HARMONI at ELT: An evolvable software architecture for the instrument pointing model

the instrument pointing model Carracedo Carballal, Gonzalo José¹; Piqueras López, Javier²; Clarke, Fraser³ ^{1,2} Centro de Astrobiología (CAB, CSIC-INTA), ³ University of Oxford

Introduction

HARMONI is the first light visible and near-IR integral field spectrograph for the ELT. In order to achieve its maximum resolution level, both HARMONI and ELT must co-operate in closed loop mode, correcting its pointing continuously. This is done by measuring the position of natural guide stars (NGS) outside the science field (in the so-called technical field) using a guiding probe in the form of a mobile mirror named Pick-Off Arm (POA). Since the POA must be installed in a controlled-temperature environment, ELT's focal plane must be relayed from the Nasmyth platform to the POA by means of focal plane relay optics.

This design introduces a series of optomechanical stages that will affect the pointing measurements by systematic and random error contributions. To correct the former and characterise the impact of the latter (as well as the performance of any necessary corrective model), simulations of the pointing error measurement process are required.

We introduce **harmoni-pm**: a Python-based simulator prototype which, departing from a geometric optics modelisation of the instrument, attempts to reproduce the main drivers of the instrumental pointing error. harmoni-pm features a software architecture that is resilient to instrument model refinements and enables performance analyses of corrective models based on simulated calibrations. Results showed that the relay optics are the main drivers of the instrumental pointing error (order 200 μ m).

The current simulator has been also critical in the design of a corrective model that not only takes noisy measurements into account, but also error distributions thereof. This motivated the development of a Bayesian corrective model that is able to integrate the uncertainty of noisy measurements into the posterior knowledge of the final corrective model parameters.



Instrument calibration. HARMONI is integrated with a deployable Geometric Calibration Unit (GCU), which inserts a calibration mask directly into the focal plane. This calibration mask consists of a pattern of bright points whose locations are known beforehand. Measurements of the location of subsets of these points will be used to calibrate the pointing model by means of an appropriate corrective model.

Methods



The effect of uncalibrated field distortions. Simulations of the current instrument showed that the mechanical and optical elements between the Nasmyth Focal Plane and the guide probe detector introduce systematic pointing errors of order 200 μ m. This translates to more than 50 mas in the sky.



$$\hat{arepsilon}\left(x+iy
ight)=\overrightarrow{lpha}\cdot\overrightarrow{Z}_{x+iy}=\sum_{i=0}^{J-1}lpha^{j}\hat{Z}_{j}\left(rac{x+iy}{R_{fp}}
ight)$$

The corrective model in a few words. The corrective model consists of a truncated expansion up to the first *J* complex Zernike polynomials (\hat{Z}_j) , which encode 2D coordinates as complex numbers. In addition to their orthogonality (which prevents any intrinsic overlapping of information between polynomials), each one of them represents a physically meaningful contribution to the instrumental error (top). The parameters of the corrective model are the coefficients of the expansion (α^i , bottom). Assuming a classical calibration scheme, at least *J* pointing error measurements are necessary in order to find α^i .

Results

Simulated calibrations showed that only the first 6 Zernike polynomials are necessary to achieve the accuracy goal. **The first 10 Zernike polynomials** plummet any structure in the calibration residual below the measurement noise. A calibration pattern named Optimal Concentric Sampling¹ (OCS), which distributes the sampling points in concentric circles, exhibits the best immunity to noise tested so far.



Other goal of harmoni-pm was to compare the performance of the classical calibration approach with respect to its Bayesian counterpart. In order to do so, multiple pointing error measurements with increasing number of OCS calibration points were executed. In a second stage, these measurements were used to calibrate the corrective model, first using the classical approach, then using the Bayesian approach.

Results showed that, in most cases, **2 calibration points** are enough to achieve the calibration residual goal of 13 µm. This error is measured with respect to the 3rd quartile of the set of residuals measured along the relayed focal plane. This is not surprising: once the higher-order distortions –introduced by the relay optics– are calibrated, they are not expected to change much between posterior calibrations. The differential pointing error between calibrations is mostly due to mechanical contributions (e.g. repeatability errors of the GCU mask deployment, derotator errors...), which are encoded by only two of the lower-order polynomials.



We departed from a simplified instrument model and identified several potential refinements. This resulted in an abstraction that encodes the different contributions to the pointing error as a composition of bidirectional 2D-to-2D coordinate transforms. Each transform represents a conceptually different contribution to the pointing error, and leaves the door open for future improvements of the instrument model.

This abstraction motivated a software architecture that, in a first instance, decouples the instrument model from the simulation logic itself. Instrument model parameters are defined not as fixed value scalars, but as statistical distributions that are evaluated either at manufacture time (e.g. manufacturing tolerances), calibration session time (e.g. repeatability of the positioning of the GCU mask) or calibration time (e.g. instabilities of the POA positioning).

The resulting implementation enabled not only simulations of the pointing error, but also simulations of the behavior of the imaging detector of the POA and simulations of the calibration process. Typical data products take the form of heatmaps of the pointing error and the residual, pointing error histograms and statistical distributions of the coefficients of the corrective model.



An evolvable software architecture. The simulator features a componentbased architecture that enables transparent and concurrent improvement of both the simulator logic and the instrument model definition. Terminal components (e.g. command line scripts) are coloured in yellow.



The impact of the calibration pattern. A solution to the calibration problem can still be found if we reduce the number of calibration points to the number of coefficients of the corrective model. However, the sensitivity to measurement noise increases and the residual becomes highly dependent on the particular choice of calibration points (i.e., the calibration pattern). Calibration simulations made by harmoni-pm enabled testing of random patterns, spiral patterns (left) and Optimal Concentric Sampling¹ (right).

$$egin{aligned} &\sigma_E^2 \sim \mathcal{IG}(a_n,b_n)\ &\overrightarrow{lpha} \sim \mathcal{N}(\overrightarrow{lpha}_n,\sigma_E^2oldsymbol{\Lambda}_n^{-1})\ &\widetilde{arepsilon}(x+iy) \sim \mathcal{N}(\overrightarrow{lpha}\cdot\overrightarrow{Z}_{x+iy},\sigma_E^2)\ &p(\overrightarrow{lpha},\sigma_E^2| ilde{arepsilon}_1,\dots, ilde{arepsilon}_k) \propto p(ilde{arepsilon}_1,\dots, ilde{arepsilon}_k|\,arepsilon,\sigma_E^2)p(ec{lpha},\sigma_E^2) \end{aligned}$$

The Bayesian calibration problem. Classical calibration methods require at least as many calibration points as complex coefficients in the model. Additionally, some coefficients are more sensitive to the daily variations of the systematic pointing error than others. Fortunately, Monte-Carlo sampling of the results of different classical calibrations showed that the distribution of calibration coefficients can be modeled as a multivariate Gaussian. This distribution is centered around certain mean model solution and certain covariance matrix $\sigma^2_E \mathbf{A}^{-1}$, with σ^2_E being the measurement noise.

This motivated a Bayesian calibration method, which connects the posterior probabilities of the model coefficients with its prior probabilities and actual measurements of the instrumental pointing error. Additionally, by choosing **conjugate priors** for both the model coefficients and the measurement noise, we can obtain closed-form expressions for the parameters of the posterior distributions, with the most complex operation being the inversion of a symmetric $2J \times 2J$ matrix². This results in a significant improvement of the calculation time, as no Monte-Carlo sampling is necessary.

The most evident benefit of this strategy is that, since higher-order terms of the Zernike expansion (caused by static optical aberrations in the relay optics) are not expected to change much between observations, fewer pointing error measurements (even just 1) may be enough to have a model residual below the calibration goal of 13 μ m.

In future work, we expect to have a more realistic description of the instrument, as well as integrating manufacturing effects in the modelisation of the relay optics. Another line of investigation – motivated by the reductions of the calibration time achieved by the Bayesian calibration– will be the study potential simplification of the GCU mask pattern (which currently involves more than 400 reference points).

Conclusions

- 1. Current simulations show that the main driver for the instrumental distortion is the relay optics.
- 2. The current instrument model indicates that a minimum of 10 Zernike polynomials is necessary to compensate for these distortions.
- 3. Optimized Concentric Sampling (OCS) exhibits a good immunity to measurement noise.
- 4. Simulated calibrations are a good source of prior distributions for Bayesian calibrations.
- 5. Bayesian calibration results into a significant speed-up of the calibration time (reductions from 10 to 2 required calibration points have been observed).

References

- Ramos-López, Darío & Sánchez-Granero, Miguel & Fernández Martínez, Manuel & Martínez-Finkelshtein, Andrei. (2016). Optimal sampling patterns for Zernike polynomials. Applied Mathematics and Computation. 274. 247-257. 10.1016/j.amc.2015.11.006.
- 2. Wundervald, B. (2019). Bayesian Linear Regression, Technical Report, June 2019, doi: 10.13140/RG.2.2.28385.97121

Contact info: Gonzalo José Carracedo Carballal PhD student

E-mail: gcarracedo@cab.inta-csic.es Personal webpage: <u>https://actinid.org</u>

