"Deep Images of the Galactic Center with GRAVITY" GRAVITY Collaboration (2021)

20.04.2023

Interferometry - Young's experiment





Interferometer output



We use two independent correlators (beam combiners) and define the Complex Visibility -> V(u,v)

real and imaginary parts -> information about the amplitude and phase

u,v - E-W and N-S spatial frequencies [wavelengths]











We have the Complex Visibility V(u,v) - how do we obtain the image?

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From the Citter-Zernike theorem: V(u,v) is a 2D Fourier transform of the image:

 $T(I,m)=F^{-1}[V(u,v)]$ - the sky brightness distribution

where I and m are E-W and N-S angles in the tangent plane [radians]



























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Deep Images of the Galactic Center with GRAVITY

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 $\mathsf{GRAVITY}$ - testing general relativity by measuring the orbits of stars passing near the central BH

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Solution -> search for fainter stars

VLTI GRAVITY observations



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Model fitting is a powerful method to extract the desired information, but we do not know where the stars may be present

Common solution: the CLEAN algorithm

This is possible thanks to the fact that $F(I_1+I_2)=F(I_1)+F(I_2)$

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Problem: CLEAN depends on the linearity and invertibility of the Fourier transform - this is not true for the GRAVITY observations due to the instrumental effects

Solution: Bayesian forward modeling -> non-linear and non-invertible terms can be handled straightforwardly

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- descent minimization, but its limited to convex likelihood and prior formulations

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= new code -> GRAVITY-RESOLVE (G^R)
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- 256^2 pixels limit imposed by the angular resolution
- All pixels in the image are statistically independent
- Vast majority of pixels will be dark.

$$\mathcal{P}\left(I_{\rm Img}\right) = \prod_{i}^{N_{\rm pix}} \frac{q^{\alpha}}{\Gamma\left(\alpha\right)} I_{\rm Img}(i)^{-\alpha-1} \exp\left[\frac{-q}{I_{\rm Img}(i)}\right].$$
 (2)

- i pixels in the image
- Γ Gamma function

q and α - user defined variables, set to reflect the fact that max(l)=1 and the image may contain 1 star to the order of magnitude

Gamma prior is conjugate to Poisson likelihood

• Some known stars separately added by adding a prior on their expected positions -> helps convergence

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- Spectral distribution of Sgr A is approximated with two powerlaws

- Fiber damping
- Optical aberrations
- Bandwidth smearing



Fixes time-variable instrumental effects (e.g. atmospheric conditions)

Self calibration by using closure phases formed over a triangle of telescopes

$$\phi_{i,j,k} = \arg \left(v_{i,j} \, v_{j,k} \, v_{k,i} \right) \,,$$

Thanks to this we can estimate errors

Number of dimensions

 $d = 256^2$ image of faint sources $+ 2 \times N_{exp}$ Sgr A* light curves+ 2Sgr A* position $+ 3 \times N_{PS}$ point sources position and flux $+ 6 \times N_{exp}$ amplitude self-calibration+ 2spectral indices

 $\sim 7 \times 10^4$.

A high number of dimensions -> very expensive calculation of posterior

Solution: Metric Gaussian Variational Inference

Covariance measured using the Fisher information metric

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Fisher information metric = a covariance of gradient of the probability function as function of random variables



Multivariate Gaussian distribution

$$G(\boldsymbol{\xi}|\bar{\boldsymbol{\xi}}, \boldsymbol{\Xi})$$

 ξ - standardized coordinates for each degree of freedom - prior is given by a unit Gaussian with zero mean

 Ξ - covariance - first estimated using the Fisher metric

The real mean $\bar{\xi}$ and covariance Ξ are found interatively

How well our posterior surrogate fits the real posterior?

$\mathsf{D}_{\mathcal{K}\mathcal{L}}(\mathsf{P}||\mathsf{Q}) = \int_{x} p(x) * \log(p(x)/q(x)) dx$



$$\bar{\boldsymbol{\xi}}_{i+1} = \min_{\bar{\boldsymbol{\xi}}} \int \mathrm{d}\boldsymbol{\xi} \, \boldsymbol{\mathcal{G}}\left(\boldsymbol{\xi} | \, \bar{\boldsymbol{\xi}}, \Xi_i\right) \ln \left[\frac{\boldsymbol{\mathcal{G}}\left(\boldsymbol{\xi} | \, \bar{\boldsymbol{\xi}}, \Xi_i\right)}{\mathcal{P}\left(\boldsymbol{\xi} | \, \boldsymbol{d}\right)} \right].$$

How do we calculate this if we don't know the real posterior?



$\mathcal{P}(I|d) \propto \mathcal{P}(d|I) \mathcal{P}(I)$

The evidence term (marginal) $\mathsf{P}(\mathsf{d})$ incomputable, but luckily it is invariant

$$\bar{\boldsymbol{\xi}}_{i+1} = \min_{\bar{\boldsymbol{\xi}}} \int \mathrm{d}\boldsymbol{\xi} \, \boldsymbol{\mathcal{G}}\left(\boldsymbol{\xi} | \, \bar{\boldsymbol{\xi}}, \Xi_i\right) \ln \left[\frac{\boldsymbol{\mathcal{G}}\left(\boldsymbol{\xi} | \, \bar{\boldsymbol{\xi}}, \Xi_i\right)}{\mathcal{P}\left(\boldsymbol{\xi} | \, \boldsymbol{d}\right)} \right].$$

We switch between estimating $\bar{\xi}$ using the Kullback-Leibler divergence and covariance Ξ using the Fisher metric

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This integral is calculated by calculating a mean of random sample from the approximate posterior distribution-> we can sample multi-modal posterior distributions and avoid problems with the convergence by switching the seed

They calculated ten independent imaging runs -> good enough to capture the dominant modes of the posterior, but not enough to estimate the relative weights reliably

Instead, consistency between different paintings was used as a sanity check

The sensitivity and selection of arbitrary parameters tested on a mock data set $% \left({{{\mathbf{r}}_{\mathbf{r}}}_{\mathbf{r}}} \right)$



Results



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Results from the CLEAN algorithm



GRAVITY-RESOLVE (G^R) has a problem with fast moving sources In GRAVITY-RESOLVE (G^R) error bars had to be scaled by hand and by trial-and-error