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The 70th Workshop on Gravitational Waves and Numerical Relativity **APCTP Topical Research Program 2023**



Identifying and Mitigating Transient Noises for Gravitational Wave Detectors

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Contents

- Introduction GW detection & Noise Mitigation
- CAGMon Tool:
 - Goal & Workflow
 - Code Test
- MIC Parameter Optimization
- Application to GW Data
 - Magnetic Field Transients from Lightning Strokes
 - Periodic Noises from Air Compressors
 - Glimpse of Gravity Gradient Noise from Winds
- Low-frequency Noise Mitigation using Bandgap Engineering
- Conclusions



Gravitational-wave Detection and Noise Mitigation

- GWs detected from BBHs, BNS, NSBH sources by LIGO, Virgo, and KAGRA collaborations
- It opens new era of observational astronomy, together with EM, so called 'multi-messenger astronomy'
- GW detectors on Earth have enormous noises sources that affect to the detection of GWs - environmental and instrumental origins
- Thus understanding and mitigating them are of great importance for successful GW signals – 'Detector's characterization'



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Why Glitch Studies in Gravitational Wave Detection?

- **Glitch** transient noisy triggers that have nothing to do with gravitational wave signals caused by instrumental faults or environmental changes.
- These are very harmful to detecting gravitational wave signals if they are around the event time lowering the signalto-noise ratio (SNR).
- They are also harmful to compute a false-alarm probability (FAP) since glitches with high SNR can generate significant background triggers with high SNR. Eventually, they increase the FAP for a certain event candidate.
- Some glitches have similar shape and behavior to the chirp-like signals raising FAP and lowering significance. (ex. blip transient)
- For this reason, glitches in the gravitational wave data should be well-understood, mitigated, or removed if possible.
- Detector's characterization understanding glitches and their origins in the viewpoint of the detector and its environment.





Frequency [Hz]

Potential noise sources

Uncorrelated noise: this contribution is well-estimated using time shifts Anthropogenic noise - human activity in rooms / chambers, infrequent ground motion, noises from nearby locations not entering the room during taking data monitored by arrays of accelerometers, seismometers, and microphones Earthquakes - 0.03~0.1Hz (higher if epicenter nearby)

* Majorly R-wave most likely impact the DQ - up-converted to high-f. : monitored by a network of seismometer at the site.

Radio Frequency (RF) modulation - faults in the 45MHz electro-optic modulator driver can cause the 10-2000Hz CBC band noises : Data vetoed not analyzed

Blip transients - short transient noise btw 30-250Hz

- symmetric "teardrop" shape
- Unidentified yet
- contribute to most significant background triggers



Potential noise sources

Correlated noise: noise sources that may affect both detectors almost simultaneously - potentially imitate a GW event: not captured by time shifts for the background estimation

Potential electromagnetic noise sources

- lightning strikes, solar events, solar-wind driven noise, RF communication

- if it is very significant, witnessed with high-SNR radio receiver and magnetometers

- global strikes cause Schumann resonance but the magnetic amplitude is an order of pico-Tesla (not affected in h(t))

- nearby lightning strikes produce audio-frequency magnetic fields by lightning current (>hundreds of kA); affect h(t), detected by the magnetometers at the detectors

- Electromagnetic fields in audio-frequency band generated by human and solar sources has no effect in h(t) at the detectors.

- Electromagnetic fields outside the audio-frequency band may be concerned because LIGO can be affected by the 9 and 45MHz RF modulations.

Cosmic ray showers - no coupling between showers and h(t)





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CAGMon - Correlative Analysis Glitch Monitor

- **CAGMon** is a glitch monitoring tool between channels using correlation scores
- It is trigger-based and compute "Correlation Value" between GW and Aux. channels at a certain Trigger time
- With these values, one finds which aux. channels among many channels proposed by ETGs are statistically involved with the correlation to the glitch in GW channel
- For comparision, basic correlation algorithms are
 - Pearson's R correlation : linear correlation measure
 - Kendall's tau correlation : non-parametric linear measure by ranking
 - Maximal Information Coefficient : nonlinear measure
- Correlation Matrix (TFCMap) at a given trigger time
 - Correlation information between GW and Aux Channels
 - Linear and Nonlinear correlation information



Pearson Product-moment Correlation Coefficient

• Definition

$$\rho = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^{n} (y_i - \bar{y})^2}} \quad \text{std. of x \& y}$$



drawback for discriminating non-linearity



Interpretation of Pearson R Coefficient						
0.70~	Very strong positive correlation					
0.40~0.69	Strong positive correlation					
0.30~0.39	Moderate positive correlation					
0.20~0.29	Weak positive correlation					
-0.19~0.19	No or negligible correlation					
-0.20~-0.29	Weak negative correlation					
-0.30~-0.39	Moderate negative correlation					
-0.40~-0.69	Strong negative correlation					
-0.70~	Very strong negative correlation					

Kendall's tau Correlation Score

Definition

$$\tau = \frac{2(C-D)}{n(n-1)}$$

C: # of concordant pairs D: # of disconcordant pairs

for two random variables, x and y, - if xi > xj & yi > yj or xi < xj & yi < yj :concordant - if xi > xj & yi < yj or xi < xj & yi > yj: disconcordant tau has the value between -1 and 1.

tau	Interpretation
0.5~1.0 or -1.0~-0.5	Strong positive (negative) correlation
0.0~0.49 or -0.49~0.0	Weak positive (negative) correlation
0	No correlation



Maximal Information Coefficient

Definition MIC uses the mutual information score defined by igodol

$$I(X;Y) = \int_{Y} \int_{X} p(x,y) \log\left(\frac{p(x,y)}{p(x)p(y)}\right) dxdy$$

Maximum of Mutual information over all possible grid

$$I^*(D, x, y) = \max I(D|_G)$$

Characteristic Matrix

$$M(D)_{x,y} = \frac{I^*(D, x, y)}{\log\min\{x, y\}}$$

Maximal Information Coefficient

$$\operatorname{MIC}(D) = \max_{xy < B(n)} \{ M(D)_{x,y} \}$$

Ref) Reshef, D. N.; Reshef, Y. A.; Finucane, H. K.; Grossman, S. R.; McVean, G.; Turnbaugh, P. J.; Lander, E. S.; Mitzenmacher, M.; Sabeti, P. C. (2011). "Detecting Novel Associations in Large Data Sets". Science. **334** (6062): 1518–1524





Computing MIC: Simple Example

Probability of a box = # of data points in that box



 $p(x, y) \log \left(\frac{p(x, y)}{p(x) p(y)} \right) = 0.25 \log \left(\frac{0.25}{0.4 \times 0.5} \right) \approx 0.056$



0

-0.0336

0

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0 O

0

<u>о</u> О

0

0.0304

0

0.0134

0

+

o 0

= 0.153

Comparison: Pearson R vs. MIC



For linear relationship, MIC ~ (Pearson r)²

Pearson r=-0.4 Pearson r=-0.8 Pearson r=0.0 Pearson r=-1.0 MIC=0.1 MIC=0.2 MIC=0.6 MIC=1.0 Pearson r=-0.0 Pearson r=-1.0 Pearson r=-1.0 Pearson r=-1.0 MIC=0.3 MIC=1.0 MIC=1.0 MIC=1.0 Pearson r=-0.0 Pearson r=-0.0 Pearson r=-0.0 Pearson r=0.1 MIC=0.4 MIC=0.4 MIC=0.6 MIC=0.1 A States 100



CAGMon: Feasibility Test

Question:

At a given trigger time,

ETG finds that the trigger in GW channel has timing-coincidence with triggers in 11 auxiliary channels

Q) How many triggers in those channels are statistically related to the glitch in the **GW channel from the viewpoint of data correlation?** Furthermore, can we detect a nonlinearity for computing MIC between channels?

GPS(sec+ms) 9xxxxxxx 516.0 SNR 0.0 signf 11.006 ChName signf dt dur freq npts

```
AuxCh1 8.775 -0.073 0.003 1352.3 711.0
AuxCh2 9.483 -0.063 1.862 269.8 966.0
AuxCh3 14.982 0.031 0.85 32.7 40.0
AuxCh4 8.222 0.046 0.103 32.6 9.0
AuxCH5 29.763 0.0 1.357 34.0 46.0
AuxCh6 31.797 0.0 1.59 34.0 46.0
AuxCh7 54.079 -0.016 1.482 34.0 46.0
AuxCh8 13.848 -0.016 0.264 34.0 32.0
AuxCh9 53.882 -0.016 1.41 34.0 49.0
AuxCh10 10.752 0.015 0.331 32.0 55.0
AuxCh11 18.932 -0.016 0.746 41.2 102.0
```



Trigger-based Analysis Scheme





Omicron generates 11 aux. channel triggers in 32-4096 Hz

	Frequency Range	Pearson R	Ktau	MIC
_DAQ_32_2048	512-1024	0.43	0.09	0.13
OUT_DAQ_32_2048	512-1024	0.39	0.13	0.16
_DAQ_32_2048	512-1024	0.59	0.04	0.13
DUT_DAQ_32_2048	512-1024	0.49	0.05	0.13

select channels with corr. value > 0.25 (> mild correlation)





Trigger-based Analysis Scheme: Nonlinear Example



GPS(sec+ms) 959203889.0 812.0 SNR 0.0 signf 25.918 ChIndx ChName signf dt dur freq npts 58 L1_ISI-OMC_CONT_RY_IN1_DAQ 8.409 0.04 0.011 344.8 228.0 79 L1_OMC-QPD1_SUM_OUT_DAQ 647.327 -0.093 6.28 80.7 1893.0 84 L1_OMC-QPD3_P_OUT_DAQ 607.505 -0.046 2.983 100.2 984.0 86 L1_OMC-QPD4_P_OUT_DAQ 754.049 -0.042 2.328 195.9 982.0 145 L1_TCS-ITMX_PD_ISS_OUT_AC 8.822 -0.007 0.02 70.4 49.0

Frequency Range	Pearson R	Ktau	MIC
64-128	0.02	0.04	0.43
64-128	0.02	0.01	0.31

















Time-Series Analysis Scheme



Time Series Monitoring

ASC (Alignment Sensing Control) Channels - nonlinearity



Correlation Matrix via PCC between Auxiliary and GW Channels

GPS:1131170420_Dur:1_Stride:0.125

L1:ASC-AS_A_DC_PIT_OUT_DQ L1:ASC-AS A DC YAW OUT DQ L1:ASC-AS_A_RF36_I_PIT_OUT_DQ L1:ASC-AS_A_RF36_L_YAW_OUT_DO L1:ASC-AS_A_RF36_Q_PIT_OUT_DQ L1:ASC-AS_A_RF35_Q_YAW_OUT_DQ L1:ASC AS A RE45 I PIT OUT DO L1:ASC-AS_A_RF45_I_YAW_OUT_DQ L1:ASC-AS_A_RF45_Q_PIT_OUT_DO L1:ASC-AS_A_RF45_Q_YAW_OUT_DQ L1:ASC-AS_B_DC_PIT_OUT_DQ L1 ASC AS B DC YAW OUT DO L1:ASC-AS_B_RF36_I_PIT_OUT_DQ L1:ASC-AS_B_RF36_I_YAW_OUT_DO L1:ASC-AS_B_RF36_Q_PIT_OUT_DQ L1:ASC-AS_B_RF36_Q_YAW_OUT_DQ L1:ASC AS B RF45 I PIT OUT DO L1:ASC-AS_B_RF45_I_YAW_OUT_DQ L1:ASC-REFL_A_DC_PIT_OUT_DQ L1:ASC-REFL_A_DC_SUM_OUT_DQ L1:ASC-REFL_A_DC_YAW_OUT_DQ L1:ASC-REFL A RF45 | PIT_OUT_DO L1:ASC-REFL_A_RF45_I_YAW_OUT_DQ L1:ASC-REFL_A_RF45_O_PIT_OUT_DO





-10000

-20000

_30000 _8000

-6000 -4000 -2000 0



Frequency (Hz)



e-CAGMon Tool: Goal and Workflow start Identifying (non-)linear association with GW channel read initial config and other auxiliary channels that monitor the fetch and load t-series data environment / instrumental disturbance $\rho(x, y) = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}}$ verify data • 200,000 aux. channels in LIGO/Virgo - wind, flawness zero array padding acceleration, seismic vibration, temperature, $\tau(x,y) = \frac{(c-d)}{{}_{n}C_{2}}$ data pre-processing magnetic fields etc $MICe(x, y, \alpha, c) = \max_{ab < B(n)} \left\{ \frac{\max I^{[*]}(S, k, l)}{\log_2 \min(k, l)} \right\}$ matched Use three correlation measures: Pearson's correlation sampling freq. resampling coefficient (PCC), Kendall's tau coefficient (K-tau) / compute PCC, K-tau, Maximal Information Coefficient (MIC) MIC post-processing/ $I(x; y) = \sum_{x, y} p_{xy}(x, y) \log \frac{p_{xy}(x, y)}{p_x(x)p_y(y)}$ compute statistic generate plots / build result page end



e-CAGMon Tool: Code Test





e-CAGMon Tool: MIC Parameter Optimization

Practical issues while computing and interpreting the MIC:

- 1. How is the MIC value differently varied under the different types of background noises in data?
- 2. What is the reliable sampling rate and data size? How do they influence the computing cost?
- 3. When we handle the data from multi-channel devices with different sampling rates, does the resampling

process affect MIC results? If so, what is the best way of resampling to obtain a reliable MIC score?

• **EX)** For any two random variables, the correlation should vanish,

but MIC does not, depending upon the sample size

 \rightarrow at least 12,000 sample size recommended



e-CAGMon Tool: MIC Parameter Optimization

Functionally associated two data samples:

Association type	Function	Y. Che One C
Linear	Y(X) = X	Y(t) = F(X)
Quadratic	$Y(X) = 4(X - \frac{1}{4})^2$	
Cubic	$Y(X) = 128(X - \frac{1}{3})^3 - 48(X - \frac{1}{3})^3$	$^{2}-12(X-\frac{1}{3})$
Sinusoidal: period 1/2	$Y(X) = \sin(4\pi X)$	functional relation
Sinusoidal: period 1/4	$Y(X) = \sin(16\pi X)$	in the table
Fourth-root	$Y(X) = X^{1/4}$	n
Circular	$Y(X) = \pm \sqrt{1 - (2X - 1)^2}$	1.0
Stepwise	$Y(X) = 0 \text{ if } X \leq 1/2 \text{ or } 1 \text{ if}$	X > 1/2

- Null hypothesis: H₀
- **Alternative hypothesis:** *H*₁
- **Given parameters of** $\epsilon = (\alpha, c)$ in $MIC^{e}(X, Y, \epsilon)$

 $S_1^{5\%}(\epsilon) \equiv \{MIC^e(X(t), Y(t), \epsilon) > D_0^{95\%}(\epsilon)\}, \text{ where } D_0^{95\%}(\epsilon) \in S_0^{95\%}(\epsilon)$

which are greater than an element of the set for the null

hypothesis.

The statistical power \mathcal{P}^{MICe} defined as the ratio between the # of

true positive samples and the # of alternative samples:

 $\mathscr{P}^{MICe}(\epsilon) \equiv \frac{N[D_1^{5\%}(\epsilon)]}{N_1}, \text{ where } D_1^{5\%}(\epsilon) \in S_1^{5\%}(\epsilon).$

• Computing cost of MICe: $\mathcal{O}(c^2 B(N)^{5/2}) = \mathcal{O}(c^2 N^{5\alpha/2})$

0.8 -11 MICe/Power 0.2 0.0 seconds Ð











e-CAGMon Tool: MIC Parameter Optimization - Statistical Power





e-CAGMon Tool: MIC Parameter Optimization - Statistical Power







e-CAGMon Tool: MIC Parameter Optimization - Heatmap under AUPC





e-CAGMon Tool: MIC Parameter Optimization - Heatmap under AUPC





e-CAGMon Tool: MIC Parameter Optimization - MaxAUPC vs. MinComCost



Gaussian Noises



e-CAGMon Tool: MIC Parameter Optimization - MaxAUPC vs. MinComCost **GW** Detector Noises





e-CAGMon Tool: MIC Parameter Optimization - MaxAUPC vs. MinComCost



Gamma Noises



e-CAGMon Tool: MIC Parameter Optimization - MaxAUPC vs. MinComCost



Brownian Noises



e-CAGMon Tool: MIC Parameter Optimization

Table 2. Table of proposed optimal parameters of $\epsilon = (\alpha, c)$ for data samples (N) under various background noises. The selected parameters provide the best averaged AUPC. The relative computational cost is the relative value calculated based on the computational time of each noise with N = 512. The runtime solely depends on the selected α , N, and c, regardless of the choice of the noise type.

Noise Type	Ν	α	с	Averaged AUPC	Relative Computing Cost	Runtime (sec)
	512	0.35	7.0	5.434	1.000	$7.2779 imes 10^{-4} \pm 5.1360 imes 10^{-6}$
	1024	0.35	2.0	6.899	1.286	9.4907×10 ⁻⁴ ±5.3110×10 ⁻⁵
Gaussian Noise	2048	0.30	5.0	9.166	1.625	$1.1988 imes 10^{-3} \pm 3.5905 imes 10^{-5}$
	4096	0.25	7.0	11.465	3.069	$2.2643 imes 10^{-3} \pm 5.1274 imes 10^{-5}$
	8192	0.25	7.0	13.742	5.694	$4.2009 \times 10^{-3} \pm 1.5290 \times 10^{-5}$
	512	0.55	7.0	8.535	1.000	$1.4158 imes 10^{-2} \pm 5.4217 imes 10^{-5}$
	1024	0.50	7.0	11.092	1.040	$1.4721 \times 10^{-2} \pm 6.6200 \times 10^{-5}$
GW Detector Noise	2048	0.55	6.0	14.164	4.561	$6.4571 \times 10^{-2} \pm 5.8023 \times 10^{-4}$
	4096	0.55	6.0	16.566	10.781	$1.5264 imes 10^{-1} \pm 4.1442 imes 10^{-3}$
	8192	0.50	7.0	18.199	13.330	$1.8872 \times 10^{-1} \pm 3.7194 \times 10^{-4}$
	512	0.6	7.0	16.752	1.000	$2.9842{\times}10^{-2}\pm8.6986{\times}10^{-5}$
	1024	0.50	7.0	18.234	0.493	$1.4721 \times 10^{-2} \pm 6.6200 \times 10^{-5}$
Gamma Noise	2048	0.45	7.0	18.955	0.531	$1.5858 \times 10^{-2} \pm 9.5062 \times 10^{-5}$
	4096	0.40	7.0	19.346	0.466	$1.3906 \times 10^{-2} \pm 4.6712 \times 10^{-5}$
	8192	0.40	7.0	19.614	1.069	$3.1898 \times 10^{-2} \pm 4.4971 \times 10^{-5}$
	512	0.60	6.0	13.320	1.000	$2.2202{\times}10^{-2}\pm5.4714{\times}10^{-5}$
Brownian Noise	1024	0.55	7.0	15.736	1.613	$3.5811 imes 10^{-2} \pm 2.3834 imes 10^{-3}$
	2048	0.50	6.0	17.495	1.252	$2.7804 imes 10^{-2} \pm 1.0220 imes 10^{-4}$
	4096	0.50	5.0	18.652	2.014	$4.4709 imes 10^{-2} \pm 8.6971 imes 10^{-5}$
	8192	0.50	5.0	19.367	4.886	$1.0848 \times 10^{-1} \pm 2.1029 \times 10^{-3}$



e-CAGMon Tool: MIC Parameter Optimization

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Application to GW Data I : Lightning Strokes PRD 106, 042010 (2022) Coefficients Trend K1:PEM-MAG_BS_BOOTH_BS_Z_OUT_DQ (stride: 2.0 seconds) Gifu ← → Toyama MICe --- median - PCC --- median - Kendall --- median 0.16









Event time(GPS)	Associated auxiliary channels ^a	MICe	$Med(MICe)^{b} (10^{-2})$	ρ	$\mathrm{Med}(\rho)(10^{-2})$	τ	$\operatorname{Med}(\tau)(10^{-2})$
	K1:PEM ^c -MAG_BS_BOOTH_BS_Z_OUT_DQ	0.079	2.210	0.021	0.212	0.022	0.172
March 22, 2020	K1:PEM-MAG_BS_BOOTH_BS_Y_OUT_DQ	0.050	2.210	0.052	0.250	0.015	0.275
02:38:39-41UTC	K1:PEM-MAG_BS_BOOTH_BS_X_OUT_DQ	0.026	2.188	0.040	0.266	0.001	0.197
(1268879937.38	K1:PEM-MAG_EXC_BOOTH_EXC_X_OUT_DQ	0.021	1.499	0.064	0.423	0.047	0.521
-1268879939.38)	K1:PEM-MAG_EYC_BOOTH_EYC_Z_OUT_DQ	0.069	2.309	0.1 41	0.709	0.045	0.474
	K1:PEM-MAG_SR_BOOTH_SR_Z_OUT_DQ	0.022	2.271	0.052	1.595	0.040	1.458

Application to GW Data II : Air Compressor Noises

- Correlated peaks with a harmonic f=26.5Hz in 2.58hours/day
- New discovery in KAGRA should be handled for noise mitigation



34

Application to GW Data III : Gravity Gradient Noise from Winds

- Strong winds found in day time (9AM-7PM) between valley of IKENO Mt.
- **PEM MIC channels are** affected by this wind effects in the underground facilities
- **Strong non-linear** correlations between MIC-**GW channels**



PRD 106, 042010 (2022)





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PRD 106, 042010 (2022)













Application to GW Data III : Scenario & Simulation





Mitigation of Low-Frequency Noise by using Bandgap Engineering

D. J. Griffiths, 'Introduction to Quantum Mechanics'

Let us consider a periodic potential in one-dimensional space: V(x) = V(x + a)

then, **Bloch's theorem**: the solution to the Schrödinger's eqn,

$$-\frac{\hbar^2}{2m}\frac{d^2\psi}{dx^2} + V(x)\psi = E\psi$$

can be taken to satisfy the condition: $\psi(x + a) = e^{iKa}\psi(x)$ for some constant *K*

• At x = 0, ψ must be continuous, then: $1)B = e^{-iKa}[A\sin(ka) + B\cos(ka)]$ And for the derivatives, $\lim_{\epsilon \to 0} \left(\left. \frac{d\psi}{dx} \right|_{\pm \epsilon} - \frac{d\psi}{dx} \right|_{\epsilon} \right) = \frac{2m\alpha}{\hbar^2} \psi(0)$ 2) $\rightarrow kA - e^{-iKa}[kA\cos(ka) - kB\sin(ka)] = \frac{2m\alpha}{k^2}B$ Combining 1) and 2) gives: $\cos Ka = \cos ka + \frac{m\alpha}{\hbar^2 k} \sin ka$ Let $z \equiv kz$, $\beta \equiv \frac{m\alpha a}{\hbar^2}$, then $f(z) \equiv \cos(z) + \beta \frac{\sin(z)}{2}$ 38 •





Mitigation of Low-Frequency Noise by using Bandgap Engineering

D. J. Griffiths, 'Introduction to Quantum Mechanics'

Let us consider a periodic potential in one-dimensional space: V(x) = V(x + a)

then, Bloch's theorem: the solution to the Schrödinger's eqn,

$$-\frac{\hbar^2}{2m}\frac{d^2\psi}{dx^2} + V(x)\psi = E\psi$$

can be taken to satisfy the condition: $\psi(x + a) = e^{iKa}\psi(x)$ for some constant *K*





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Eigen value problem on IBZ: 2D bandgap structure



Eigen value problem on IBZ: 2D bandgap structure

Eigen value problem on IBZ: 3D bandgap structure m В А 0 m -20 m 0 -10 0 10 m -20 -30 Soil 20 y Z x structural steel beams -20 m D 5 • • • m z=0 z=-3 z=-6 z=-9 -10 z=-15 -0 -20 ź→x

12 beams

Eigen value problem on IBZ: 3D bandgap structure

Bandgap Diagram

Eigen value problem on IBZ: 3D bandgap structure

Eigen value problem on IBZ: 3D bandgap structure

45

Eigen value problem on IBZ: Realistic Case of KAGRA Detector

С

Solid Mechanics:

$$\rho \frac{\partial^2 \mathbf{u}}{\partial t^2} = \mathbf{F}_v - \nabla_X \cdot \mathbf{P}^T$$

P is the 1st Piola-Kirchhoff stress tensor **F** is the deformation gradient

Inhomogeneous Helmholtz eq: ${\bullet}$

$$\frac{1}{\rho c^2} \frac{\partial^2 p}{\partial t^2} + \nabla \cdot \left(-\frac{1}{\rho} (\nabla p - \mathbf{s}_d) \right)$$

Boundary condition on solid & air surface

$$\mathbf{n} \cdot \left(-\frac{1}{\rho} (\nabla p - \mathbf{s}_d) \right) = -\mathbf{n} \cdot \ddot{\mathbf{u}}, \ \mathbf{F}_A$$

Eigen value problem on IBZ: Realistic Case of KAGRA Detector Seismic-Acoustic Multiphysics: Newtonian noise (w/ Metamaterial) Seismic-Acoustic Multiphysics: Newtonian noise (w/o Metamaterial) В Α * 0.1 Hz * 0.1 Hz 60 100 -•-1 Hz → 1 Hz 50 Microphone Ch. 🔶 3 Hz ← 3 Hz 80 40 - 5.5 Hz 5.5 Hz 30 el (dB) (dB) Coefficients Trend K1:PEM-MIC_IXC_FIE 🔶 10 Hz 🗕 10 Hz 60 20 --- median --- PCC 0.16 10 0.5 0 0 0.14 -10 0.12 ₾ 0.4 Valı -20 0.10 -30 0.3 ā ā 0.08 -40 σ σ 5 unos 0.06 -50 0.2 -20 -60 0.04 Total **Total** -70 -80 -60 -90 Active Active 10 -100 -80 Time [hours] from 2020-04-1 -110 15 15 10 20 10 20 0 5 Coefficients Trend K1:VIS-BS_TM_OPLEV PCC median 3.0 0.065 **★ 0.1** Hz × 0.1 Hz 7.5 2.5 0.06 -**→** 1 Hz 🔶 3 Hz → 3 Hz Value (ed) 0.055 0.05 WB 0.045 2.0 RMS (Pa) 0.6 - 5.5 Hz - 5.5 Hz 6.5 cient 🔶 10 Hz 🔶 10 Hz 5.5 1.0 ure. 0.04 0.5 ន 4.5 0.035 b 0.0 0.03 Active Ľ, 0 10 0.025 Time [hours] from 2020-04-1 2.5 0.02 1Ū **Vibration Isolation Ch.** 0.015 <u>1</u> 11 1.5 0.01

0.5

20

15

10

y-coordinate (m)

5

0.005

0 - 1000

Seismic Ch.

median

Wind meter

Conclusions

- CAGMon Tool presents a reliable correlation index between two channels
- In particular, it provides a non-linear correlation measure by computing MIC
- The optimal parameter selection method of MIC was provided empirically by testing some datasets under various noise backgrounds (Jung et al., PTEP2022)
- We discovered some interesting correlations by applying this tool to GW Data: (Jung et al., PRD2022)
 1) Confirmed magnetic field transients from lightning strokes
 2) Found new periodic noises originating from air compressors
 3) Found glimpse of gravity gradient and acoustic noises from strong winds, in particular, dominant in the Y-arm tunnel
- This tool can be utilized for identifying and understanding the association and causal relationship between the GW channel and the environmental channels of GW detectors.
- The noise found in the KAGRA wind meter and PEM channels can be removed by using bandgap engineering, which can be verified by the multiphysics simulation at a certain condition. This method can be applied to the next-generation GW detector's noise mitigation. (JJOH, PTEP2023)

Conclusions

Prevent a sudden lockloss of the interferometer caused by

- nearby earthquakes ullet
- anthropogenic activities (traffic etc) lacksquare
- collective up-converting effect of gravity gradient noises lacksquare
- this will enhancing the DataQuality by reducing low frequency noises
 - no lockloss by transient seismic vibrations (continuous observation)

Cosmic Explorer, Einstein Telescope etc

