Gravitational wave data analysis

Lecture I



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• I won't talk about general relativity

- I won't talk about technical details of detectors
- I won't go through all the techniques for different sources

I will go trough:

- Data conditioning techniques
- Optimal detection filter
- Transient signal search
- Application of Machine Learning techniques to GW



Introduction to GW



(1)

BY

A. EINSTEIN and N. ROSEN.

ABSTRACT.

The rigrous solution for cylindrical gravitational waves in given. For the convenience of the reader the theory of gravitational waves and their production, already known in principle, is given in the first part of this paper. After encountering relationships which cast doubt on the existence of *rigrous* solutions for undulatory gravitational fields, we investigate *rigrous* possible of cylindrical gravitational waves. It turns out that rigrouss solutions exist and that the problem reduces to the usual cylindrical waves in exclidence space.

I. APPROXIMATE SOLUTION OF THE PROBLEM OF PLANE WAVES AND THE PRODUCTION OF GRAVITATIONAL WAVES.

It is well known that the approximate method of integration of the gravitational equations of the general relativity theory leads to the existence of gravitational waves. The method used is as follows: We start with the equations

 $R_{\mu\nu} - \frac{1}{2}g_{\mu\nu}R = -T_{\mu\nu}$

We consider that the $g_{\mu\nu}$ are replaced by the expressions

credits F. Di Renzo



Free propagation along "z-axis" in vacuum ($T_{\mu\nu} = 0$):

$$\Box h_{\mu\nu} = 0 \implies h_{\mu\nu}(t, z) = h_{\mu\nu}e^{i(kz - \omega t)} \quad \text{with} \quad \omega/c = k$$

Gravitational Waves (1916)



Credit:Teviet Creighton

Solution The GW search: a long history





The detector





ITF detector and their sensitivity







GW astrophysical sources





Why more than 1 detector?

Source localization using only timing for a two-site network yields an **annulus** on the sky.

For three detectors, the time delays restrict the source to two sky regions which are mirror images with respect to the plane passing through the three sites.

With four or more detectors, timing information alone is sufficient to localize to a single sky region, $<10 \text{ deg}^2$ for some signals.



arXiv:1304.0670

- 2 detector → 100 -1000 deg²
- I 3 detector → 10 100 deg²
- 4 detector \rightarrow < 10 deg²



The O-run timeline

The detector strain sensitivity is the minimum *detectable* value of the strain produced by an incoming GW:

 \Rightarrow It is determined by the **detector noise**.

BNS inspiral range: the distance, averaged over GW polarizations and directions in the sky, at which a single detector can observe with matched-filter Signal-to-noise Ratio (SNR) of 8 the inspiral of two neutron stars.



https://observing.docs.ligo.org/plan/





GRAVITATIONAL WAVE MERGER DETECTIONS → SINCE 2015

OBSERVING RUN ——I	01 2015-	2016		02 2016-2017								03a+b 2019-2020	
		23 14 36 0W151012	14 27 21 0W151224	31 - 20 49 0W179184	1) F.a. 18 DW170408	10 34 80 cw170f2t	31 - 24 56 gwr/2080e	11 25 53 6W370814	1.5 1.3 12.8 owtroarr	от 19 60 синтрата	40 29 65 DW179623	105 GW179463	26 18 41 GW179568
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	12 7.7 19 00197216	31 1.2 32 600191219	45 25 76 6W191222	82 000191230	v 1.9 11 sw200105	-34 78 61 GW200112	5.9 1A 7.2 DH/200115	42 33 71 6W200128	ан ал 60 бикаролан	10 7.3 17 6w200202	30 27 63 GW200208	51 12 61 owrsecae	14 27 60 600205260
	24 2.8 27 6W200210	51 50 78 GW200716	11 78 62 64700219	141 www.coszan	29 28 64 GHI20220	40 33 69 GW206226	19 14 32 69/10115	38 20 56 cw105313	28 15 42 6W210104	34 14 47 ewiteties	34 28 59 69/100111	13 7.8 20 6w700314	34 14 53 6w201112
KEY													
BLACK HOLE			NEUTRON STAR				Note that the mass which is why the f	s estimates shown here do n Inal mass is scenetimes larg	at include uncertainties, in than the sam of the		14		KIC

PRIMARY MASS FINAL MASS

UNCERTAIN OBJECT SECONDARY MASS DATE

UNITS ARE SOLAR MASSES 1 SOLAR MASS = 1.989 x 10³⁰kg than the primary plus the secondary mass.

The events listed here pass one of two thresholds for detection. They either have a probability of being astrophysical of at least 52%, or they page a false plane rate threshold of less than 1 per 3 years.





Image credit: Carl Knox,Hannah Middleton, Federica Grigoletto, LVK



GW170817: the first multi-messenger event



Abbott et al. 2017 and refs. therein





https://gracedb.ligo.org/superevents/public/O4/

GW Detections

O4 Significant Detection Candidates: **81** (92 Total - 11 Retracted) O4 Low Significance Detection Candidates: **1610** (Total)





GW detector data

• Time series sequences... noisy time series with low amplitude GW signal buried in



Time series

- A time series x[n] is a sequence of data points measuring a physical quantity at successive times spaced at uniform time intervals.
- We say that x[n] is a stationary process, if its statistical description does not depend on n.







Signal processing utilities

Encapsulating the data information



Autocorrelation function

Definition

Given a discrete random process x[n] we define the *mean* as

$$\mathscr{E}\{x[n]\} = \mu_x$$

Definition

The autocorrelation function (ACF)

$$r_{xx}[k] = \mathscr{E}\{x^*[n]x[n+k]\}$$



Autocovariance function

Definition

The autocovariance function is defined as

$$c_{xx}[k] = \mathscr{E}\{(x^*[n] - \mu_x)(x[n+k] - \mu_x)\} = r_{xx}[k] - |\mu_x|^2$$

Similar definition for cross-correlation bewteen x[n] and y[n]. Some properties of ACF:

$$r_{xx}[0] \ge |r_{xx}[k]|$$
 $r_{xx}[-k] = r^*_{xx}[k]$ $r_{xy}[-k] = r^*_{yx}[k]$



Power Spectral Density

Definition

We define the *Power Spectral Density* (PSD)

$$P_{xx}(f) = \sum_{k=-\infty}^{k=\infty} r_{xx}[k] \exp(-i2\pi fk) \quad P_{xy}(f) = \sum_{k=-\infty}^{k=\infty} r_{xy}[k] \exp(-i2\pi fk)$$

This relationship between PSD and ACF is often known as Wiener-Khinchin theorem.

The PSD describe the content in frequency in power of the signal x[n]. In the following we will refer to $P_{xx}(f)$ as PSD The PSD is periodic with period 1. The frequency interval $-1/2 \le f \le 1/2$ will be considered as the fundamental period. The ACF is the inverse Fourier transform of the PSD and hence

$$r_{xx}[0] = \int_{-1/2}^{1/2} P_{xx}(f) df$$





One particular process is the discrete white noise. It si defined as a process having as ACF

$$r_{xx}[k] = \sigma_x^2 \delta[k]$$

where $\delta[k]$ is the delta function.

The PSD of such a process is a flat function with the same value for all the frequency f



$$P_{xx}(f) = \sigma_x^2$$





Gaussian random process

A Gaussian sthocastic process is one for which each set $\{x[n_0], x[n_1] \dots x[n_{N-1}]\}$ is distributed as a multivariate Gaussian PDF. If we assume that the process is stationary with zero-mean, then the covariance matrix is the autocorrelation matrix \mathbf{r}_{xx}

$$\mathbf{r}_{xx} = \begin{bmatrix} r_{xx}[0] & r_{xx}[-1] & \dots & r_{xx}[-(N-1)] \\ r_{xx}[1] & r_{xx}[0] & \dots & r_{xx}[-(N-2)] \\ \vdots & \vdots & \ddots & \vdots \\ r_{xx}[N-1] & r_{xx}[N-2] & \dots & r_{xx}[0] \end{bmatrix}$$
(1)
$$r_{xx}[k] = \mathscr{E}\{x^*[n]x[n+k]\}.$$
(2)

We can write the probability density function of a real random gaussian process a

$$P[\mathbf{x}] = \frac{1}{(2\pi)^{N/2} |\mathbf{r}_{xx}|^{1/2}} e^{\mathbf{x} T \mathbf{r}_{xx}^{-1} \mathbf{x}}.$$
 (3)



White random Gaussian process

It is a process x[n] with mean zero and variance σ_x^2 for which

$$x[n] \sim N(0, \sigma_x^2) \qquad -\infty < n < \infty$$

$$r_{xx}[m-n] = \mathscr{E}(x[n]x[m])) = 0 \qquad m \neq n$$

where $x \sim N(\mu_x, \sigma_x^2)$ means that x[n] is Gaussian distributed with a probability density function

$$p(x) = \frac{1}{\sqrt{2\pi\sigma_x}} \exp\left[-\frac{1}{2}\left(\frac{x-\mu_x}{\sigma_x}\right)^2\right] \qquad -\infty < x < \infty$$



Gaussian noise distribution

The distribution is characterized by its bell-shaped curve, which is symmetrical around the mean value. The mean, median, and mode of the distribution are all equal, and the standard deviation determines the width of the curve.







Gravitational Wave signal detection







GW Signal Detection and Matched Filter for known waveforms

- Defining the problem
- The Neyman Pearson Criteria
- The Matched Filter

Switch to pdf slides...:)



Optimal Filter is Matched Filter, if the noise minimum is gaussian distributed

Maximizing the likelihood



Noise power spectral density

Look for maxima of $|\rho(t)|$ above some threshold \rightarrow trigger





- pyCBC (Usman et al, 2015)
- MBTA (Adams et al. 2015)
- gstlal-SVD (Cannon et al. 2012)





How we detect transient signals: modeled search





CBC template generation



$$h(f) = A(f)e^{i\Phi(f)}$$

$$\Phi(f) = \sum_{k=1}^{7} (\varphi_k + \varphi_k^l \log(f))f^{(5-k)/3} + \sum_{i \neq k} \varphi_i f^i$$

$$\varphi_j \equiv \varphi_j(m_1, m_2, \vec{s}_1, \vec{s}_2) \ \forall j = k, i$$



CBC template generation





How many templates?

To cover in efficient way the parameters space, we build a templates bank requiring that the signal can be detected with a maximum loss of 3% of its SNR





LVC Phys. Rev. X 6 (2016)

Parameter estimation

 $p(\theta|d,H) = \frac{p(\theta|H)p(d|\theta,H)}{p(d|H)}.$

- MCMC and Nested Sampling
 - MCMC Random steps are taken in parameter space, according to a proposal distribution, and accepted or rejected according to the Metropolis-Hastings algorithm.
 - Nested sampling can also compute evidences for model selection.

Parameter estimation for compact binaries with ground-based gravitational-wave observations using the LALInference software library



LVC (PRL:116, 241102)

J. Veitch et al. Phys. Rev. D 91, 042003

Data mapping, preserving the info

01	Time-domain	• Time-series at the output of the detector (be careful with the sampling theorem)
02	Frequency-domain	 Fourier transform Useful for stationary data Useful for persistent signals It captures the global frequency information
03	Time-frequency domain	 Short Fourier Transform Useful for not stationary data Useful for transient signals
04	Others	 Wavelet decomposition (useful for multiresolution analysis) Q-Transform (useful for transient) Hough-transform (useful for lines)



Time-Frequency domain: STFT

The short time Fourier transform (STFT) function is simply the Fourier transform operating on a small section of the data. Here a moving window is applied to the signal and the fourier transform is applied to the signal within the window as the window is moved.

$$STFT\{x(t)\} = X(\tau, f) = \int_{-\infty}^{\infty} x(t)g(t-\tau)\exp(-2i\pi ft)dt$$





Spectrogram

To have easy access to the information of the STFT we can plot the spectrogram. It is defined as

 $\textit{Spectrogram}(\tau, f) = |X(\tau, f)|^2$

So we will have a bidimensional plot where on x-axis usually is plotted the time, on y-axis the frequency, while the color of the map is the the amplitude of a particular frequency at a particular time.





Wavelet decomposition of time series

The wavelet transform replaces the Fourier transform sinusoidal waves by a family generated by translations and dilations of a window called a wavelet.



$$W\!f(a,b)=< f,\psi_{a,b}>=\int_{-\infty}^{+\infty}f(t)rac{1}{\sqrt{b}}\psi^*(rac{t-a}{b}) dt$$

The scale of the wavelet is determined by the parameter **b**.

- When **b** is decreased, the wavelet appears more compressed, allowing it to capture high-frequency information.
- Increasing the value of **b** elongates the wavelet, enabling it to capture low-frequency information.

The location of the wavelet is determined by the parameter **a**.

- If we decrease the value of **a**, the wavelet will be shifted to the left, whereas an increase in **a** will shift it to the right.
- Note that the location of the wavelet is crucial because, unlike waves, wavelets are only non-zero within a short interval.

② Data representations





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Time-frequency-domain



Wavelet-domain



Spectrogram of V1:spectro_LSC_DARM_300_100_0_0 : start=1189644747.000000 (Sun Sep 17 00:52:09 2017 UTC)



Data preprocessing



Spectrogram of V1:spectro_LSC_PRCL_300_100_0_0 : start=1189731268.000000 (Mon Sep 18 00:54:10 2017 UTC)









We can do in frequency domain estimating the PSD









Signals in whitened data



Not Whitened

Whitened



39

Whitening in time domain

We need parametric modeling

It can be useful for on-line application

It can be implemented for non stationary noise

It can catch the autocorrelation function to larger lags





AR parametric modeling

An AutoRegressive process is governed by this relation

$$x[n] = -\sum_{k=1}^{p} a[k]x[n-k] + w[n],$$

and its PSD for a process of order P is given by

$$P_{AR}(f) = \frac{\sigma^2}{|1 + \sum_{k=1}^{P} a_k \exp(-i2\pi kf)|^2}$$

Kay S 1988 Modern spectral estimation: Theory and Application Prentice Hall Englewood Cliffs



Advantages of AR modeling

 Stable and causal filter: same solution of linear predictor filter

$$\hat{x}[n] = \sum_{k=1}^{P} w_k x[n-k]$$

$$e[n] = x[n] - \hat{x}[n]$$
$$\varepsilon_{min} = r_{xx}[0] - \sum_{k=1}^{P} w_k r_{xx}[-k],$$

$$w_k = -a_k$$

 $\varepsilon_{min} = \sigma^2$

Wiener-Hopf equations





PSD AR(P) Fit



Cuoco et al. Class.Quant.Grav. 18 (2001) 1727-1752 and Cuoco et al.Phys.Rev.D64:122002,2001



Control The effect of whitening







Searches for unmodeled signals

What we do for signals with unknown waveforms



Computer simulation of gravitational waves emitted by a supernova. Credit: J Powell / B Mueller





- Strategy: look for excess power in single detector or coherent/coincident in network data
- Example cWB

(https://gwburst.gitlab.io/)

- Time-domain data preprocessed
- Wavelet decomposition
- Event reconstruction

Burst search

How we detect transient signals: un-modeled search

Coherent WaveBurst was used in the first direct detection of gravitational waves (GW150914) by LIGO and is used in the ongoing analyses on LIGO and Virgo data.



Time-Frequency maps of GW150914: Livingston data (left), Hanford data (right) First screenshot of GW150914 event

Phys. Rev. D 93, 042004 (2016) Class.Quant.Grav.25:114029,2008



Coherent WaveBurst

Excess power are selected from a set of wavelet time-frequency maps Data from both detector are combined together

Triggers are analyzed coherently to estimate signal waveform, wave polarization, source location, using the constrained likelihood method



Selects the best fit waveform which corresponds to the maximum likelihood statistic over a 200000 sky positions



The event are ranked using a variable η_c

 E_c > Normalized coherent energy between the two detectors E_n > normalized noise energy derived by subtracting the reconstructed signal from the data

$$=\sqrt{\frac{2E_c}{(1+E_n/E_c)}}$$

 η_c





Coherent WaveBurst

- End-to-end multi-detector coherent pipeline
 - o construct coherent statistics for detection and rejection of artifacts
 - performs search over the entire sky
 - estimates background with time shifts





Time-Frequency distribution by SNR slice

V1:Hrec_hoft_16384Hz: Time frequency glitchgram





1000 million and a second and a

Section From a glitch-gram to Event selection

- Select the trigger in coincidence among the detector \Leftrightarrow
- Perform data quality check
- Apply veto procedure
- Define the coincidence level of detection





PhysRevLett.116.061102

 $> 5.1\sigma$

 $> 5.1\sigma$

GW150914

4σ5.1σ

20

Low latency analysis



From few minutes to 30 mi

Pipelines running	Pipelines assess	Data Quality evaluated	Initial alert released on				
real time	the significance	autonomously for initial	order of 1 minute; Notice on				
•	of candidate	alert	order of 10 minutes				
 4 low-latency CBC search pipelines: GstLAL, MBTAOnline, PyCBC Live, and SPIIR I GW burst search pipeline: cWB (Coherent WaveBurst) 	 False Alarm Rate (FAR) based on empirically measured noise properties The initial searches focus on detection, not on estimating the parameters of the source 	GCN notice	Root IVORN Role Who Date Author WhereWhen What GraceID Packet Type Notice Type FAR Sky Map Group Pipeline CentralFreq Duration Fluence BNS, NSBH, BBH, Noise HasNS, HasRemnant	<pre>ivo://nasa.gsfc.gcn/LVC#[{T,M}]S {Preliminary,Initial,Update,Prel {observation,test} Time sent (UTC, ISO-8601), e.g. 201 LIGO Scientific Collaboration an Time of signal (UTC, ISO-8601), e.g. GraceDb ID: [{T,M}]SYYMMDabc. Ex GCN Notice type: {Preliminary,Init Numerical equivalent of GCN Notice Estimated false alarm rate in Hz URL of HEALPix FITS localization f CBC {GstLal,MGTAOnLine,PyCBC,SPIIR} N/A Probability that the source is a BNS,NSBH,NSBH merger, or terrestrial (i.e., noise) respectively Probability, under the assumption that the source is on rose, that at least one of the compact objects was a neutron star, and that the system ejected a nonzero amount of neutron star matter, respectively.</pre>	YYMMDDabc-{1,2,3}- iminary-Retraction} 8-11-01T22:34:49 d Virgo Collaboration 2018-11-01T22:22:46.654437 ample: MS181101abc ttal./update} ttal./update} ttal./update ttal./upd		



GraceDB — Gravitational-Wave Candidate Event Database

HOME PUBLIC ALERTS SEARCH LATEST DOCUMENTATION

LIGO/Virgo O3 Public Alerts

Detection candidates: 35

SORT: EVENT ID (A-Z)

Event ID	Possible Source (Probability)	UTC	GCN	Location	FAR	Comments
<u>5191117j</u>	NSBH (>99%)	Nov. 17, 2019 06:08:22 UTC	<u>GCN Circulars</u> <u>Notices VOE</u>		1 per 2.8433e+10 years	RETRACTED
<u>5191110af</u>		Nov. 10, 2019 23:06:44 UTC	<u>GCN Circulars</u> <u>Notices VOE</u>	No public skymap image found.	1 per 12.681 years	RETRACTED
<u>5191110x</u>	MassGap (>99%)	Nov. 10, 2019 18:08:42 UTC	<u>GCN Circulars</u> <u>Notices VOE</u>		1 per 1081.7 years	RETRACTED
<u>5191109d</u>	BBH (>99%)	Nov. 9, 2019 01:07:17 UTC	<u>GCN Circulars</u> <u>Notices VOE</u>		1 per 2.062e+05 years	
<u>5191105e</u>	BBH (95%), Terrestrial (5%)	Nov. 5, 2019 14:35:21 UTC	GCN Circulars Notices VOE		1 per 1.3881 years	
<u>5190930t</u>	NSBH (74%), Terrestrial (26%)	Sept. 30, 2019 14:34:07 UTC	<u>GCN Circulars</u> <u>Notices VOE</u>		1 per 2.0536 years	

https://gracedb.ligo.org/superevents/public/03/





Time since gravitational-wave signal







Can Machine learning help?

