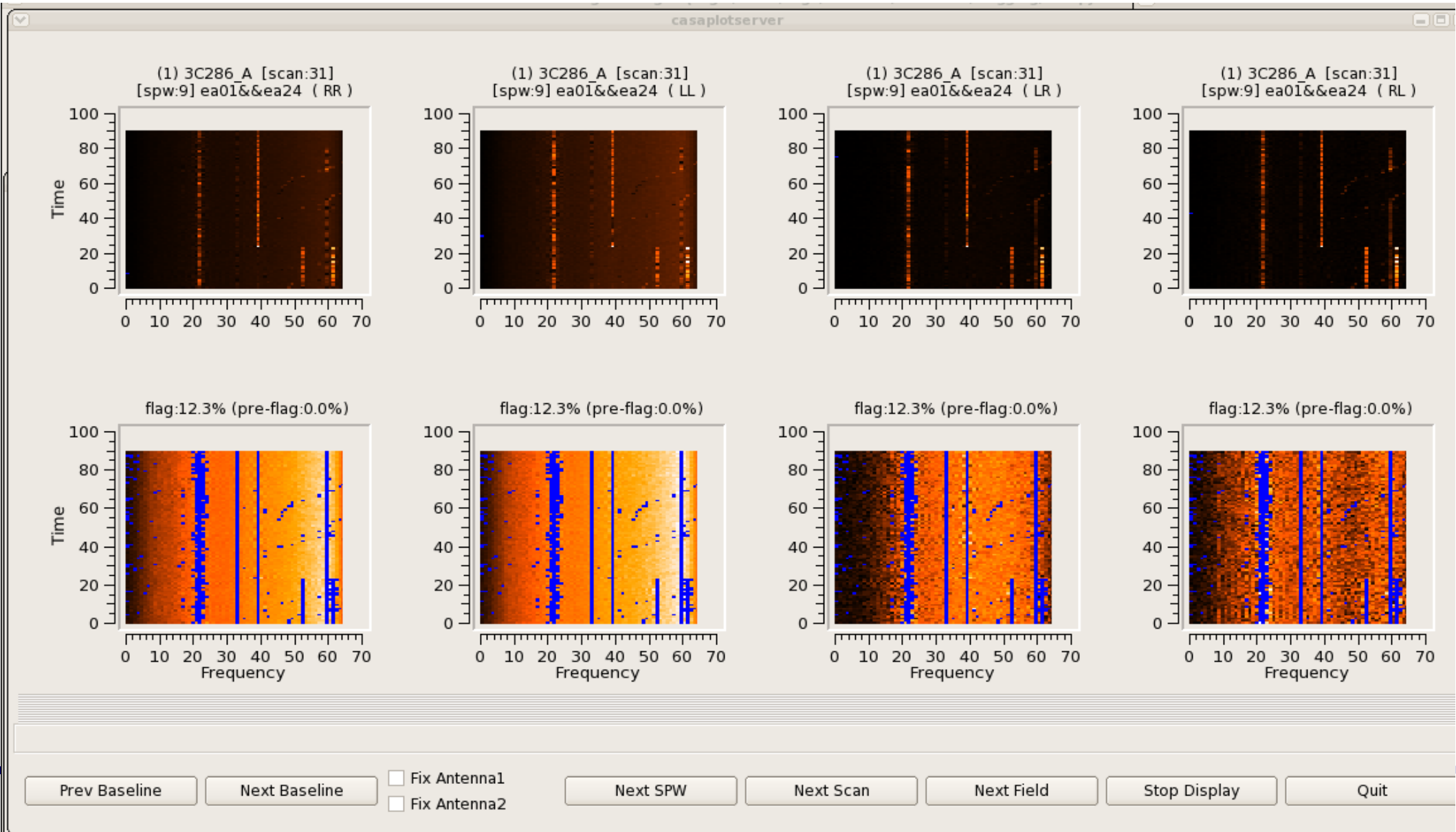
Examples of Manual Tuning

cmdlist = [“ spw='9' mode='tfcrop' extendflags=F“]



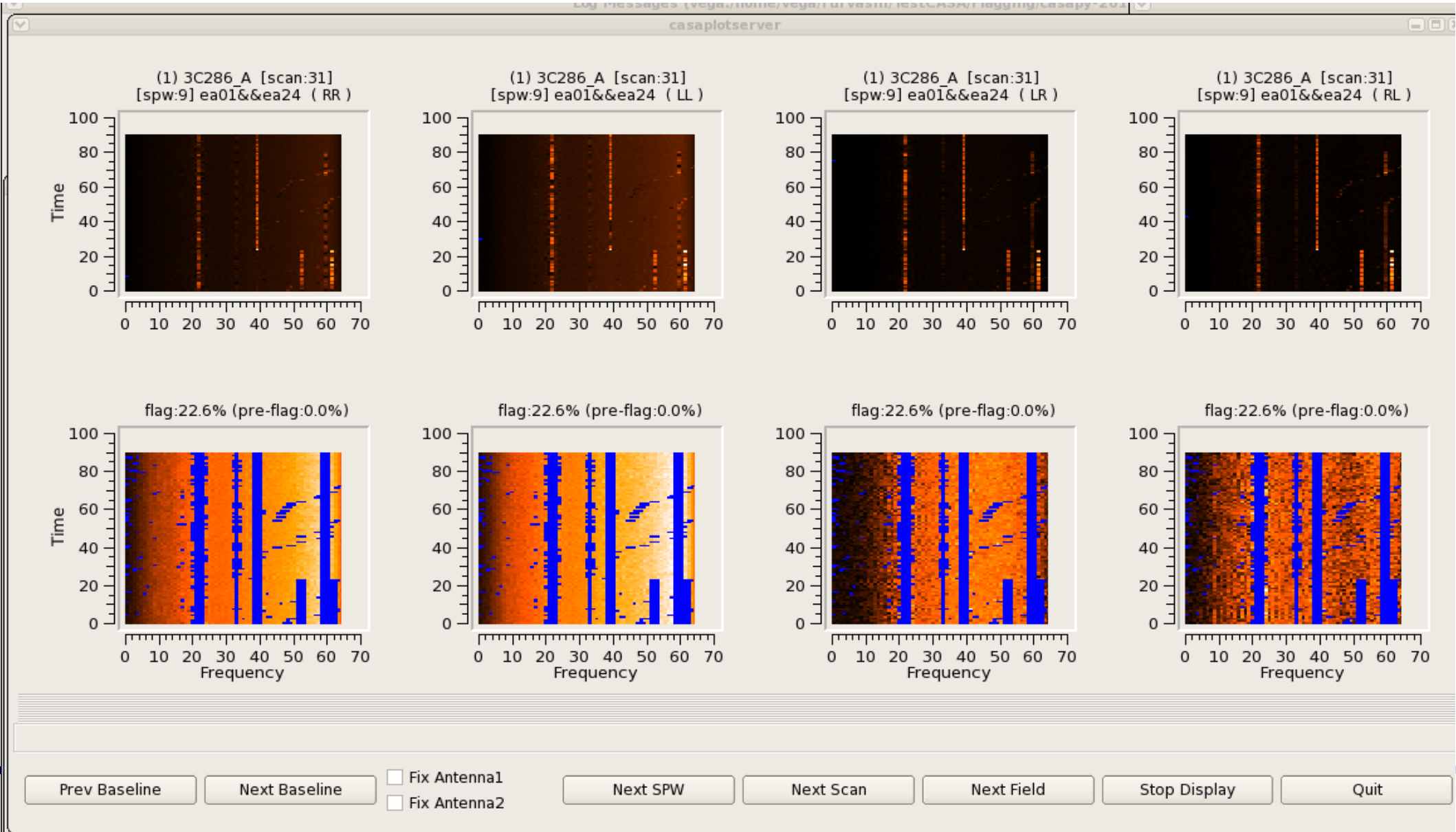
Examples of Manual Tuning

cmdlist = [“ spw='9' mode='tfcrop' extendflags=F “,
“ **spw='9' mode='extend' growtime=50.0 extendpols=T**]



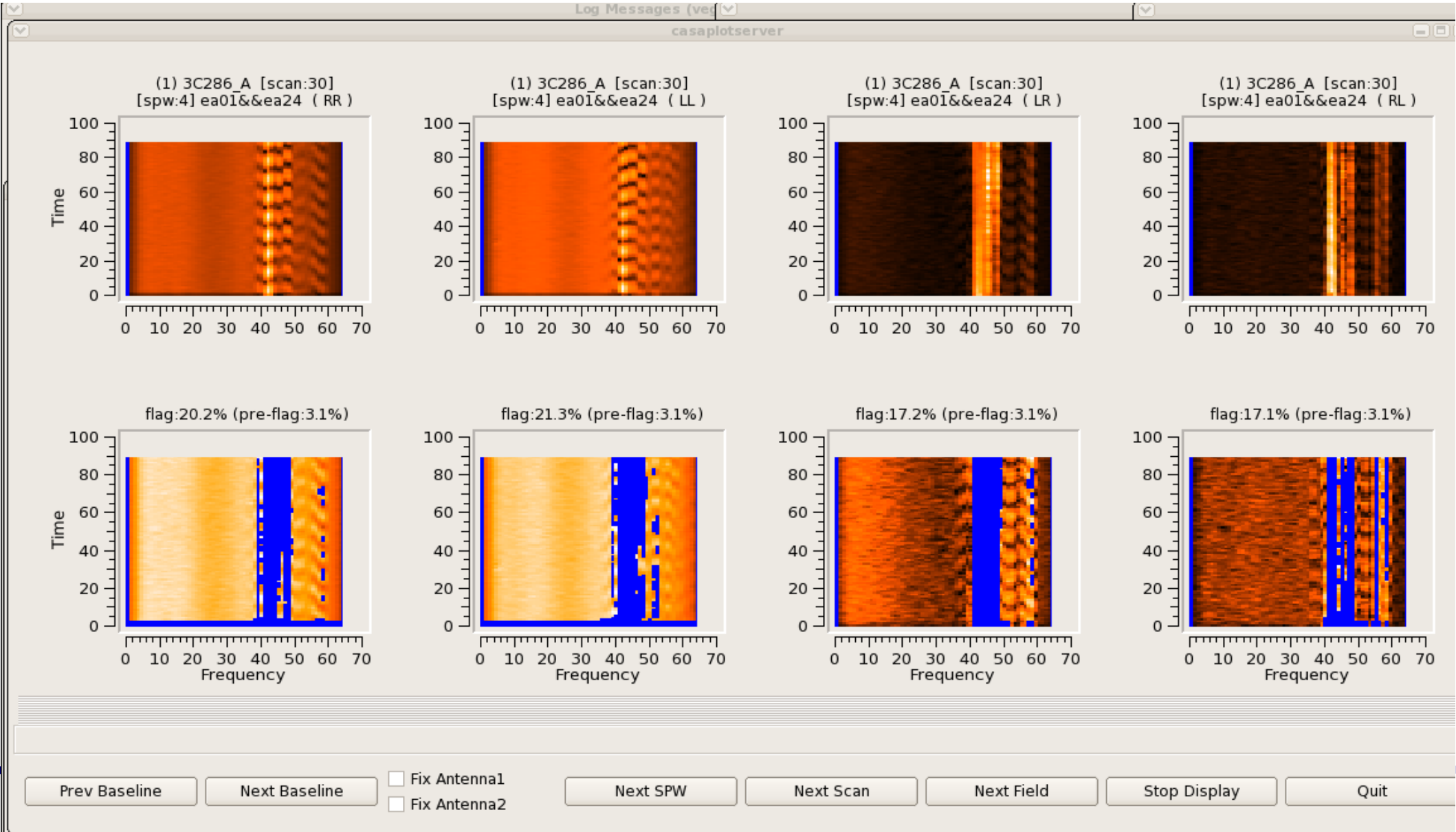
Examples of Manual Tuning

cmdlist = [“ spw='9' mode='tfcrop' **usewindowstats='sum'** extendflags=F “ ,
“ **spw='9' mode='extend' growtime=50.0 extendpols=T** “]



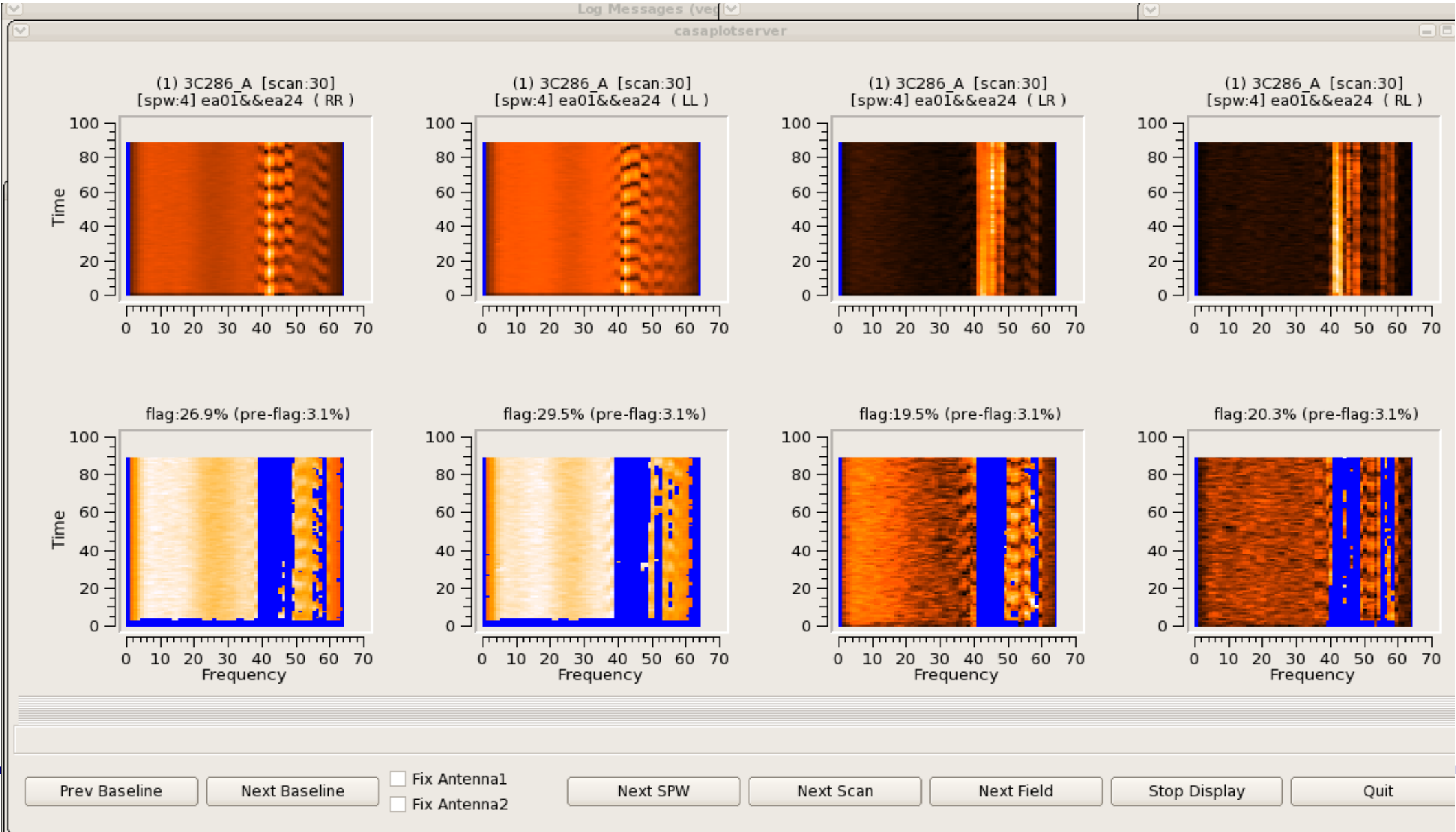
Examples of Manual Tuning

cmdlist = [“ spw='4' mode='rflag' extendflags=F“]



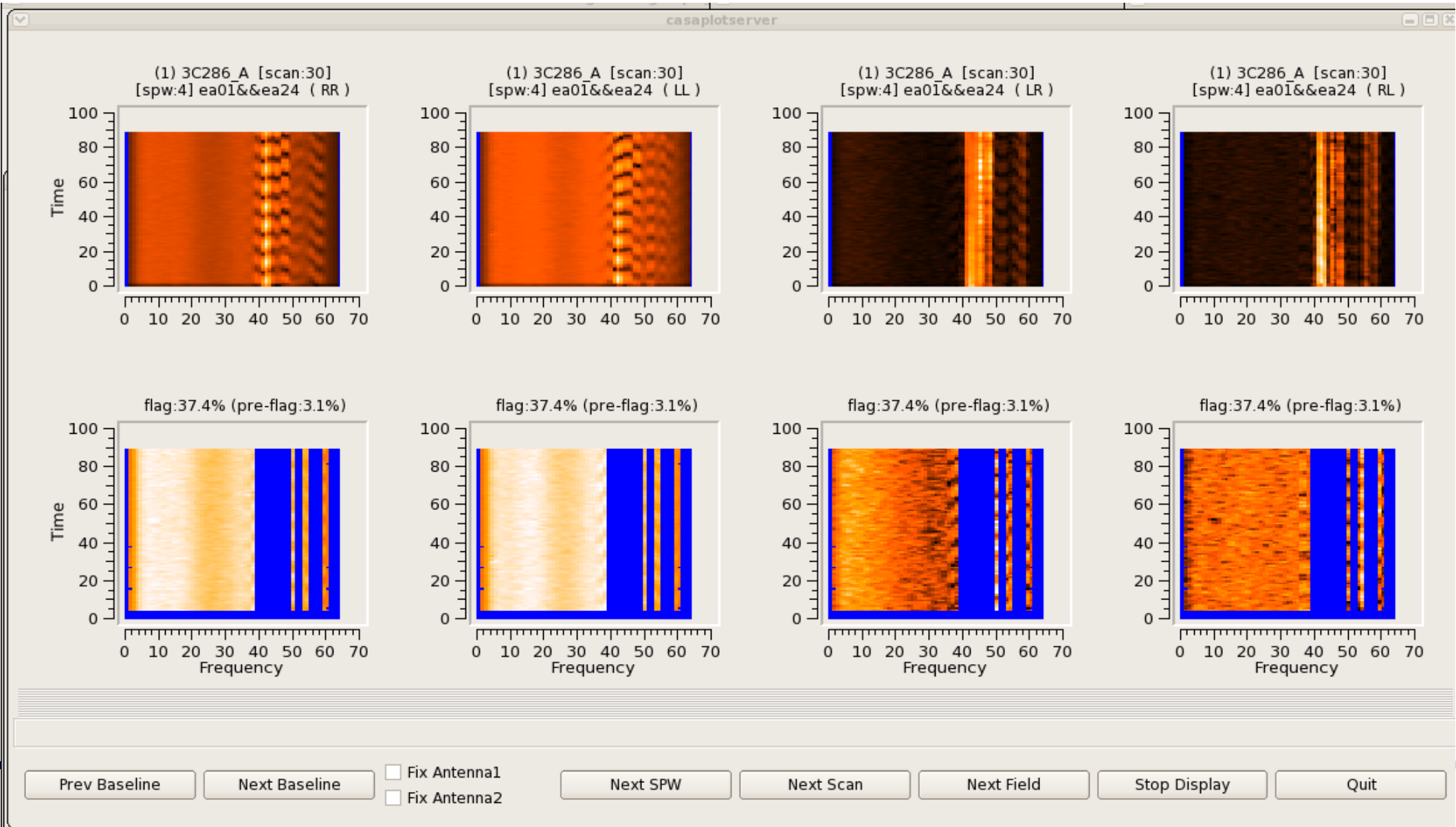
Examples of Manual Tuning

cmdlist = [“ spw='4' mode='rflag' **freqdevscale=3.0** extendflags=F“]



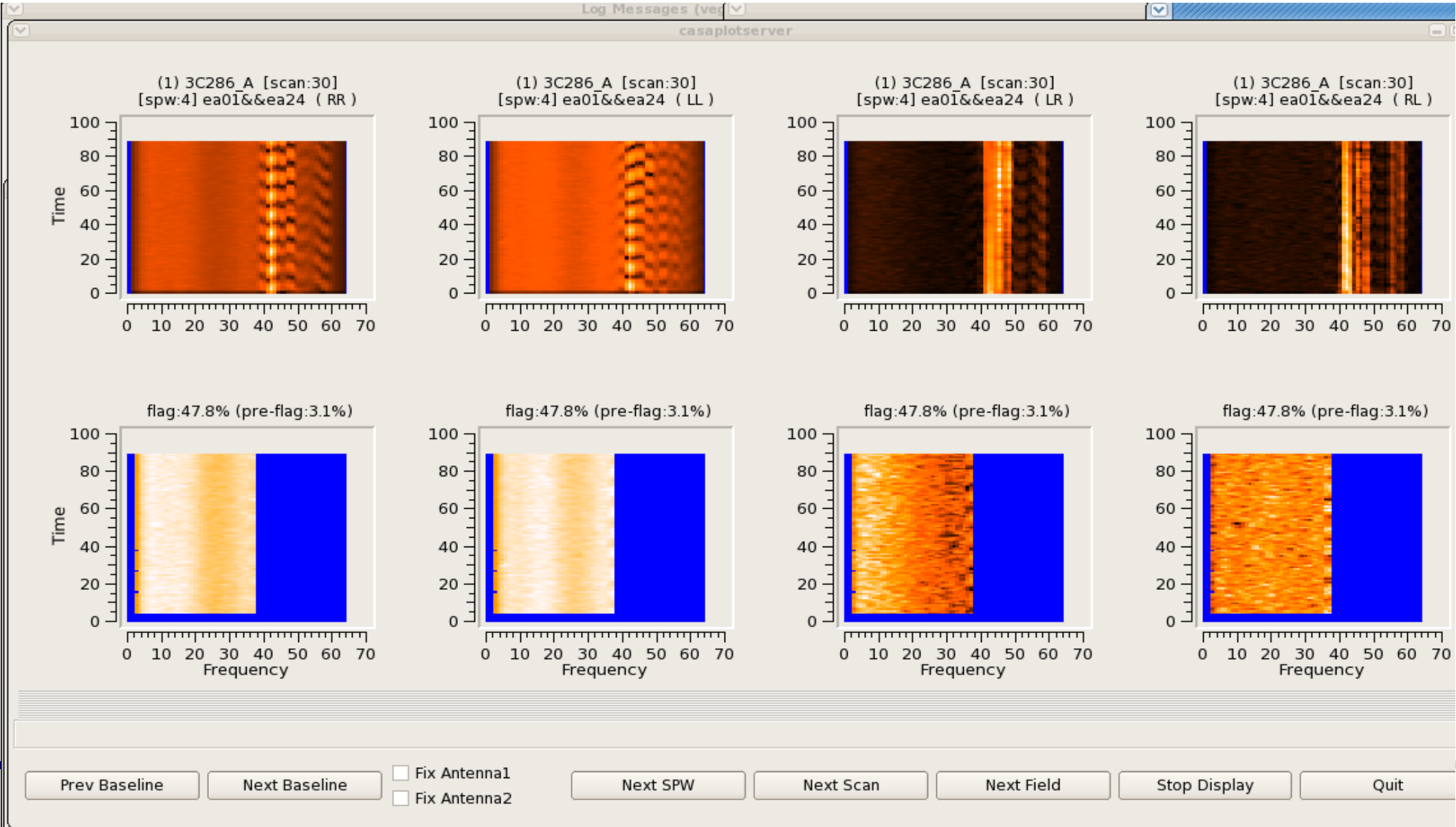
Examples of Manual Tuning

cmdlist = [“ spw='4' mode='rflag' **freqdevscale=3.0** extendflags=F “,
“ **spw='4' mode='extend' growtime=30.0 extendpols=T** “]



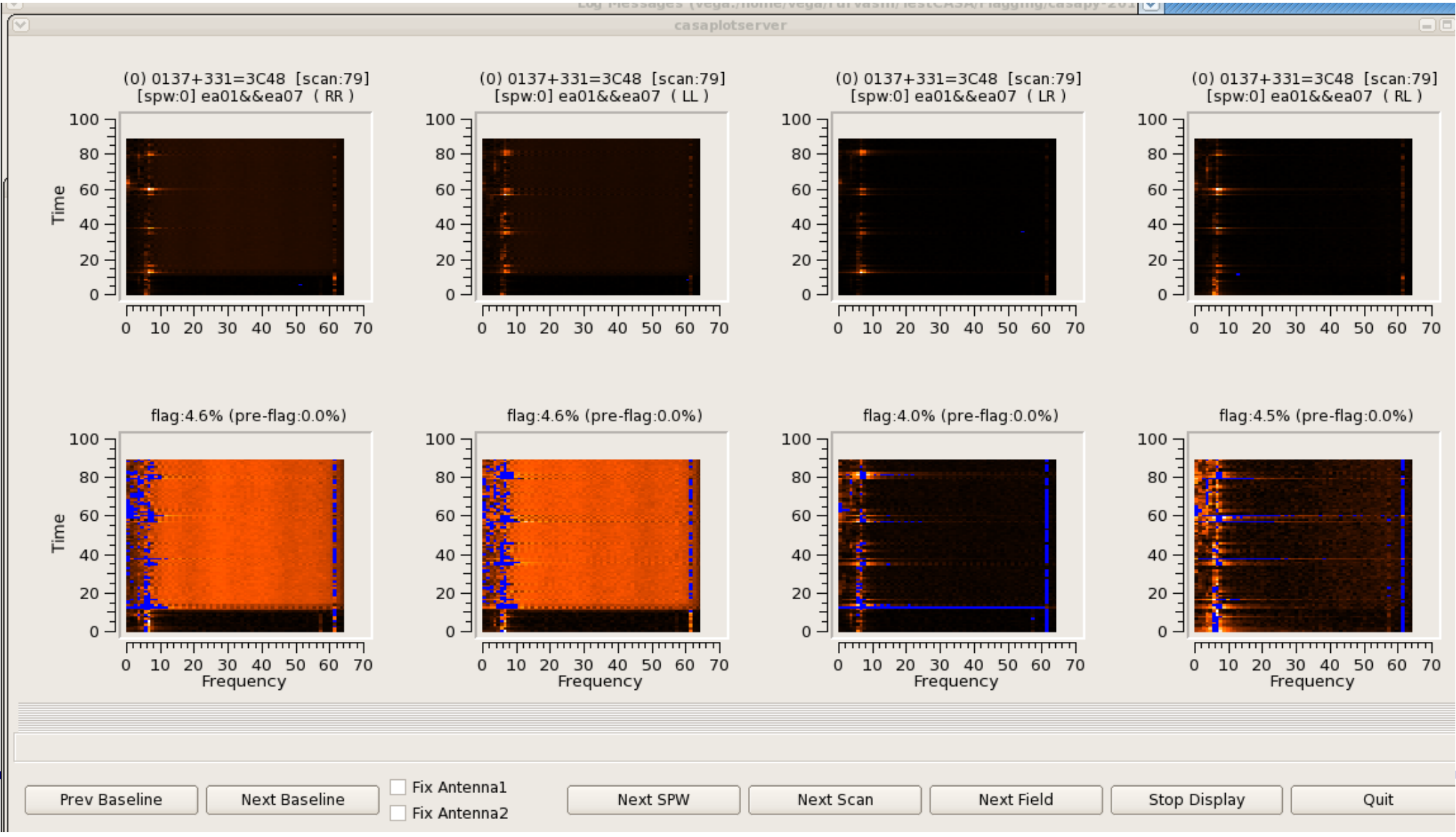
Examples of Manual Tuning

cmdlist = [“ spw='4' mode='rflag' **freqdevscale=3.0** extendflags=F “,
“ **spw='4' mode='extend' growtime=30.0 extendpols=T flagnearfreq=T** “]



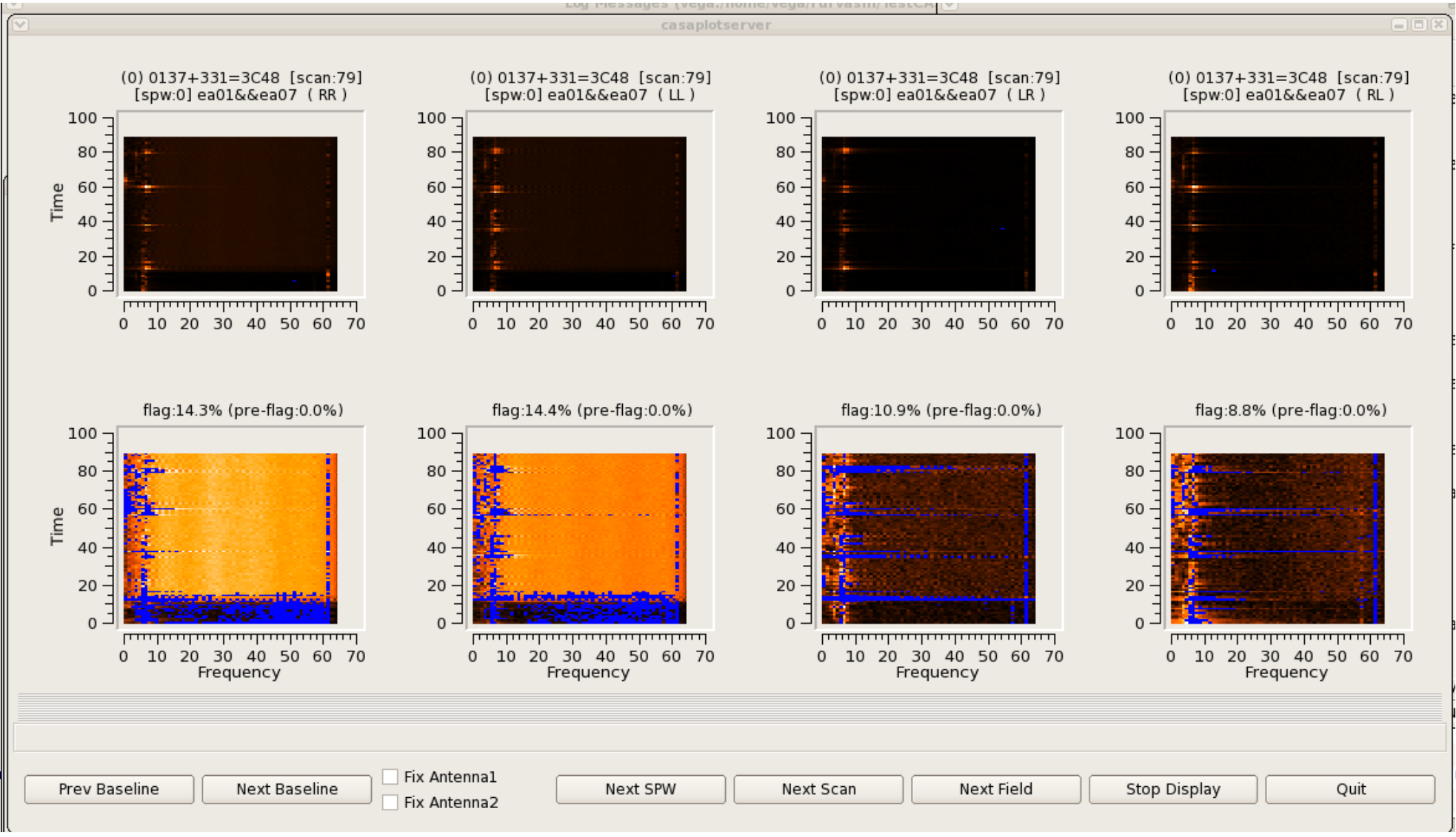
Examples of Manual Tuning

cmdlist = [“ spw='5' mode='tfcrop' extendflags=F“]



Examples of Manual Tuning

cmdlist = [“ spw='5' mode='tfcrop' **maxnpieces=4 timecutoff=2.5 freqcutoff=3.0**
timefit='poly' extendflags=F “]



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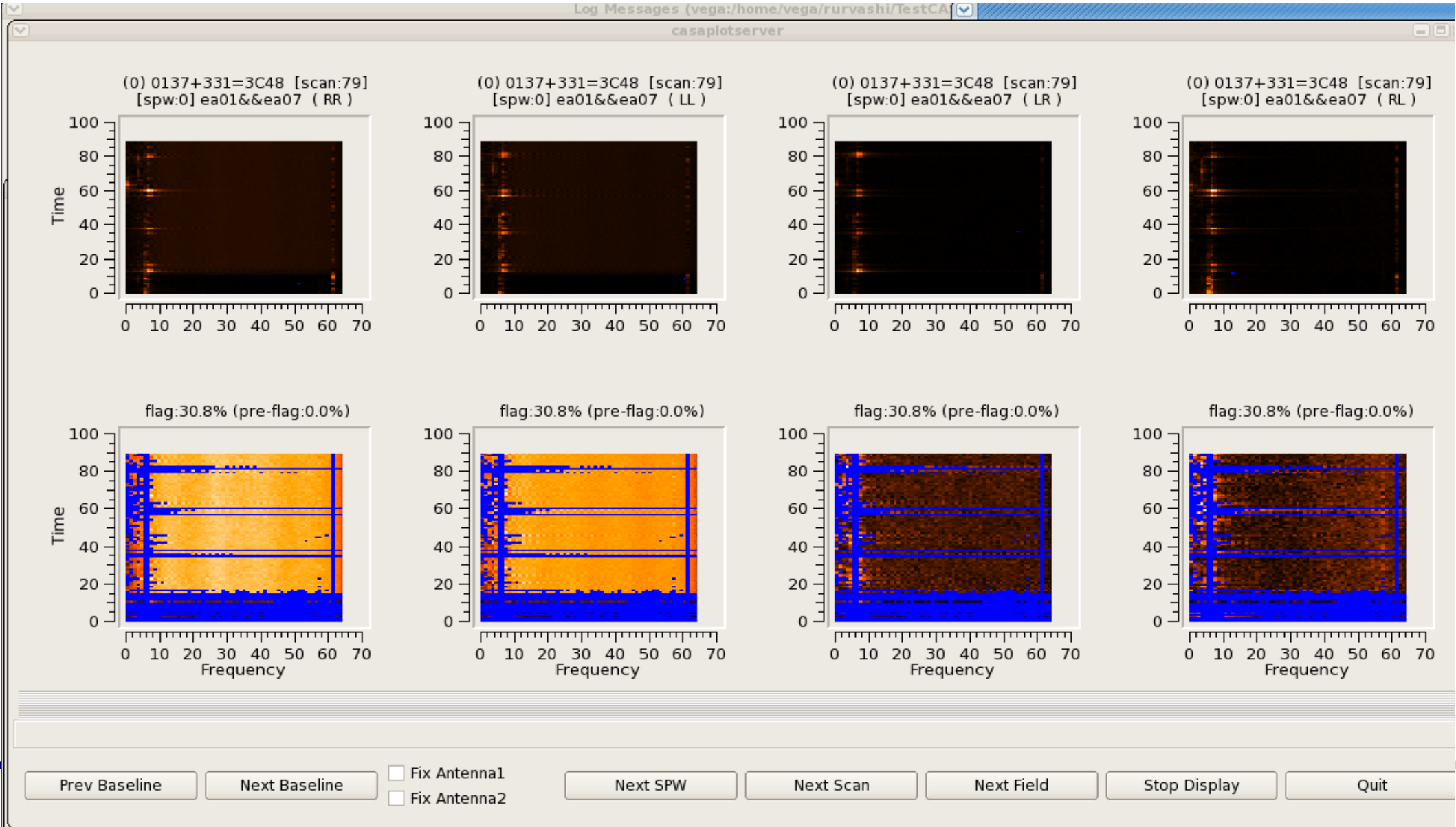
cmdlist = [“spw='5'mode='tfcrop' **maxnpieces=4 timecutoff=2.5 freqcutoff=3.0**
timefit='poly' extendflags=F“, “ **spw='5' mode='extend' growtime=50.0**
extendpols=T growfreq=50.0 “]



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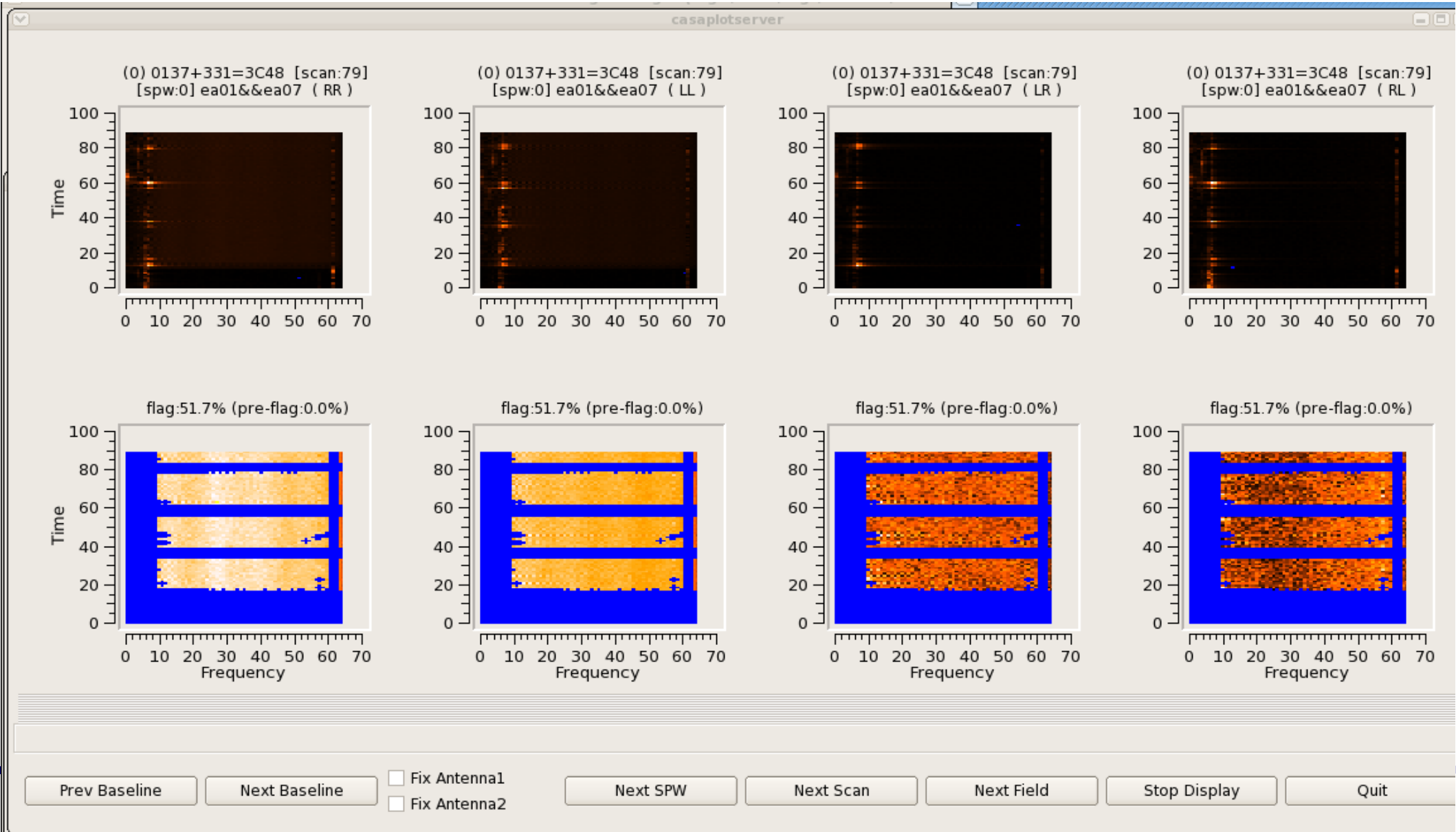
cmdlist = [“ spw='5' mode='tfcrop' **maxnpieces=4 timecutoff=2.5 freqcutoff=3.0 timefit='poly'** extendflags=F“, “ **spw='5' mode='extend' growtime=50.0 extendpols=T growfreq=50.0 flagnearfreq=T flagneartime=T** “]



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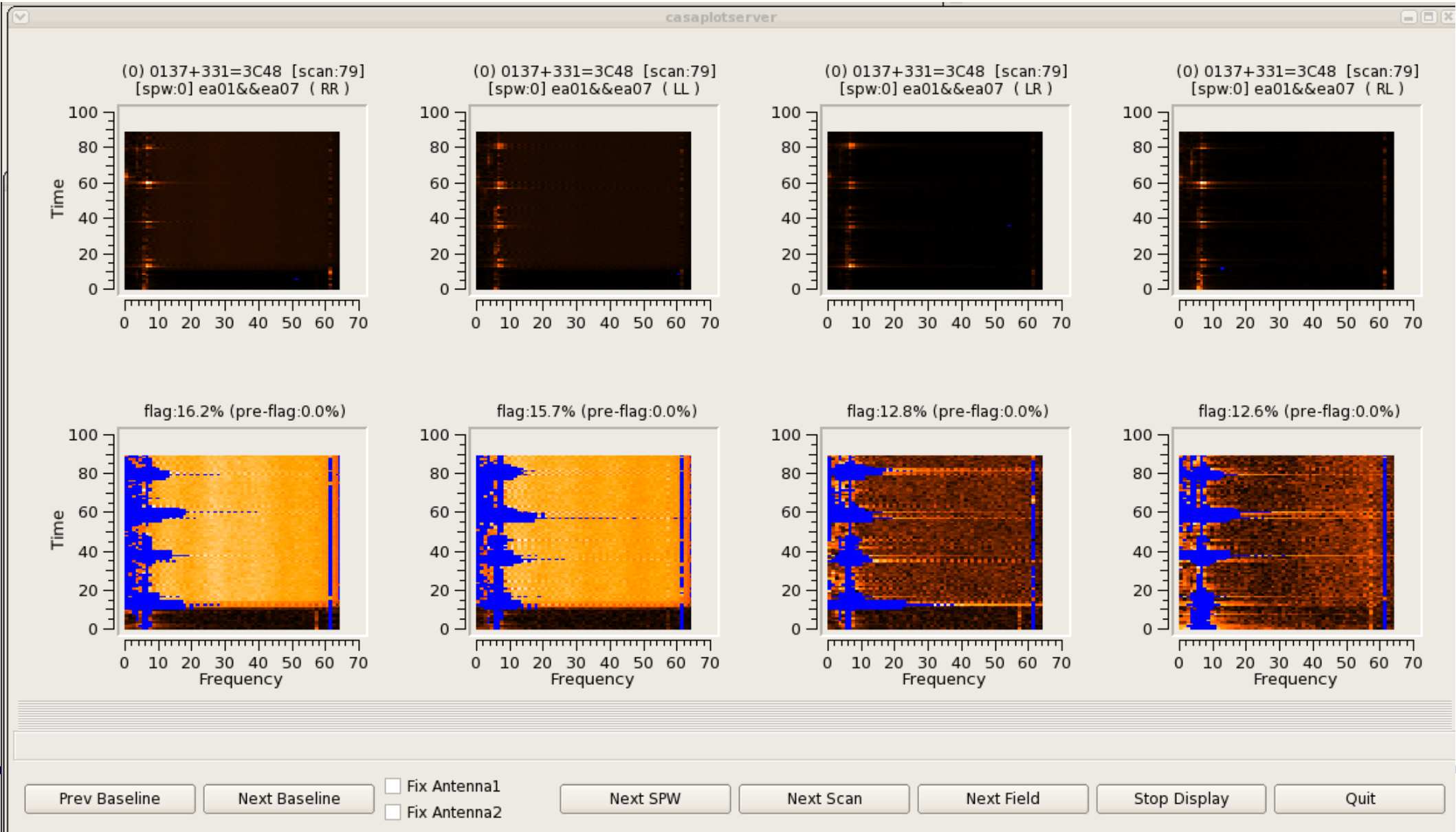

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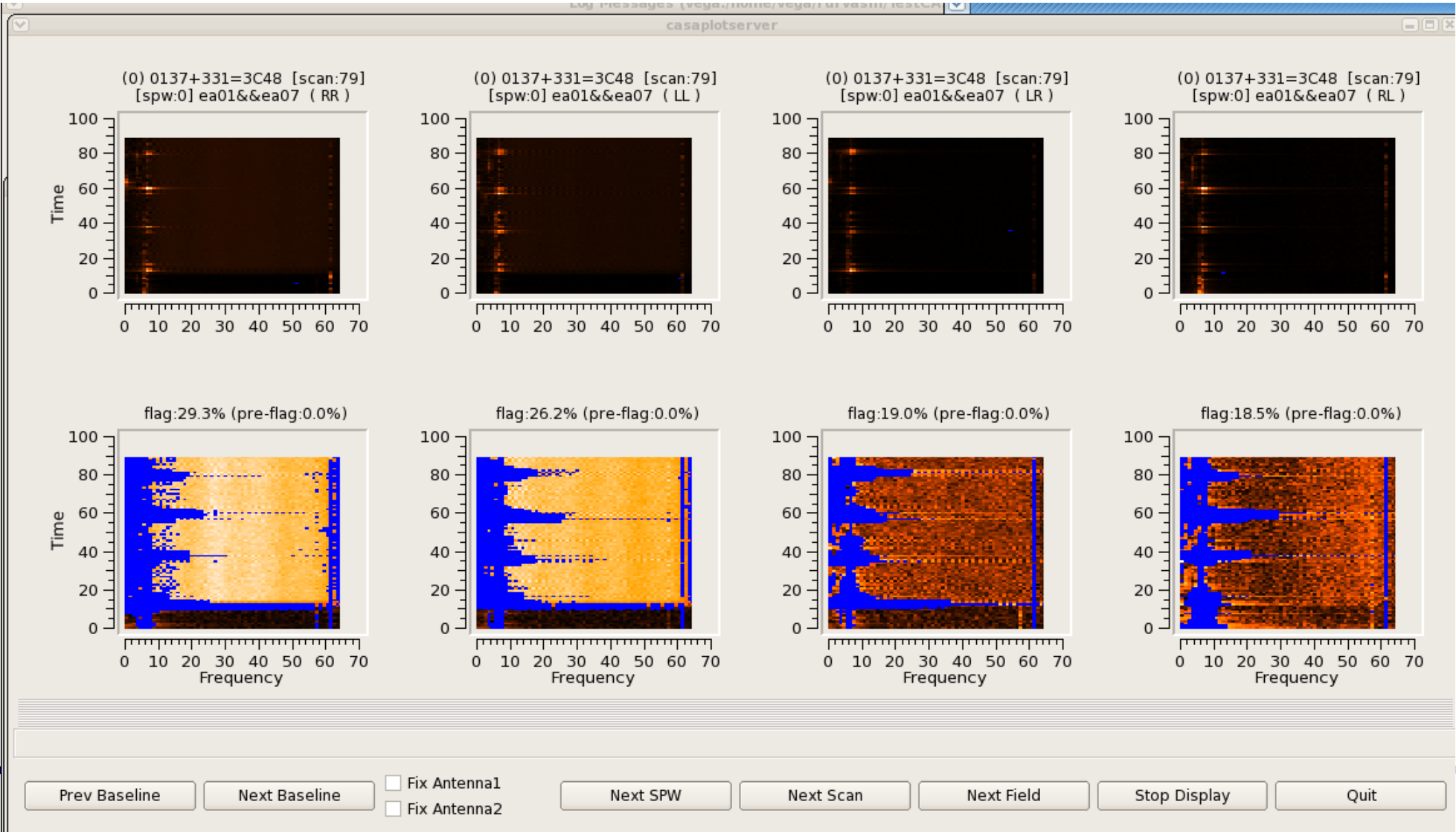
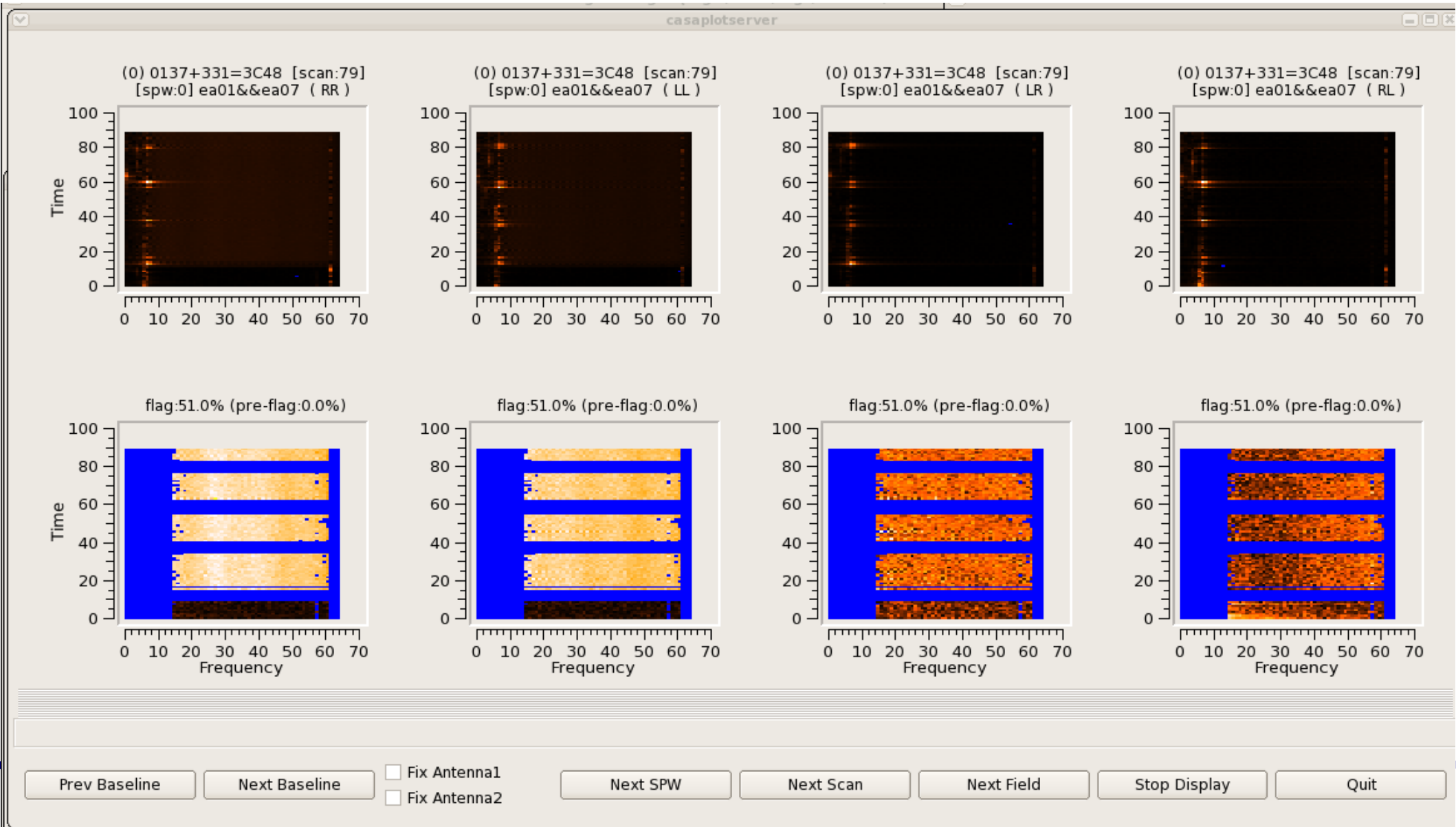


Examples of Manual Tuning

cmdlist = [“ spw='5' mode='rflag' **freqdevscale=3.0 timedevscale=3.0** extendflags=F“ ,
“ **spw='5' mode='extend' growtime=50.0 growfreq=30.0 extendpols=T** “]



Can we automate all this tuning ?

- Examples show that the algorithms CAN be tuned for optimal results.
- A human tweaks parameters and visually checks flagging quality on a small fraction of the dataset before letting it run on all the data.
- Each algorithm has a small set of really relevant parameters.

General approach :

=> Quantify ‘flagging quality’

=> Apply an algorithm that optimizes it to find best-fit parameters

=> Auto-tune parameters on a subset of the data and apply to the rest

A Genetic Algorithm for Parameter Evolution

- A search heuristic that mimics the process of natural selection, used to solve optimization problems
- Random guided search

- Steps :

  (1) Generate initial population randomly

  (2) Breed new individuals through crossover and mutation

  (3) Evaluate the population using a fitness metric

  (4) Replace the least-fit population with new individuals

  (5) Repeat from (2) and continue through several generations

  (6) Pick the parameters of the best-fit individual

Characteristics of an Individual (and the population)

- Candidate solutions (individuals) are represented by parameter sets

Individuals : TFCrop + Extend (or) RFlag + Extend

tfcrop : timecutoff, freqcutoff, maxnpieces, usewindowstats

rflag : timedevscale, freqdevscale, winsize

extend : growtime, growfreq, flagneartime, flagnearfreq, growaround

- Choices : Population size, Number of generations,
  Dropout rate, mutation rate,
  Allowed ranges for parameter values (from prior knowledge)

Reproduction (crossover)

rflag =	timedevscale	freqdevscale	winsize	growtime	growfreq	flagneartime	flagnearfreq	growaround
parent1 =	0.5	3.0	4	70.0	80.0	FALSE	FALSE	FALSE
parent2 =	1.5	5.0	2	50.0	90.0	TRUE	FALSE	TRUE

- Breed each new generation of individuals by mixing the characteristics of all pairs of parent individuals

Reproduction (crossover)

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cut

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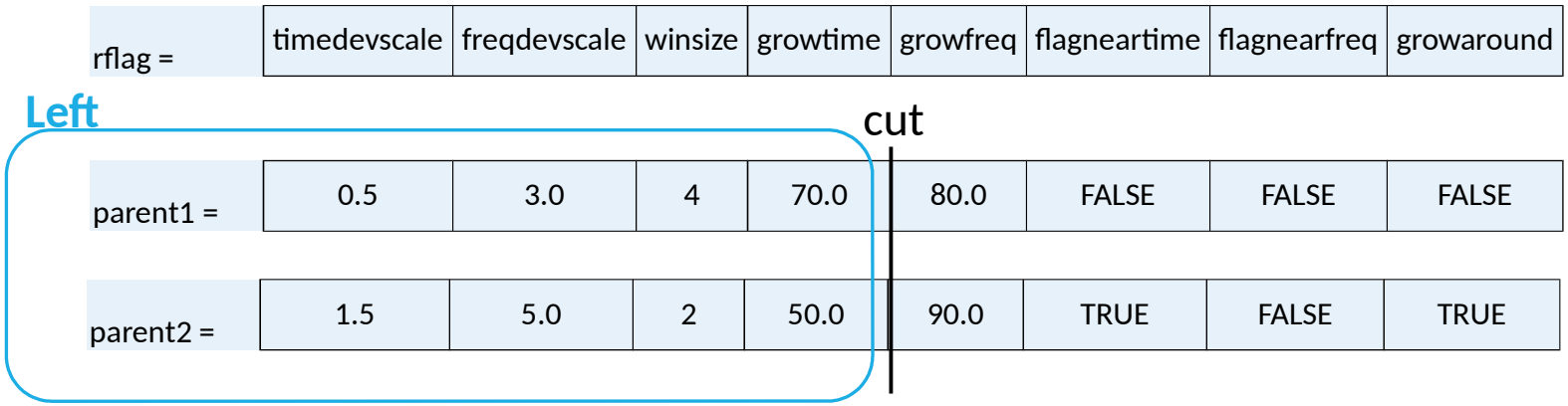

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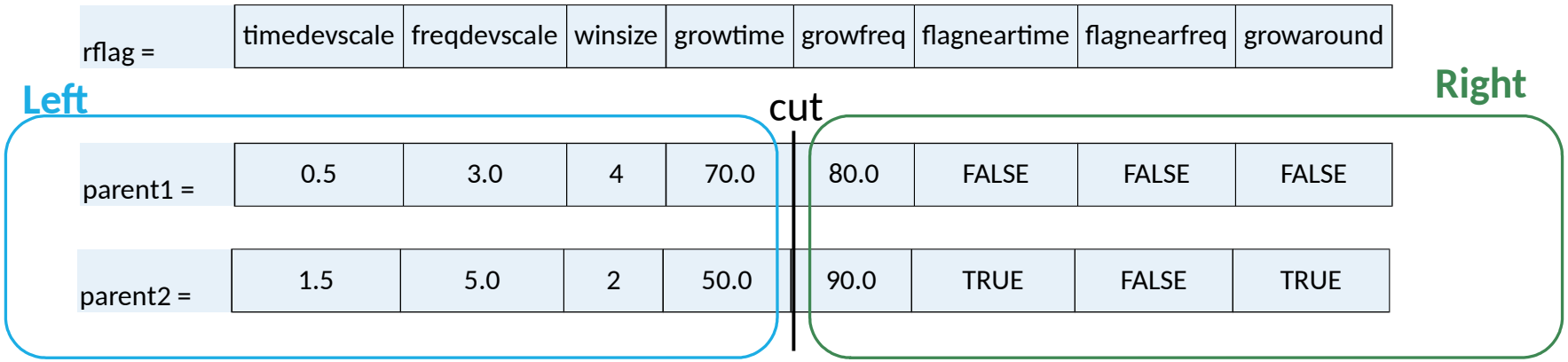

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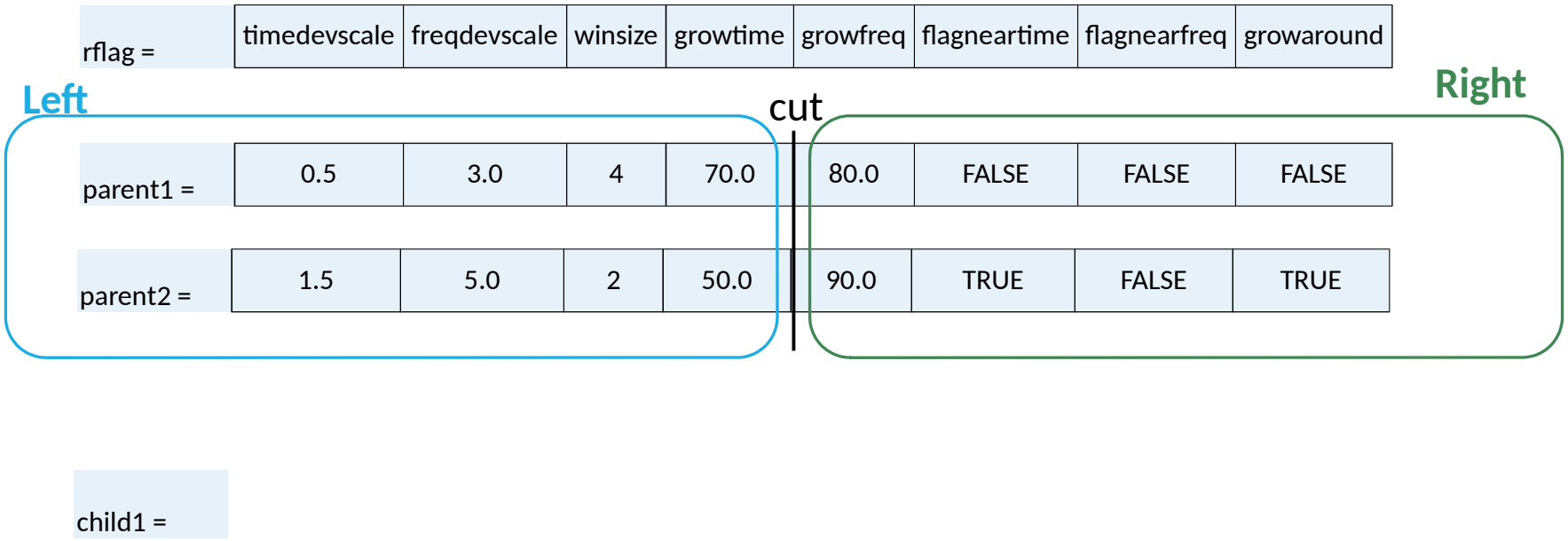

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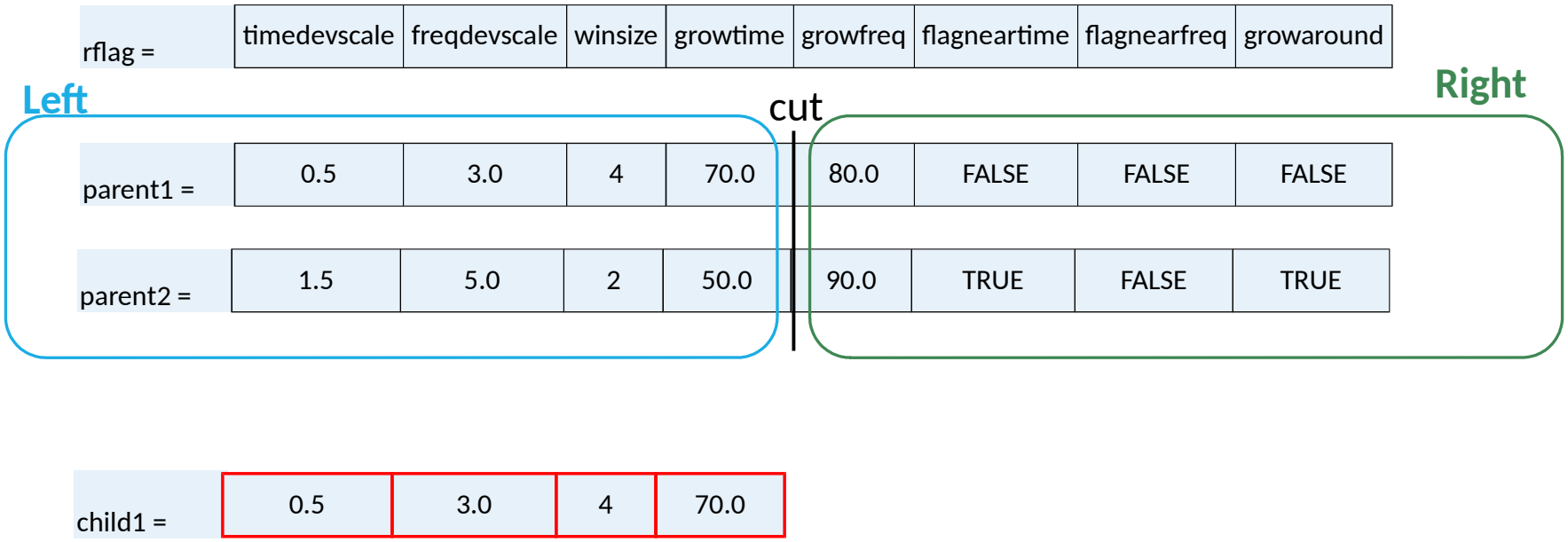

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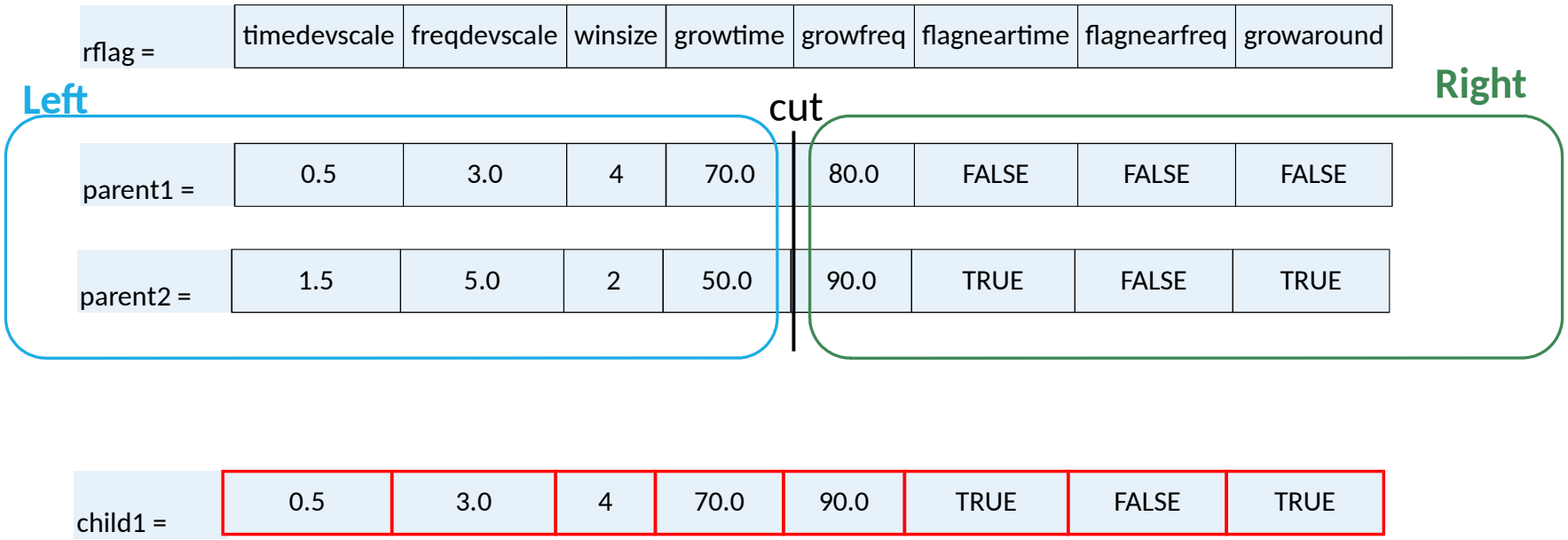

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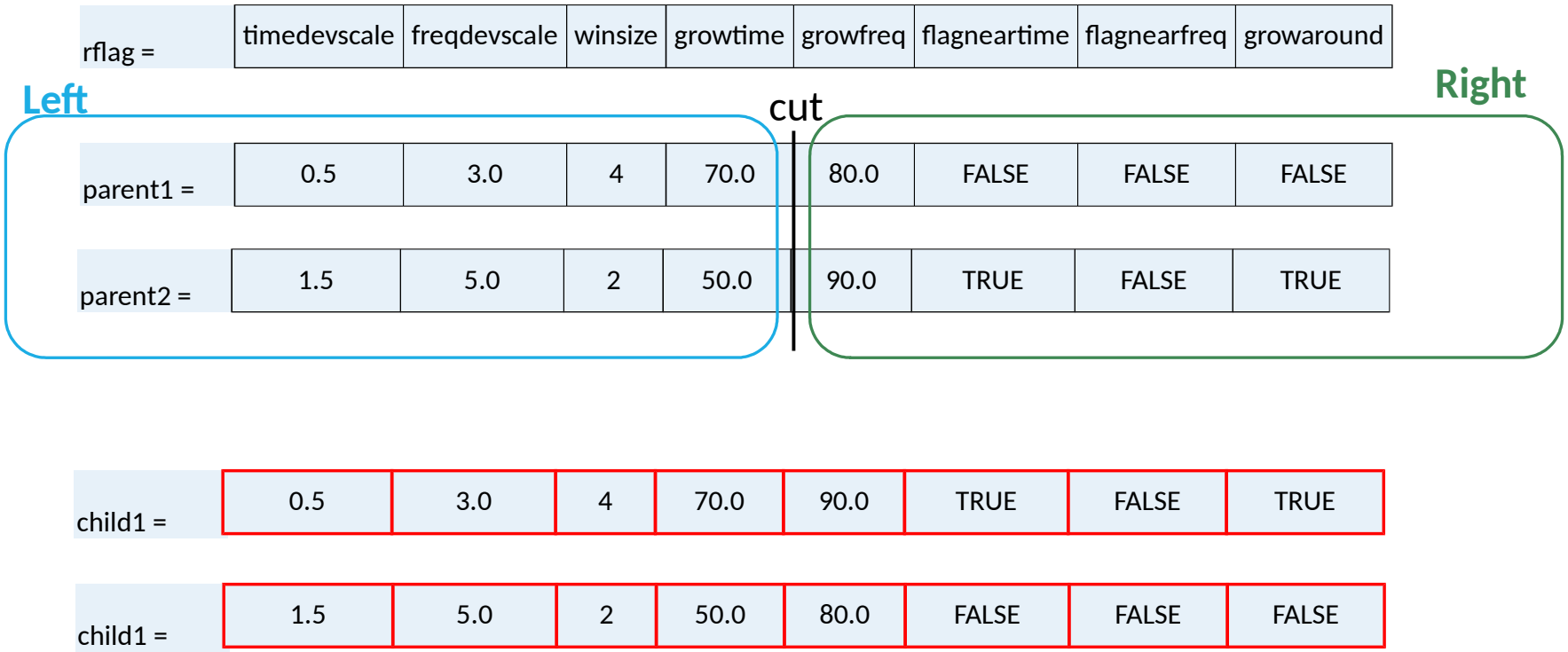
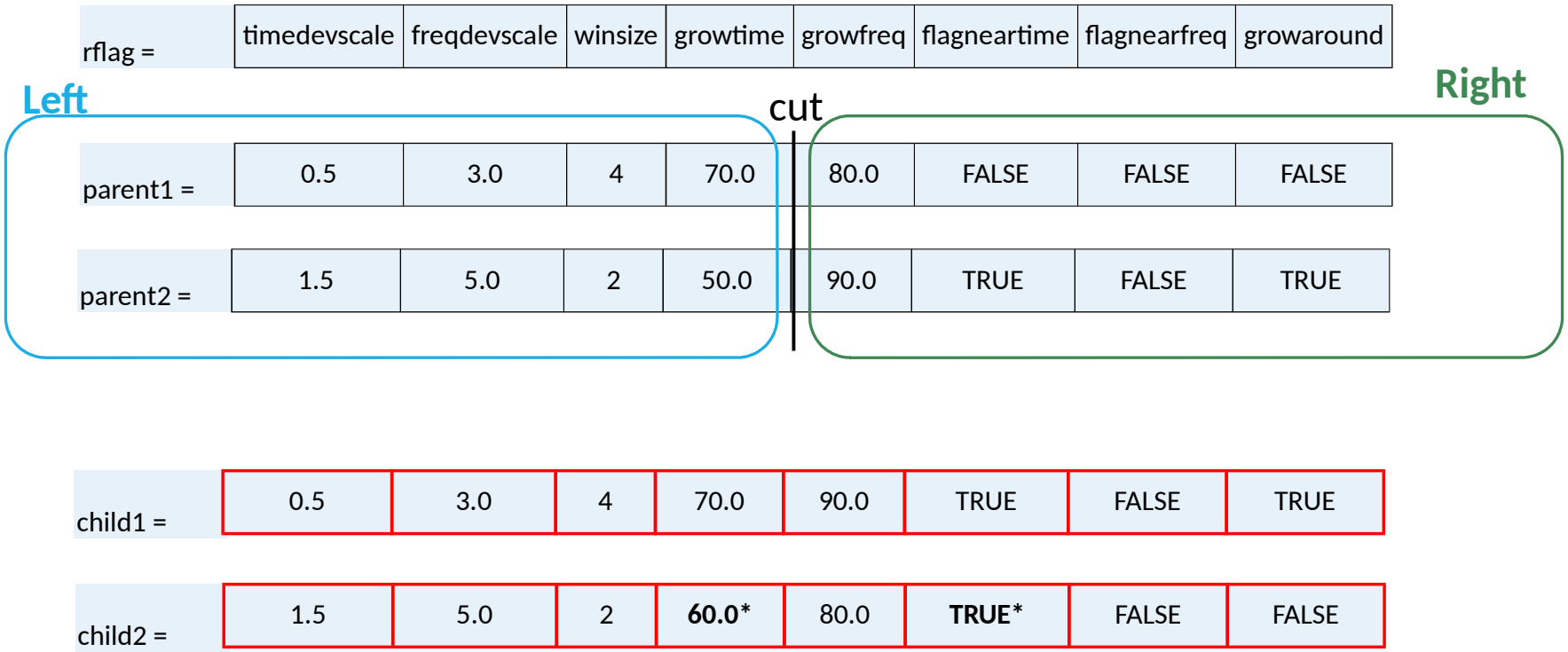


- Breed each new generation of individuals by mixing the characteristics of all pairs of parent individuals

Reproduction (crossover) + Mutation



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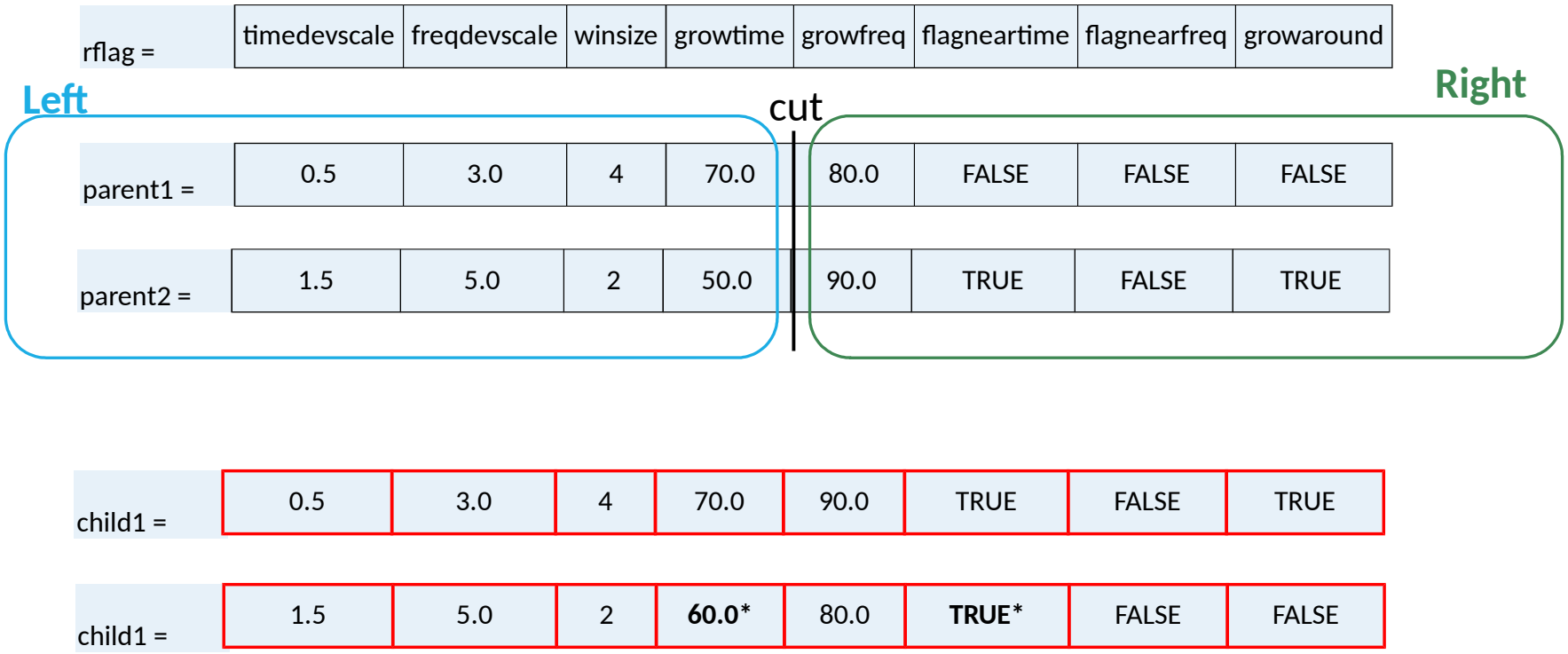
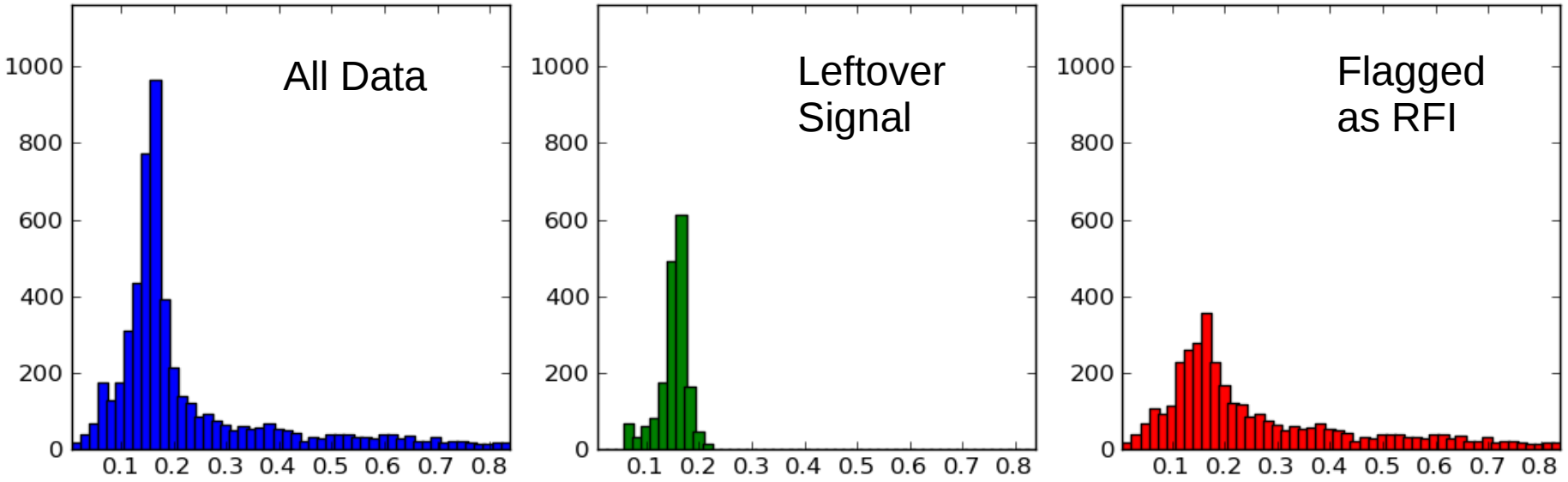
Reproduction (crossover) + Mutation + Dropout



- Breed each new generation of individuals by mixing the characteristics of all pairs of parent individuals
- Replace least-fit individuals with new ones

Fitness metric to evaluate each individual

- Compare statistics of flagged vs unflagged data
  - Flagged data should have a higher mean (or median) than unflagged data
  - Unflagged data should look Gaussian (max ~ 3-sigma)
  - Protect against over (or under) flagging (>70% flagged or 0% flagged)
- Use these criteria to compute a score that must be optimized.



Results

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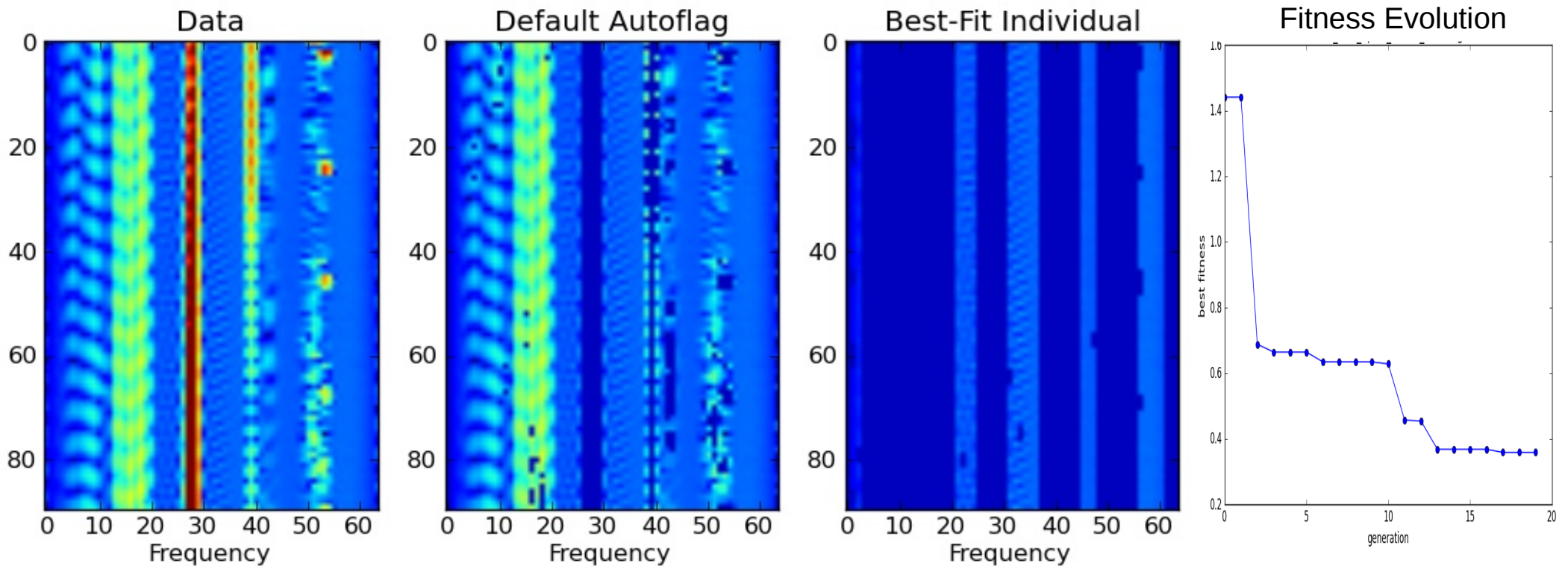
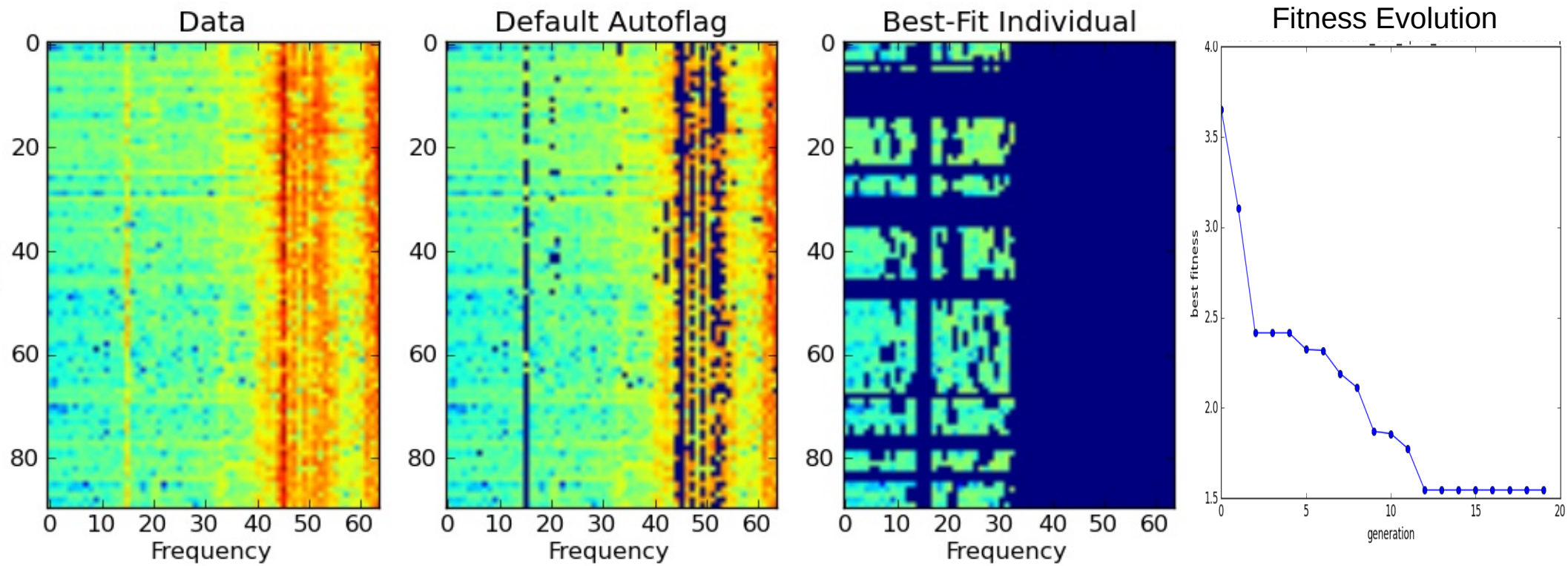


Example : A mix of bright narrowband RFI and lower level broader RFI...

cmdlist=[" mode='tfcrop' timecutoff=5.0 freqcutoff=2.0 maxnpieces=3 usewindowstats='sum' ", " mode='extend' growtime=40.0 growfreq=90.0 flagneartime=True flagnearfreq=False growaround=False"]

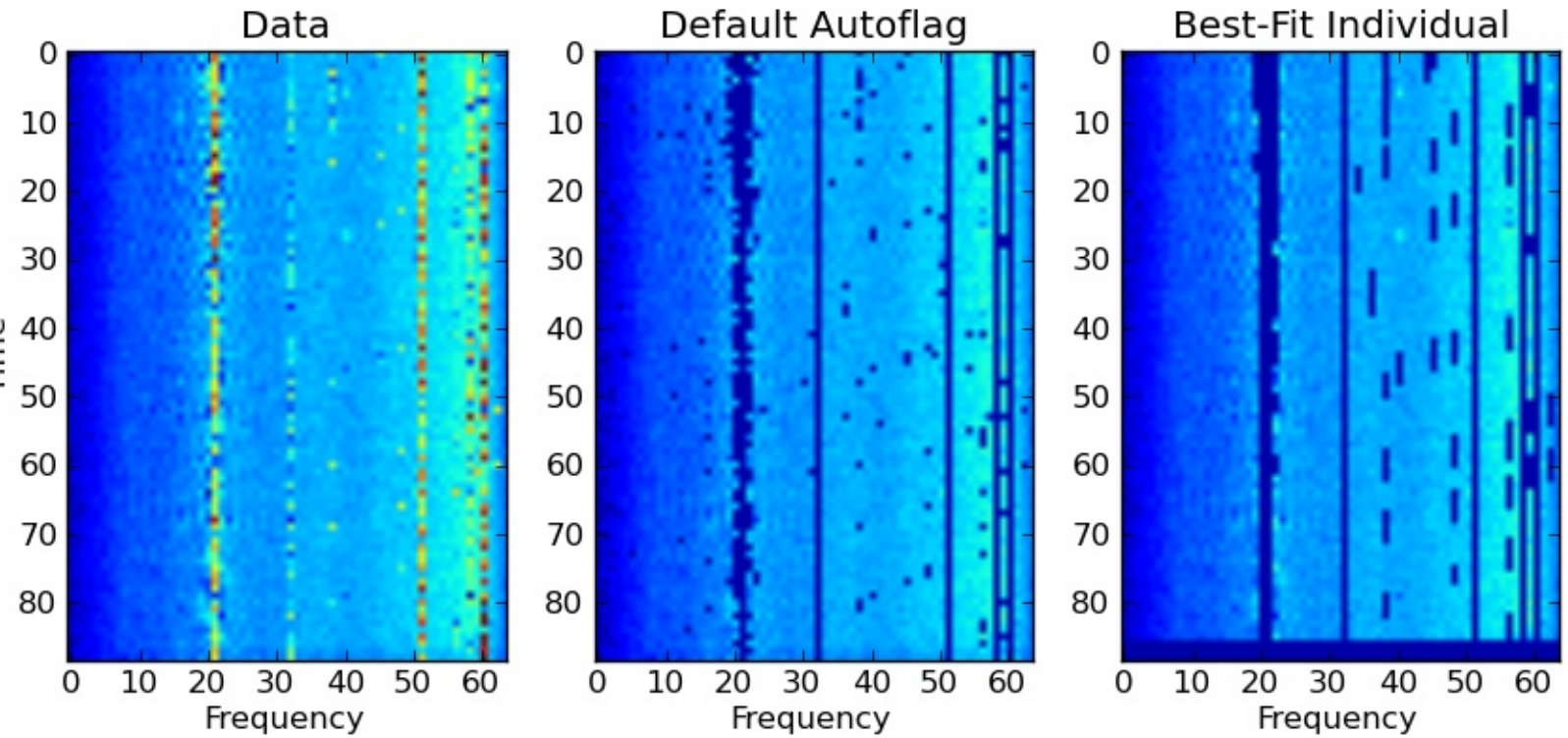
Results



Example : Most of the data are contaminated with RFI....

cmdlist=[" mode='tfcrop' timecutoff=1.5 freqcutoff=2.0 maxnpieces=7 usewindowstats='std'", " mode='extend' growtime=80.0 growfreq=70.0 flagneartime=True flagnearfreq=False growaround=False"]

Results

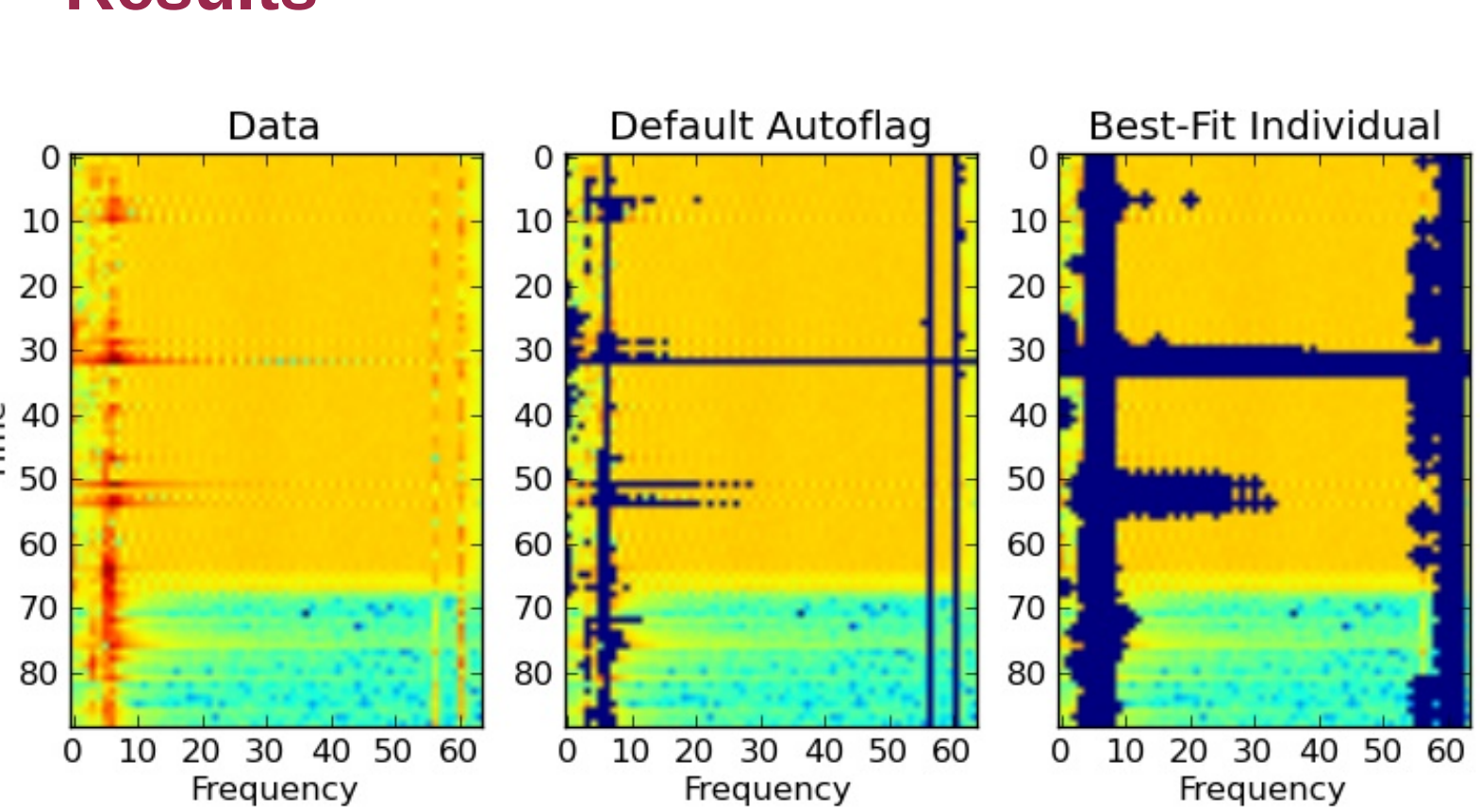


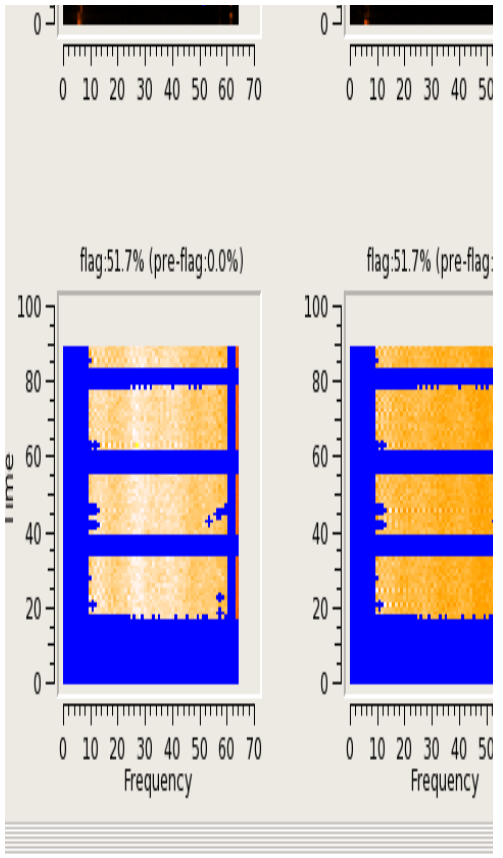
First generation produced adequate results

Example : “Easy” RFI that our algorithms are already tuned for...

cmdlist=[" mode='rflag' timedevscale=3.0 freqdevscale=5.0 winsize=3 ", "
mode='extend' growtime=70.0 growfreq=40.0 flagneartime=False
flagnearfreq=False growaround=False"]

Results





Example : Auto-tuning did not achieve results that matched hand-tuning
– Statistics didn't match what the fitness function was designed for ?

cmdlist = [" mode='tfcrop' timecutoff=4.0 freqcutoff=5.0 maxnpieces=1 usewindowstats='std'", " mode='extend' growtime=80.0 growfreq=70.0 flagneartime=True flagnearfreq=True growaround=False"]

Tuning the tuner...

Initial population count, number of generations, dropout rate, mutation rate, etc...

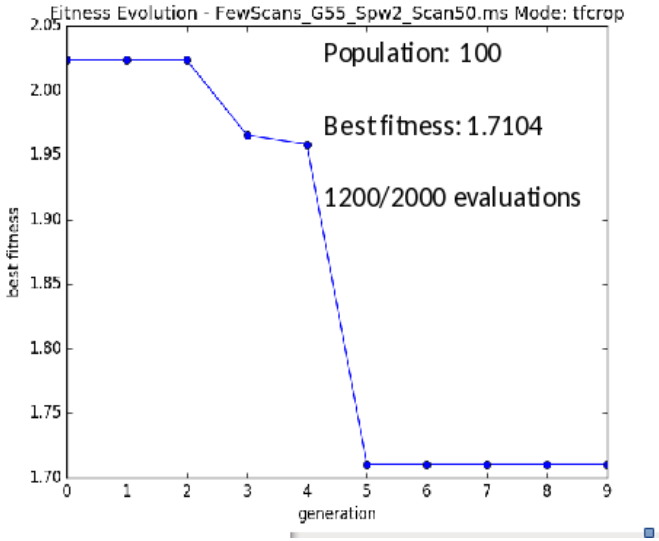
- Healthy convergence

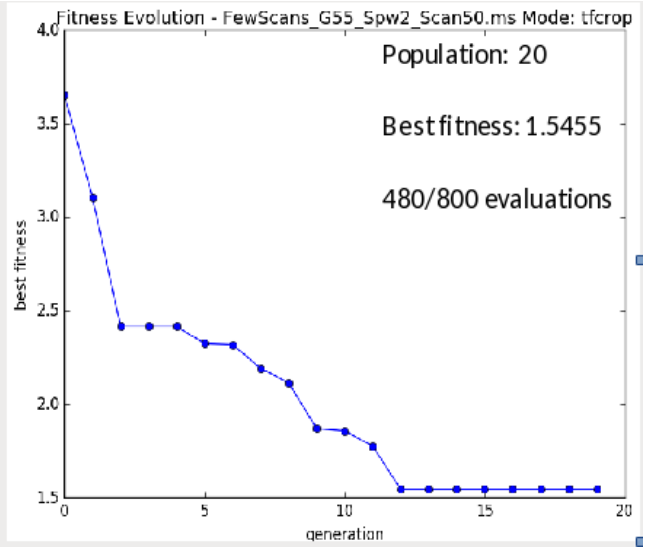
- Minimum number of required evaluations

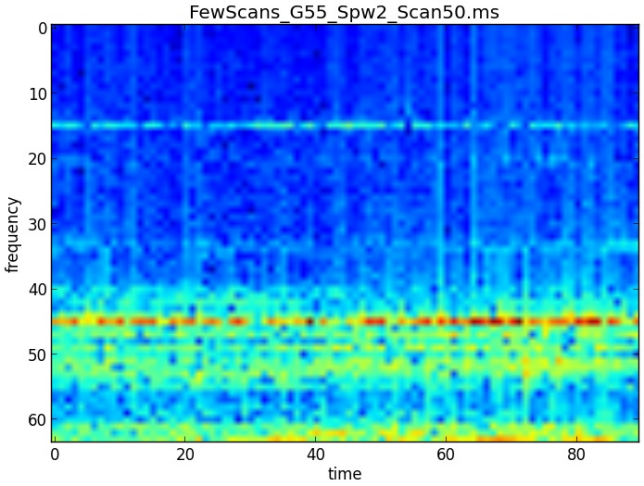
- Diversity vs Evolution

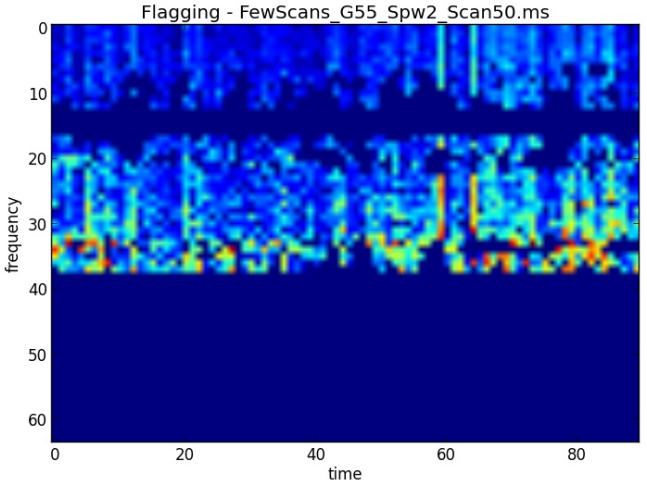
- Robust fitness function

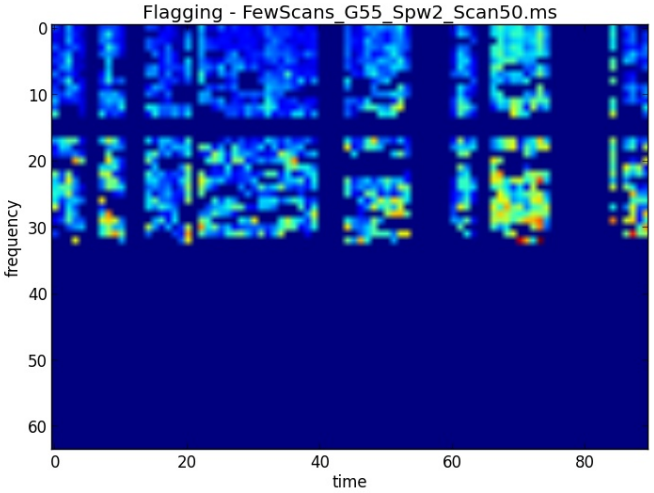
Might need tuning once per algorithm...
… but perhaps not.











Practical Usage

- For each dataset, select one or more training subsets of the data
  - Each spectral window (RFI is different across bands)
  - Each sub-array (local RFI characteristics may vary)
  - One scan, or a few scattered scans, or one baseline, or one correlation pair, etc..

  => Pick a minimal representative piece of all data that may share RFI characteristics

- On each 'training set', run the auto-tuner algorithm.
  - A few thousand evaluations of autoflag on tiny subsets of data
  - Easily parallelized (runtime went down from a couple of hours on our initial prorotype to a couple of minutes when implemented at the appropriate software level)
  - Use a-priori information about RFI characteristics to initiate the tuner – work ongoing

- Apply regular autoflag on the entire dataset using chosen parameters

Summary

- RFI affects a large fraction of several observing bands at the VLA (and many other telescopes). Projections for new instruments such as the ngVLA suggest an environment just as bad (or worse).
- The current best practice is to flag and discard affected data. Automated algorithms exist to identify and mask bad data, but they all require careful (manual) tuning for different RFI characteristics.

  => We need to automate this, especially as we move towards automated data reduction pipelines and Science-Ready Data Products.

- So far,

  - We have prototyped an auto-tuner based on a genetic algorithm that optimizes a fitness metric for flagging quality that can apply to any parameterized auto-flagger.

  - It can run automatically, given an input interferometry dataset

  - Via an efficient parallel implementation, we have demonstrated feasibility of doing this in a practical data reduction setting (especially when imperfect flagging is the main reason for manual re-reduction of pipelined data products)

- To do : More intelligent selection of training sets, algorithmic improvements to optimize the tuner, use a-priori information about RFI characteristics to initialize the tuner, etc.