Strategy for Classification of Noise Transients in Advanced Detectors

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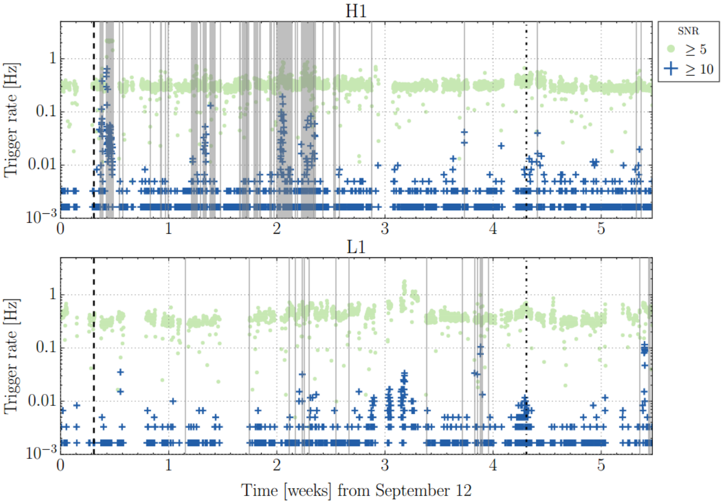
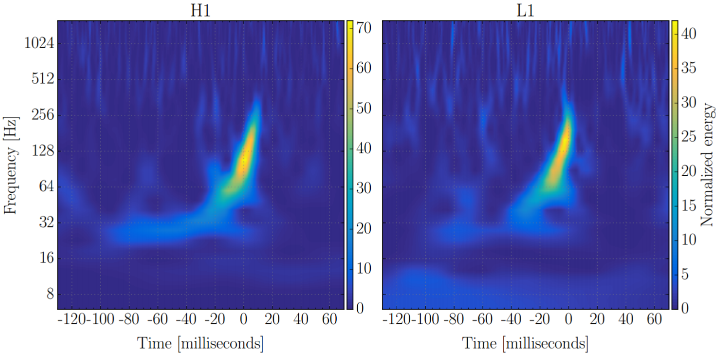
Typical glitchgram for detectors



Our 'typical' gravitational waves

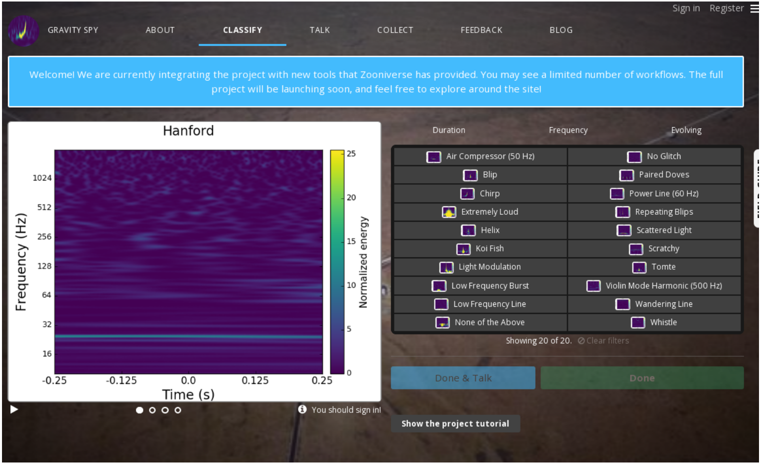


Our glitch zoo

Why Glitch Classification?

- As prompt characterization of noise will be critical for improving sensitivity, a fast method for glitch classification was needed.
- The detchar group proposed a challenge for the development of a method for automatic classification of glitches.
- We present three methods developed for automatic glitch classification.
- We started using simulated data sets to better understand the performance of the different glitch classifying codes.
- We tested our pipelines on LIGO ER7 data.

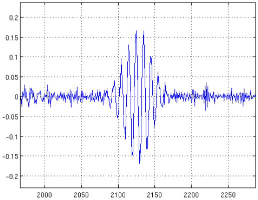
GravitySpy project

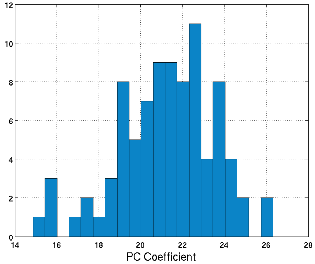


https://www.zooniverse.org/projects/zooniverse/gravity-spy

PC-LIB

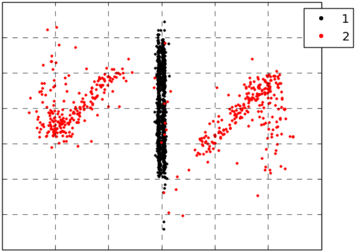
- PC-LIB is an adaptation of the parameter estimation and model selection tool LALInference.
- A set of Principal Components for a type of glitch is made using the high pass filtered time series of fifty glitches for that type.
- A linear combination of the PCs, multiplied by the PC coefficients, is then used as the new signal model in LIB for each different population of noise transient. The different signal models for each glitch population can then be used for Bayesian model selection, which can determine the type of each new noise transient that is detected in the data.
  For two competing models M_i and M_j the Bayes factor is given by the ratio of the evidences,
- Model selection can then be used to identify the correct glitch type.

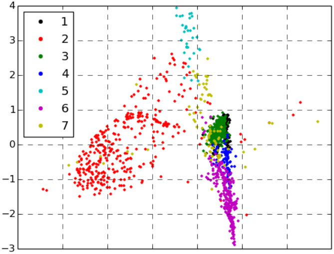




PCAT

- Principal Component Analysis for Transients (PCAT) is a python-based pipeline based on Principal Component Analysis.
- The time series of whitened glitches are stored in a matrix on which PCA is performed.
- PCAT uses the PC coefficients to classify the glitches by using a Gaussian Mixture Model (GMM) implementation of scikit-learn, which includes machine learning routines for model selection.It requires the user to specify the number of clusters and the number of principal components.
- The results of the PCA can be visualized with scatter plots of the principal component coefficients.

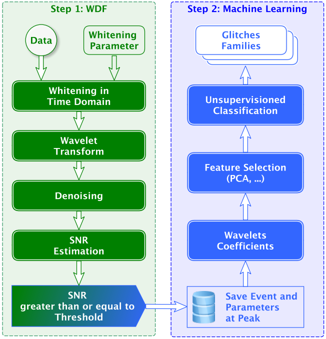


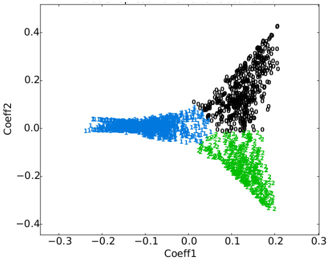


Wavelet Detection Filter (WDF)-Machine Learning

WDF is an ETG that is part of the Noise Analysis Package (NAP), developed by the Virgo collaboration.

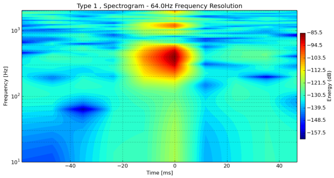
- Whitening procedure is based on a linear predictor filter.
- Wavelet domain decomposition. Thresholding. SNR estimation.
- Completely unsupervised algorithms. No target function
- Wavelets coefficients and Meta data (SNR, Freq,Duration) represents our "features"
- Features selection uses PCA transform an Spectral embedding on 2 dimensions
- The Gaussian Mixture Model (GMM) machine learning classifier is then applied to the outputs of WDF for classification.

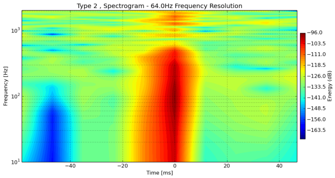




MDC: Data set 1

- To test and compare methods we create a simulated data set in aLIGO Gaussian noise.
- Data set 1 is an ideal data set where all of the glitch types are well separated in frequency and SNR.
- The data set contains 1000 sine Gaussian waveforms and 1000 Gaussian waveforms in simulated Gaussian noise.
- The sine Gaussian waveforms have a frequency = 400Hz and an SNR between 5 and 30.
- The Gaussian waveforms are centred at f = 0Hz and have an SNR between 20 and 250.



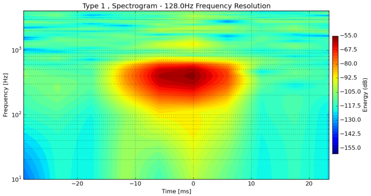


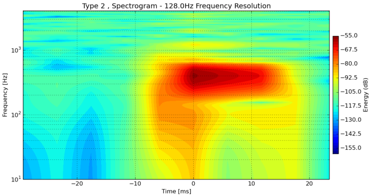
Data Set 1 Results

- Table shows the % of detected transients that were classified in each type.
- A few low frequency SG, and low SNR G were in the incorrect classes.
- Overall classification efficiency very good!

	SG	G
PCAT Type 1	99%	0%
PCAT Type 2	1%	100%
LIB Type 1	99.9%	5%
LIB Type 2	0.1%	95%
WDF Type 0	99.5%	2.4%
WDF Type 1	0.3%	46.1%
WDF Type 2	0.2%	51.5%

- We use a second data set to see if we can classify glitches by waveform morphology only.
- We use 1000 sine Gaussian waveforms and 1000 Ring-down waveforms.
- All waveforms have identical frequency 400Hz and a identical duration 2ms.
- The SNR of the simulated glitches is between 10 and 500.





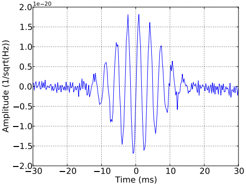
Data Set 2 Results

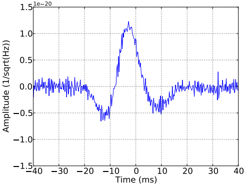
- Table shows the % of detected transients that were classified in each type.
- The few transients in the incorrect class are those with the lowest SNR.
- 5PCs PCAT, 7PCs LIB and 10 PCs WDF-ML.
- All methods can classify by waveform morphology alone.

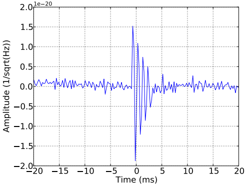
	SG	RD
PCAT Type 1	1.1%	97.4%
PCAT Type 2	98.9%	2.5%
LIB Type 1	97.8%	4.8%
LIB Type 2	2.2%	95.2%
WDF-ML Type 0	8.7%	100%
WDF-ML Type 1	48.0%	0%
WDF-ML Type 2	43.3%	0%

MDC: Data Set 3

- The third data set is to see what happens if different types have a very wide range of parameters.
- The simulated glitches are Gaussian, sine Gaussian and Ring-down waveforms at five second intervals.
- The frequencies are distributed linearly between 40-1500 Hz.
- Majority of the glitches have an SNR between 1 and 300.







Data Set 3 Results

- PCAT 20PCs, LIB 5PCs, WDF-ML 10PCs.
- All methods have the Gaussians in there own class.
- Cannot distinguish between the sine Gaussian and Ring-down waveforms when the parameter range is so large.

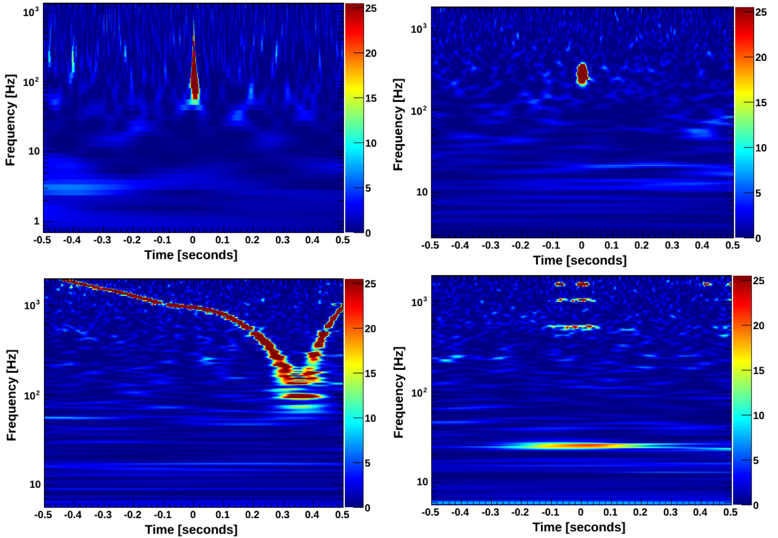
	SG	G	RD
PCAT Type 1	15.5%	0%	13.6%
PCAT Type 2	36.8%	0%	41.4%
PCAT Type 3	14.2%	0%	13.0%
PCAT Type 4	9.1%	0%	13.0%
PCAT Type 5	0.8%	0%	0.3%
PCAT Type 6	21.8%	0%	17.2%
PCAT Type 7	1.8%	100%	1.5%
LIB Type 1	39.5%	4.9%	23.8%
LIB Type 2	17.3%	88.3%	23.2%
LIB Type 3	43.3%	6.8%	53.0%
WDF-ML Type 0	89.5%	9.6%	86.9%
WDF-ML Type 1	5.9%	49.7%	7.0%
WDF-ML Type 2	4.6%	40.7%	6.1%

Classification methods for noise transients in advanced gravitational-wave detectors Class. Quant. Grav., 32 (21), pp. 215012, 2015.

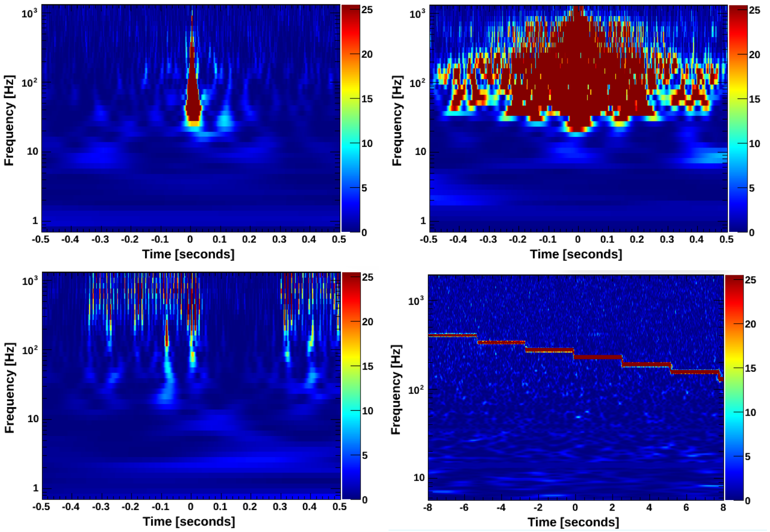
Real Data: ER7 LIGO data

- Data from the 7th aLIGO engineering run (ER7), which began on the 3rd of June 2015 and finished on the 14th of June 2015. The average binary neutron star inspiral range for both Hanford and Livingston detectors in data analysis mode during ER7 was $50 - 60$ Mpc.
- The total length of Livingston data analysed is ~ 87 hours.
- The total length of Hanford data analysed is ~ 141 hours.

Real Data: ER7 L1



Real Data: ER7 H1



Conclusion

- Jade Powell label all the glitches and classifiy them by eye. This classification is used as reference.
- In the ER7 data from aLIGO Livingston PCAT missed 90 transients and classified 95% of the remaining transients correctly.
- PC-LIB missed 33 transients and classified 98% of the remaining transients correctly.
- WDF-ML classified all transients and 97% of them were correct.
- In aLIGO Hanford PCAT missed 120 transients and classified 99% of the remaining transients correctly.
- PC-LIB missed 6 transients and classified 95% of the remaining transients correctly.
- WDF-ML classified all transients and 92% of them were correct.
- We conclude that our methods have a high efficiency in real non-stationary and non-Gaussian detector noise.

Submitted:
Classification methods for noise transients in advanced gravitational-wave detectors II: performance tests on Advanced LIGO data. Classical and Quantum Gravity, Volume 34, Number 3 (by the authors)

What's next?

- Three different methods have been developed for the fast classification of noise transients.
- Transients are split in to types by waveform morphology first, and then can be split up in to further types by frequency and SNR.
- Results are similar for all methods.
- We plan to use Dictionary Based Algorithm.
- We plan to use Images Deep Learning Classification
- Next we plan on looking at how these codes perform when using data from multiple auxiliary channels.
- We have applied WDF-ML to O1 and O2 data.
- We will apply the denoising and the machine learning procedures to the triggers produced by Omicron.
- We also want to test this tools for Virgo data.