

# Simultaneous astrometry of an image set : status report

*Pierre Astier*

*LPNHE / IN2P3 / CNRS , Universités Paris 6&7.*

15/05/2015



# Objectives

- Fitting astrometry of an image set using common objects (and possibly and external reference catalog)
  - Prior to stacking
  - Prior to simultaneous measurements on an image set (e.g. transient light curves)
  - Deriving an “instrument model”

# Sketch

- Our images are already equipped with a catalog, and a rough WCS
- **Stage 1** : associate all the catalogs
- **Stage 2** : associate with an external position catalog, if needed (set the sidereal frame)
- **Stage 3** : fit simultaneously
  - Mappings from input image coordinates to some common frame ( $\rightarrow$  WCS's)
  - Positions of the objects in common

# Associating detections of the same object

## The simple way :

- For each image
  - Load catalog and apply quality cuts
  - Match it to the “Object catalog” (in the tangent plane)
  - Add the unmatched objects to the “Object catalog”
- I know it is fast and efficient (with a 2D  $O(N_1 \log(N_2))$  matching)
- One could be worried by the outcome depending in principle of the order of input images.
- In practice, this is not serious if the WCS's are accurate enough (1-2 pixels) and blends are ignored (as they should).

# Fit : Least Squares

$$\chi_{meas}^2 = \sum_{c,d} [M_c(X_{c,d}) - P_c(F_i)]^T W_{c,d} [M_c(X_{c,d}) - P_c(F_i)]$$

Measurement  
terms

c,d : calexp, detection

$M_c$  : mapping (pixel  $\rightarrow$  TP), one per calexp

$X_{c,d}$  : measured position of the object (pixels)

$P_c$  : projection (sky  $\rightarrow$  TP)

$W_{c,d}$  : Measurement weight (1/var), transformed through  $M_c$ .

$F_i$  : (sky) position of the object (measured as  $X_{c,d}$ )

$$\chi_{ref}^2 = \sum_j [P(F_j) - P(R_j)]^T W_j [P(F_j) - P(R_j)]$$

Reference  
terms

P : some (user-provided) projection

$F_j$  : (fitted) sky position of the object

$R_j$  : sky position of the object fitted (reference catalog)

$W_j$  :  $R_j$  weight (1/var), transformed through P

# Least Squares (2)

$$\chi_{meas}^2 = \sum_{c,d} [M_c(X_{c,d}) - P_c(F_i)]^T W_{c,d} [M_c(X_{c,d}) - P_c(F_i)]$$

Measurement  
terms

...

$W_{c,d}$  : Measurement error, transformed through  $M_c$ .

.... → so  $W$  depends on some fitted parameters !

Yes, but in practice, the scale of  $M$  is extremely well known, so this can be ignored.

$$\chi_{ref}^2 = \sum_j [P(F_j) - P(R_j)]^T W_j [P(F_j) - P(R_j)]$$

Reference  
terms

$P$  : some (user-provided) projection

Why  $P(F_j) - P(R_j)$  rather than just  $(F_j - R_j)$ ?

because the distance on the sphere is **not** Euclidean

# Least Squares (3)

$$\chi_{meas}^2 = \sum_{c,d} [M_c(X_{c,d}) - P_c(F_i)]^T W_{c,d} [M_c(X_{c,d}) - P_c(F_i)]$$

- This setup accommodates the fit of mappings between images:
  - All the  $P_c$  are set to identity.
  - One of the  $M_c$  is set to identity.
  - No external catalog nor “reference terms”.
- This yields the optimal mapping between images, given position measurements and their uncertainties.

# Implementation

- Least squares with (mostly analytical) computation of derivatives (w.r.t positions and parameters).
- Sparse matrix algebra (Eigen3 package). Similar performance with Cholmod.
- About 1500 lines of new C++ code ( $\sim 10$  classes) to implement the fit and the model. Used existing (home-made) classes for everything else.
- The fit talks to the model via two abstract classes.



# Outlier removal

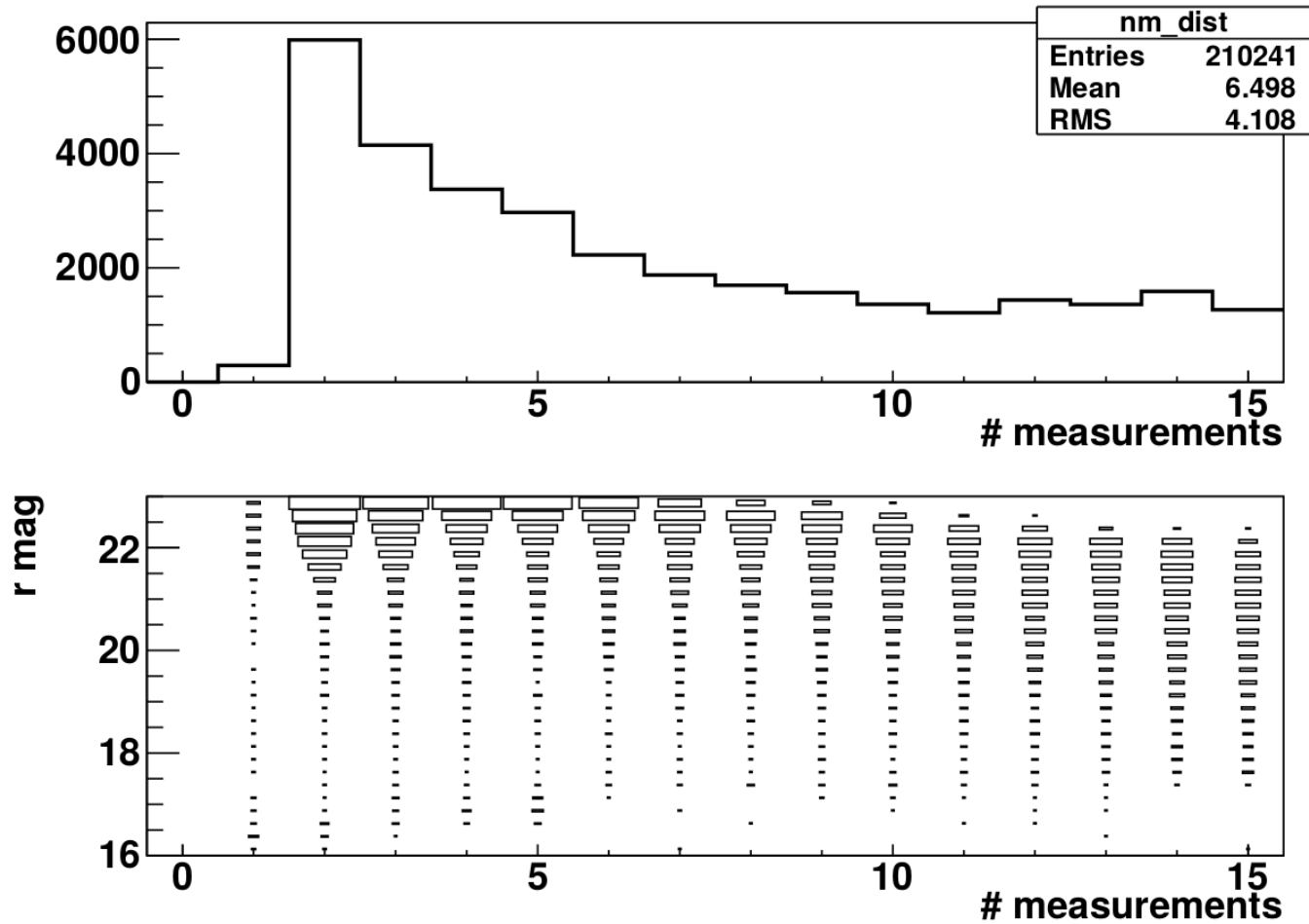
- I have not found a **canned** small-rank update of Cholesky factorizations. The only one I know about is Cholmod providing a rank-1 update.
- So I have used the following trick: do not remove in a single pass 2 outliers that constrain the same parameter.
- Would require a lot of iterations to come to zero outlier removed.
- I was not that patient: I ran it only 4 iterations.

# Trial run

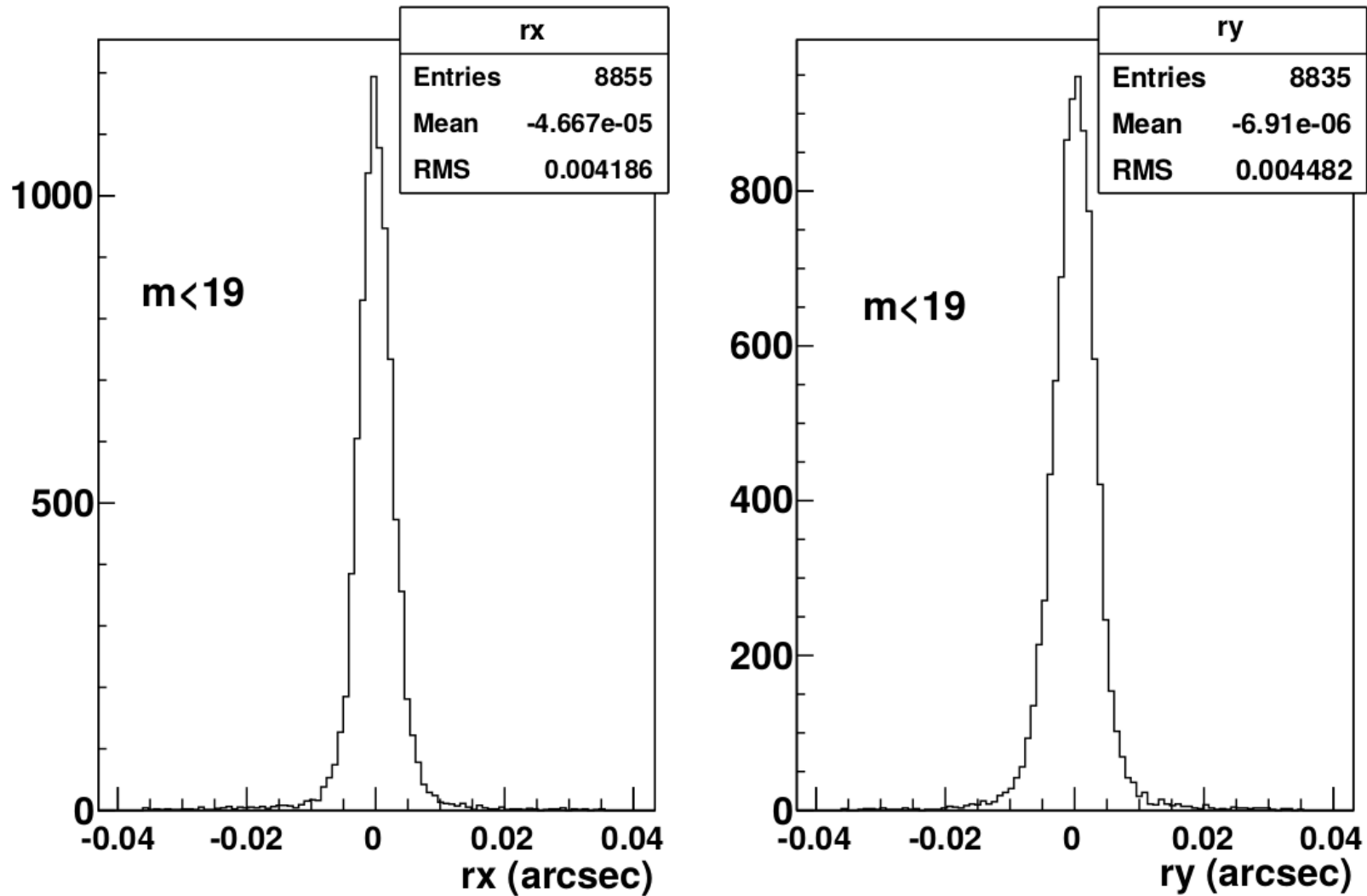
- 15 Megacam r-band 300-s exposures on D3, observed over the same lunation. 540 Calexp's.
- Use USNO-A2 for the reference catalog.
- Ignore proper motions.
- Use Gaussian-weighted positions and associated errors.
- Strict selection of measurements (no flag at all,  $S/N > 10$ ), average of  $\sim 400$  measurements/calexp
- All calexps have their own mapping parameters as if they all came from different instruments

# Trial run

- ~32,500 objects, ~210,000 measurements.



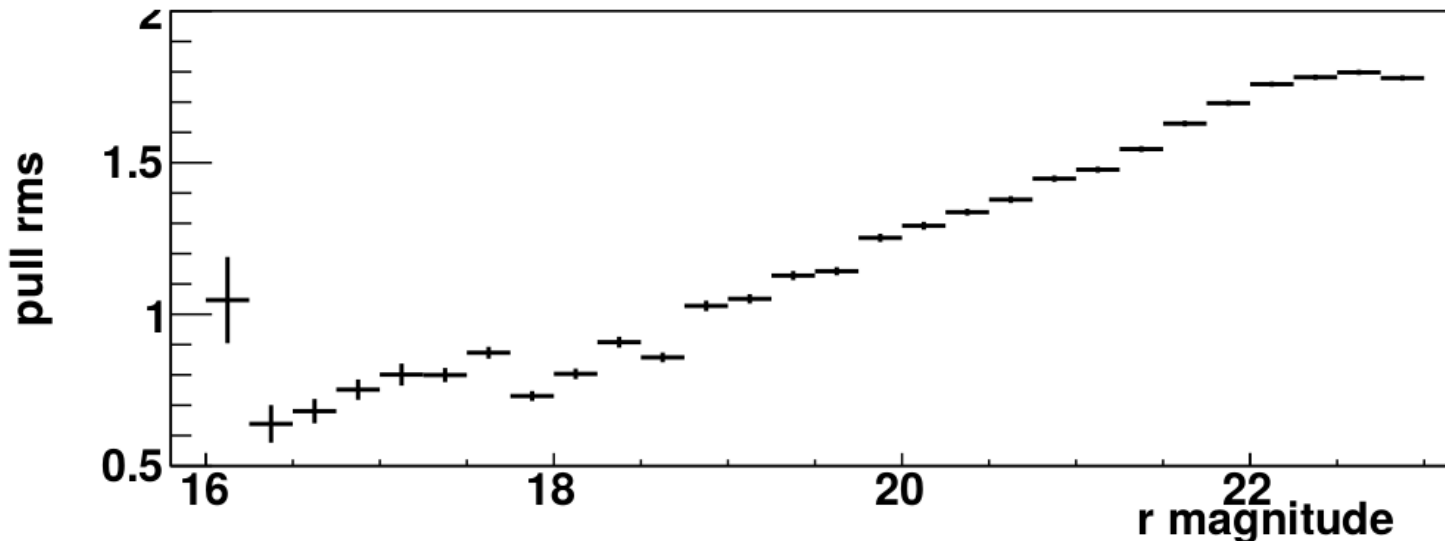
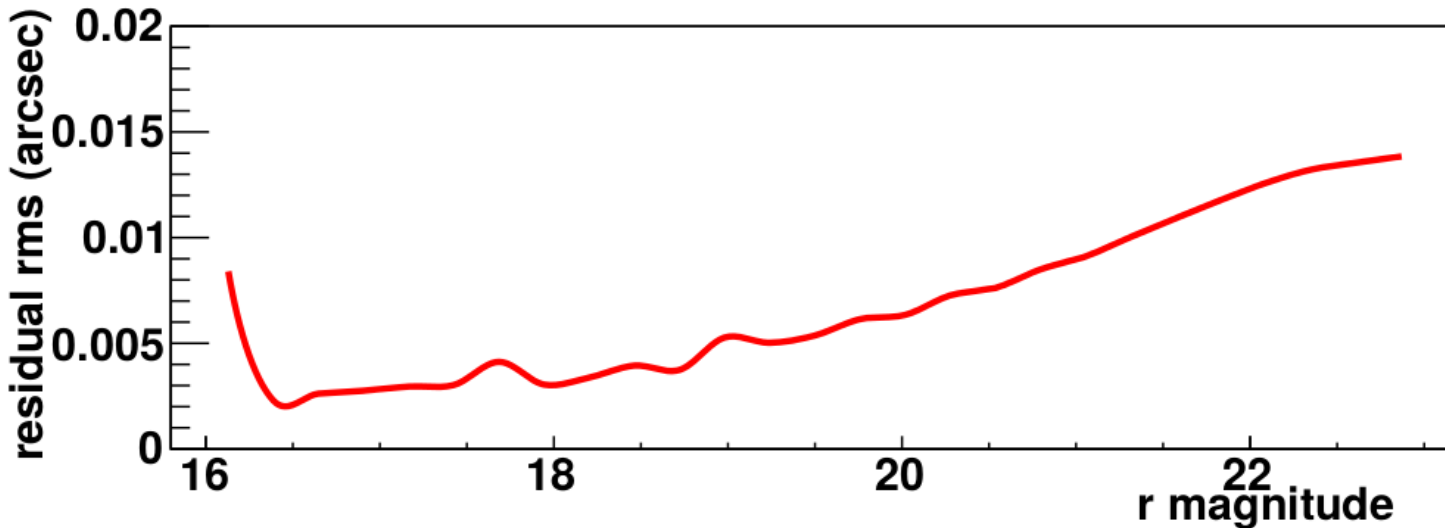
# Trial run : residuals



Residuals of the “measurement terms”, these are internal residuals

# Residuals vs mag

Use simplistic error model  $V = V_{\text{meas}} + (0.02 \text{ pix})^2$



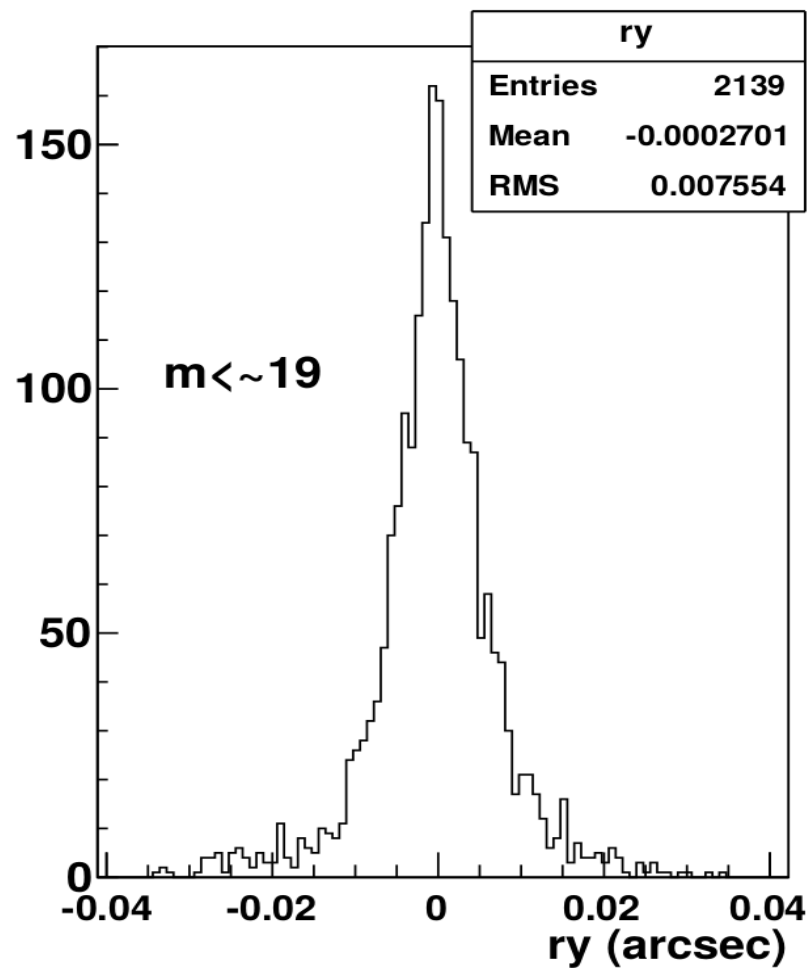
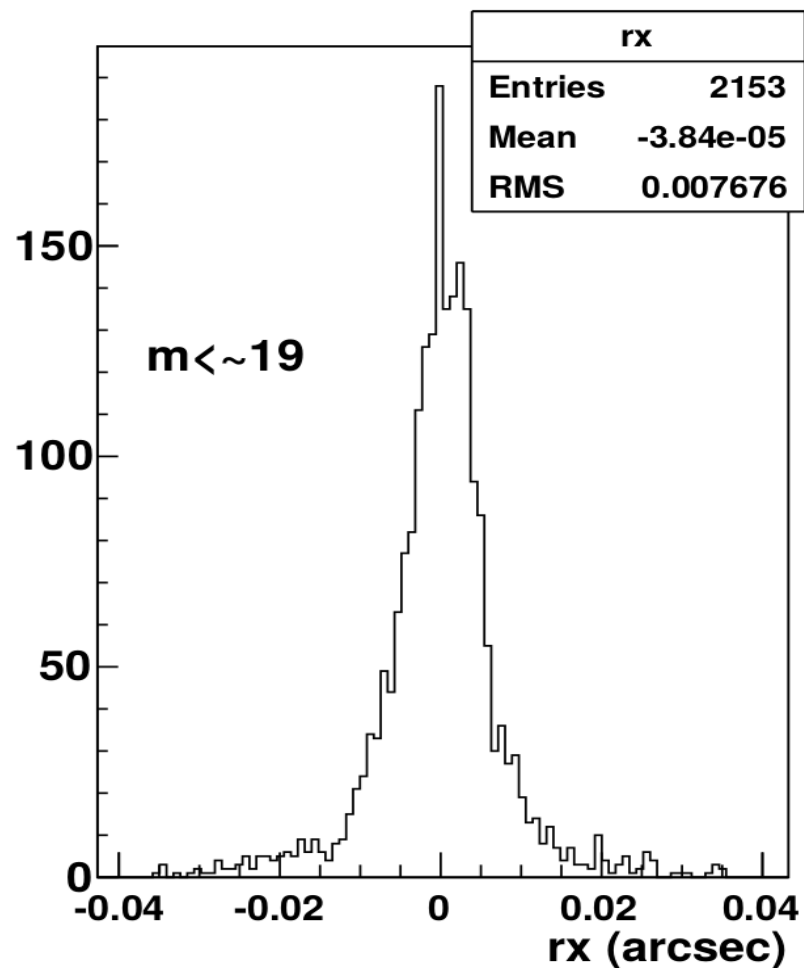
Beware : residuals are **not** Studentized, and The number of measurement is not that large

A smaller constant term would help for the bright side, but not for the faint side

Overall : it could be much worse!

# Second trial run: Suprime cam

120-s (i and z)-band exposures reduced by Augustin Guyonnet.  
12 exposures, guessed photometric scale. Exactly the same code.



# Computer resources

- Execution time: for the 15 Megacam exposures:
  - Reading the (540) catalogs :  $\sim 100$  seconds at 33% CPU
  - Associating : negligible
  - Fitting:  $< \sim 20$  s per iteration
    - Computing the derivatives :  $\sim 1$  s
    - “Squaring” the Jacobian, i.e.  $H = JJ^T$  :  $\sim 3$ s
    - Factorize-solve-update (dim=75,510, nnz=17,164,700)  $\sim 13$  s.
  - Partial fits (positions OR mappings) are solved instantly.
  - Total : 125.137u 19.769s 3:40.44 65.7% (Xeon 2.3 GHz)
- Memory reaches  $\sim 1$  GByte (not completely sure though)

## To be done (at least):

- I still have to code the mapping model for a “rigid instrument”. I would not be surprised if the residuals come out much larger. Have to think about relaxing rigidity.
- Study dispersions of faint objects (galaxies mostly).
- Proper motions, parallaxes ? the code to handle proper motions is there, but I have not implemented anything to detect “moving” stars.
- Output of mappings (i.e. WCS's)... Which format? Output of the catalog.



# (Simplified) class diagram

