

Phase Calibration/Correction for ALMA

B. Nikolic

Cavendish Laboratory, University of Cambridge

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**UNIVERSITY OF
CAMBRIDGE**



Outline

- 1 Phase errors in the mm/sub-mm
- 2 ALMA Phase Correction
 - Fast-switching
- 3 WVR Phase Correction
- 4 Algorithms!

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Causes of Phase Errors at mm/sub-mm wavelengths

Instrumental

Possible sources:

- Electronic
- Mechanical/optical

Timescales:

- Hopefully from about 30 minutes to very long timescales (e.g., diurnal cycle)

Mitigation:

- Stable designs
- Phase calibration using astronomical sources

Causes of Phase Errors at mm/sub-mm wavelengths

Atmospheric (tropospheric)

Two sources (both only important in first \sim km of atmosphere):

- Fluctuating quantity of water-vapour along line of sight ('wet')
- Fluctuating temperature of dry air along line of sight ('dry')

Two characteristic timescales:

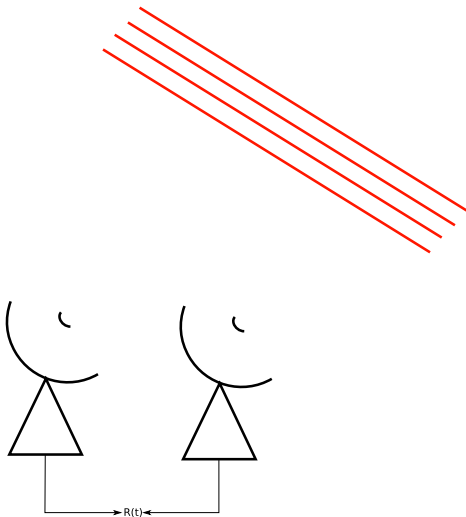
- Inner: Set by the smoothing effect of the $D = 12$ m telescope beam:

$$\approx D/\nu \sim 1 \text{ s}$$

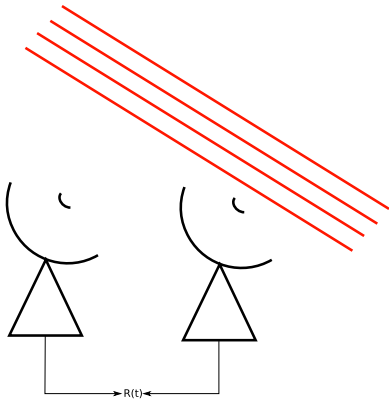
- Outer: Determined by the baseline length B :

$$5 \text{ s} \lesssim B/\nu \lesssim 20 \text{ minutes}$$

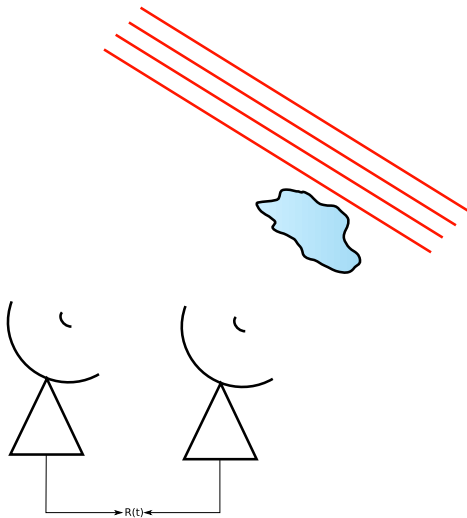
Atmospheric Phase Fluctuations



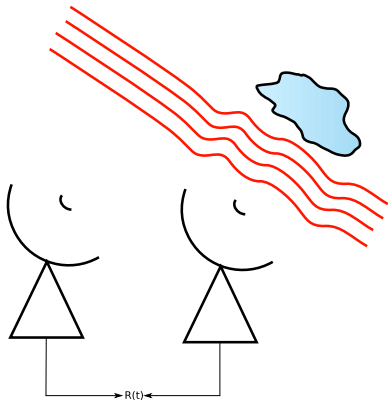
Atmospheric Phase Fluctuations



Atmospheric Phase Fluctuations

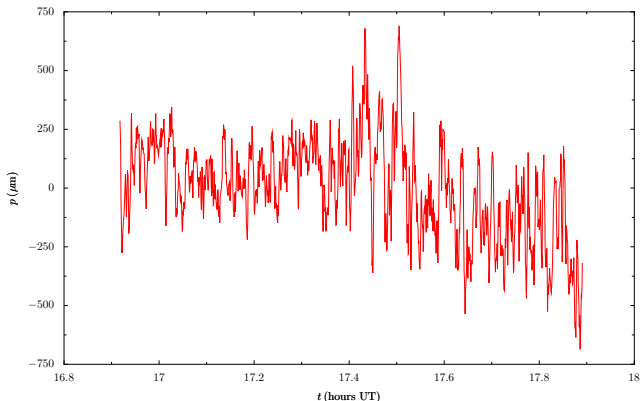


Atmospheric Phase Fluctuations



Example of observed path fluctuations

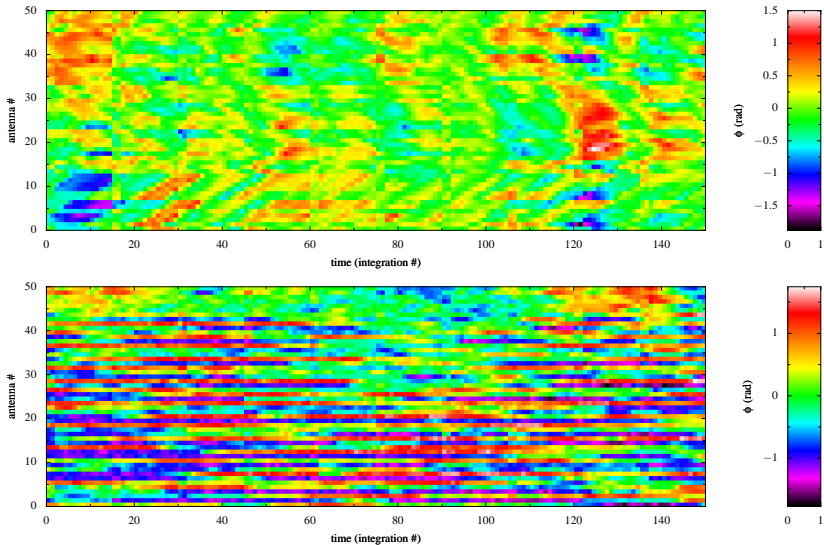
SMA, Mauna Kea, Hawaii



- Measured path fluctuation while observing a quasar
- 200 m baseline
- About 3.5 mm line-of-sight water
- $\sigma_{\phi} = 207 \mu\text{m}$.

Simulated ALMA phase errors

Details of simulations at <http://www.mrao.cam.ac.uk/~bn204/alma/>



Impact of poorly corrected phase errors

General impact on science

- Phase errors increase with baseline length
 - ⇒ limit on maximum usable baseline length
 - ⇒ limit on possible resolution
- Loss of sensitivity due to de-correlation

Impact on snapshot + mosaics

Further effects due to time-variance of phase fluctuations

- Amplitude calibration
- Astrometric accuracy

Not so much a worry at sub-mm

Small field of view + Small dynamic range of sky → less dynamic range problems due to phase errors

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ALMA phase correction strategy

Fast-switching

- Observe nearby quasars
- Calculate antenna phase errors
- Calibration cycle down to 10–15 s (fast antennas!)
- Expect calibrators about two degrees from science target
- Can calibrate at 90 GHz and transfer up to 950 GHz

+

Water Vapour Radiometry

- *Measure* atmospheric properties along the line of sight of each telescope
- Use dedicated 183 GHz radiometers on each telescope
- Measurements at about 1 Hz
- **Infer excess path**
- Correct either in correlator or in post-processing

+ Self-Calibration in a limited number of cases

Outline

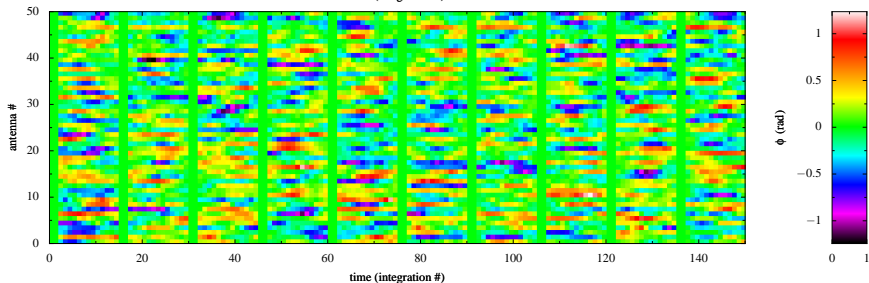
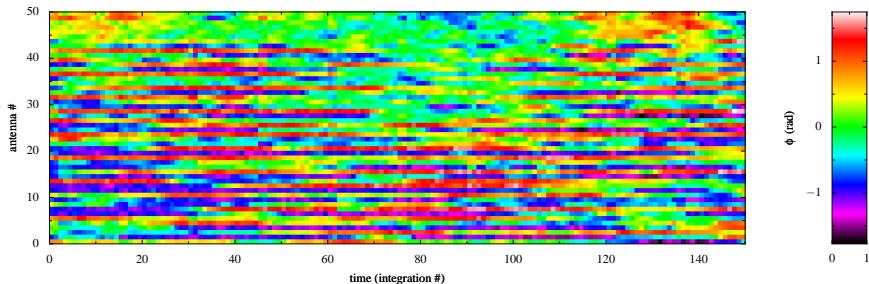
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Fast-switching phase calibration

- Use standard algorithms to determine antenna phase errors for observed visibilities
- Phase transfer from $\lambda = 3$ mm to observing frequency.
Benefits:
 - Quasars are much brighter at $\lambda = 3$ mm than in sub-mm
 - Phase errors are unlikely to be large enough to cause phase wraps
- Potential challenges:
 - Atmosphere *dispersive* in sub-mm so the transfer of gain solution requires modelling or itself needs calibration
 - Instrumental phase stability between $\lambda = 3$ mm and observing bands needs to be good
- Residual phase errors depend on atmospheric conditions and calibration cycle, but **not** on baseline length

Simulated fast-switching phase calibration

Medium configuration, 15 s cycle

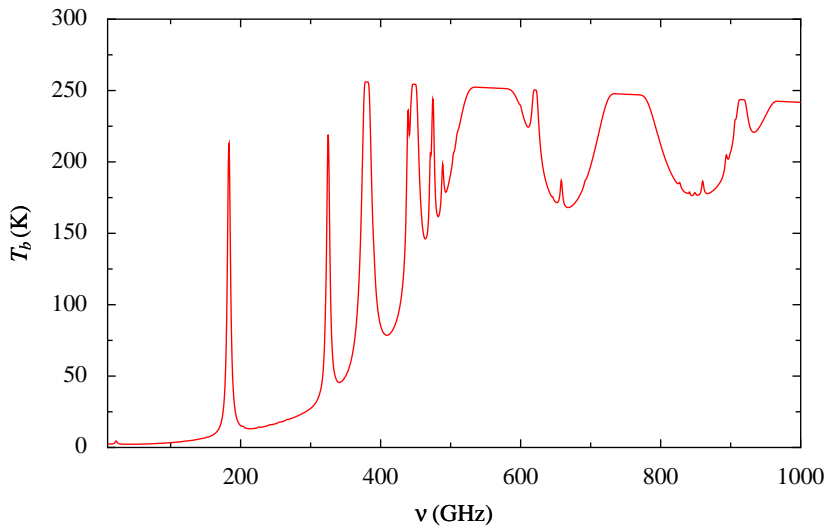


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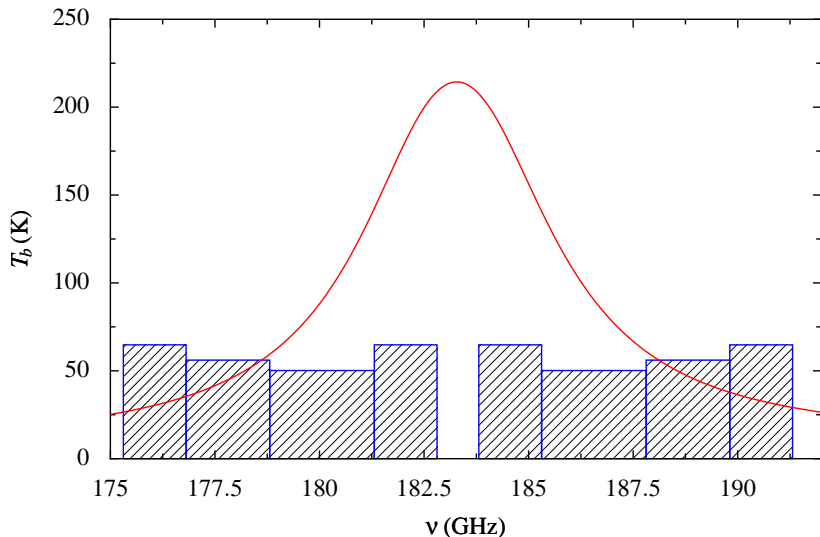
Water Vapour cm/mm/sub-mm lines

1 mm water vapour



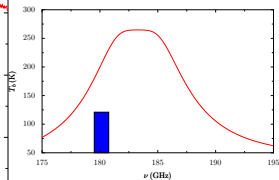
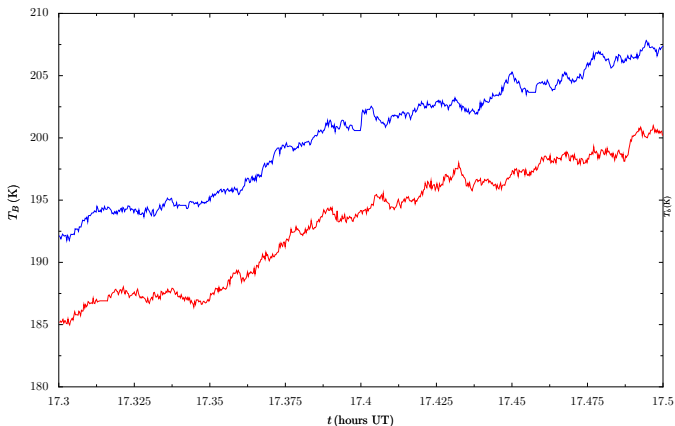
The 183 GHz Water Vapour Line

Blue rectangles are the production WVR filters



Signal from two prototype WVRs mounted on SMA antennas

From the ALMA WVR prototype testing campaign in 2006



Algorithms for WVR phase correction

δL change in excess path to antenna

$\delta T_{B,i}$ change in i -th channel sky brightness observed by a WVR

w_i weight of i -th channel

$$\delta L \approx \sum_i w_i \frac{dL}{dT_{B,i}} \delta T_{B,i} \quad (1)$$

δT_B : WVR hardware design

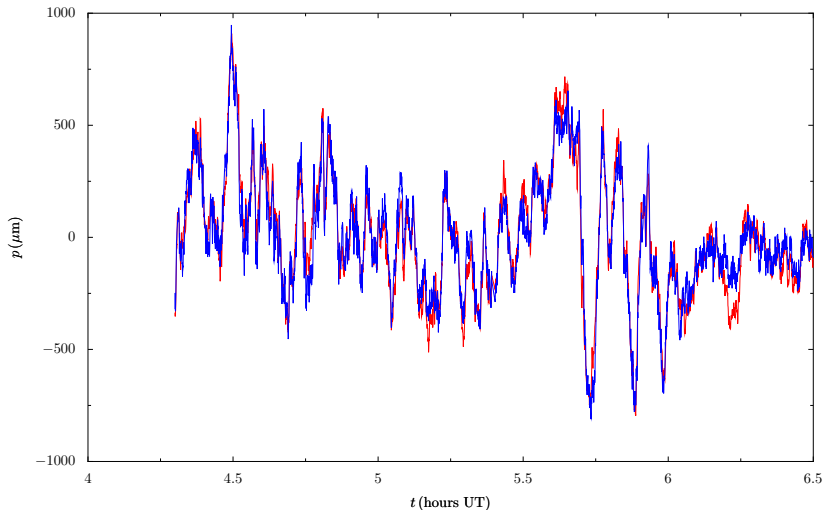
- Low noise
- High bandwidth
- High stability

$w_i \frac{dL}{dT_{B,i}}$: (primarily) algorithm design

- Optimal use of information
- Atmospheric models+physics
- Experience at the site
- 'Ancillary' information

Will this work? Optimise $w_i \frac{dL}{dT_{B,i}}$ directly as a test

SMA test data, total fluctuations: σ_L reduced from 271 to 75 μm



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WVR algorithms: available information

- Four absolute measurements of sky brightness: i.e., $T_{B,i}$ rather than $\delta T_{B,i}$
- The **observed** correlation between δL and δT_B
- Ground-level temperature, pressure, humidity, wind-speed
- Information on the profile of atmospheric temperature with height from a single 60 GHz O₂ sounder
- Library of radio-sonde measurements
- Meso-scale meteorological forecast

Will we need all of this information?

- We are aiming for *very challenging* 2% accuracy in $\sum_i w_i \frac{dL}{dT_{B,i}}$
- For operational efficiency important to understand how well phase correction will work (also the opacity too of course)

Algorithm framework: Bayesian

We are developing a Bayesian framework to optimally combine all available information together with models of the atmosphere

Why Bayesian?

We are **not interested** in model parameters such as pressure, temperature, lapse rate, turbulent layer height, etc.

All we want are the $\frac{dL}{dT_{B,i}}$

→ Marginalise *all* model parameters, get probability distributions for $\frac{dL}{dT_{B,i}}$.

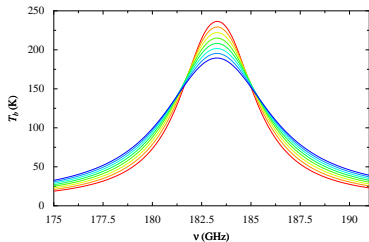
Framework features

- A model for accuracy of absolute measurements $T_{B,i}$
- Incorporate empirical $\frac{dL}{dT_{B,i}}$ as *observation*
- Other information naturally fit in as priors

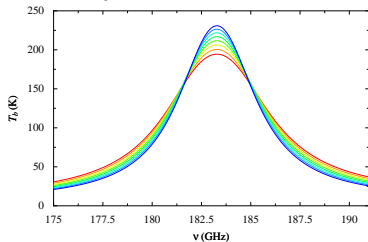
Example: Prediction of $\frac{dL}{dT_{B,i}}$ from WVR data only

Single, thin layer; prototype filter set

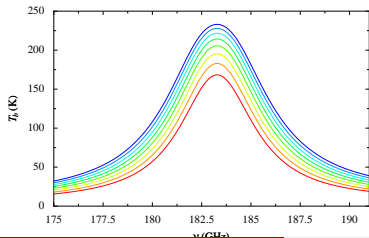
Pressure variation



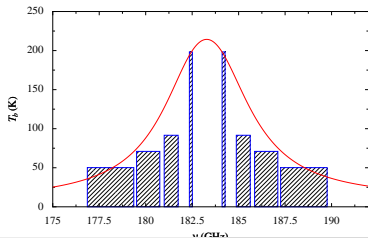
Temperature variation



Amount of Water

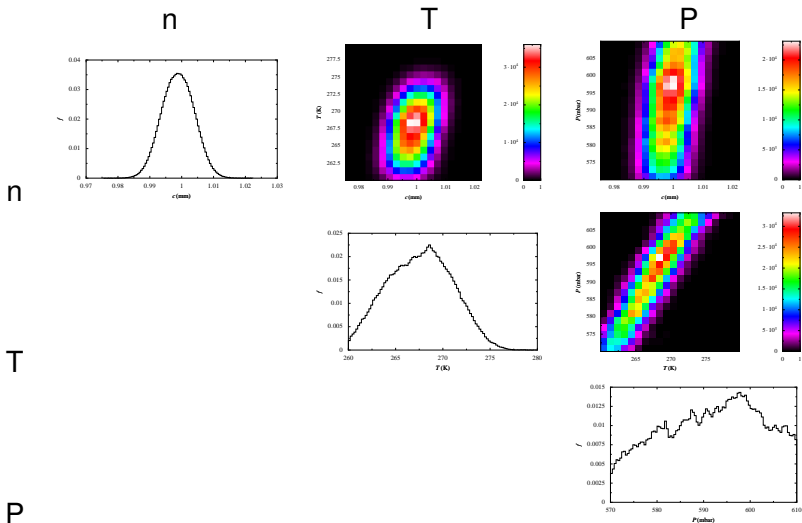


Filters



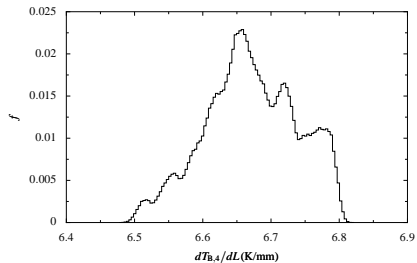
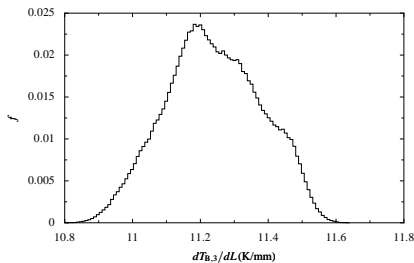
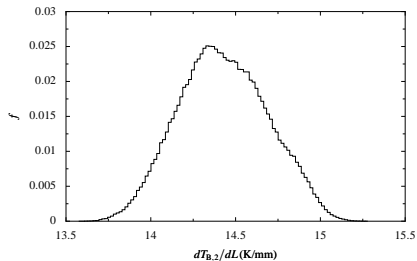
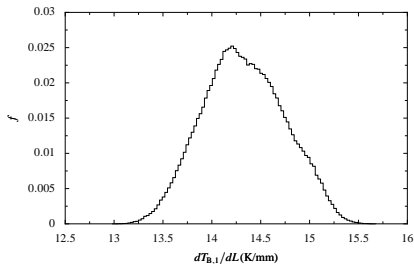
Example: Prediction of $\frac{dL}{dT_{B,i}}$ from WVR data only

Model parameters retrieval with priors



Example: Prediction of $\frac{dL}{dT_{B,i}}$ from WVR data only

Retrieved $\frac{dL}{dT_{B,i}}$



Challenges

- 15 km baselines, substantial elevation difference between parts of the array
→ need **different** set of $\frac{dL}{dT_{B,i}}$ for each antenna
- In some correlator modes, need to apply correction in semi-real-time
→ need to get the $\frac{dL}{dT_{B,i}}$ right
- ‘dry’ fluctuations: very little direct information, need to rely on correlation with ‘wet’ fluctuations
- Understanding of atmospheric physics and models