

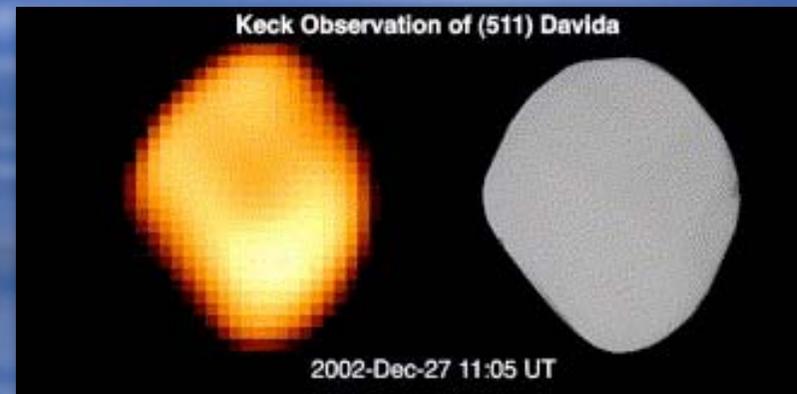
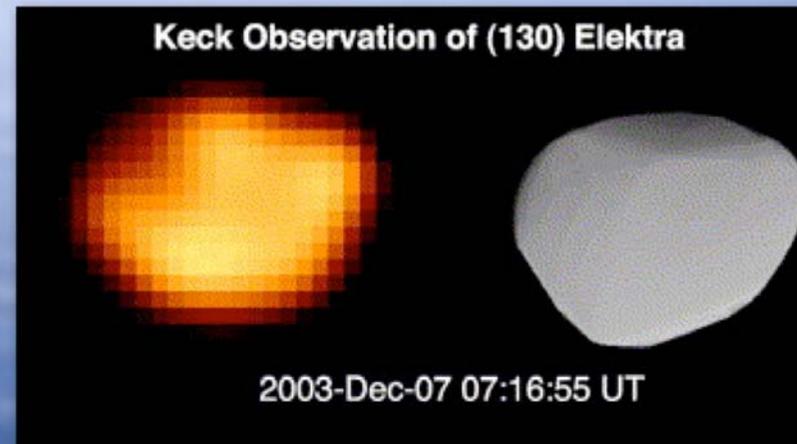
Optimal combination of data  
modes in inverse problems:  
maximum compatibility  
estimate

Mikko Kaasalainen  
Dept. of Mathematics  
Tampere UT

- Case study of complementary data modes: generalized projections
- Major mode: volumes of projections
- Minor mode: boundary curves of projections
- Solution: shape and spin state
- Astrophysical data: photometry and adaptive optics (AO)
- AO processing an inverse problem itself
- Brightness distribution  $I(u)$ ,  $u \in \mathbb{R}^2$  from AO deconvolution unreliable and prone to large contrast errors
- Boundary  $\partial\mathcal{D}$ ,  $\mathcal{D} = \{u : I(u) > \epsilon\}$  **much** more accurate
- With  $\partial\mathcal{D}$ , no modelling of the scattering properties of the surface required (and solution from volume data insensitive to scattering)

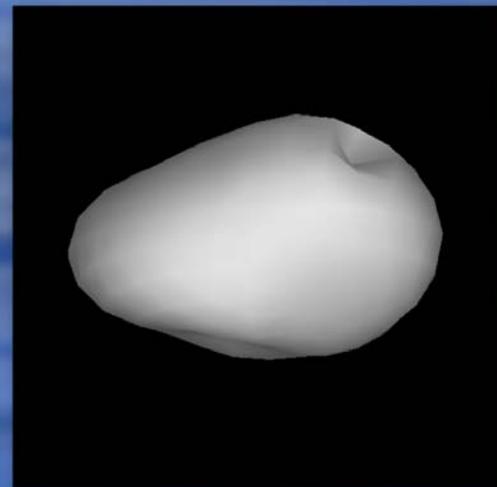
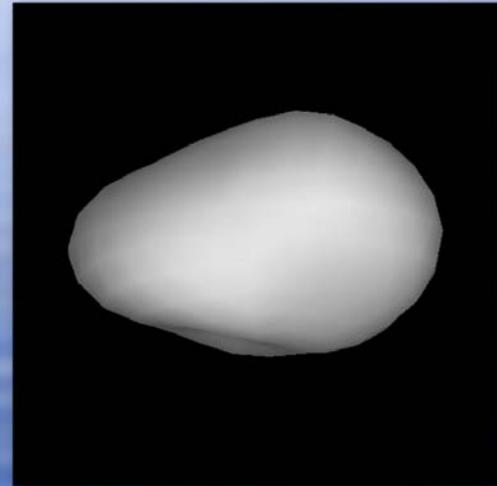
# LC + AO: consistency

- ◆ AO images and LC models are both solutions of inverse problems
- ◆ AO images agree well with independent LC-based models, so...
- ◆ ...we can expect a joint model to fit data from both sources well (not necessarily always the case, esp. with LCs+ delay-Doppler radar)



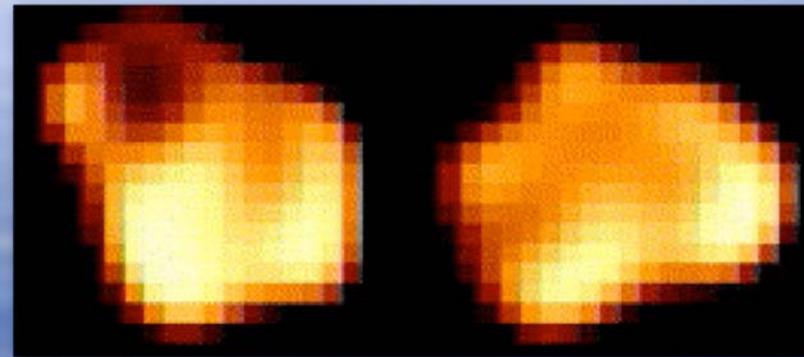
# Multidatoinversion

- ◆ Minimize a joint  $\chi^2$  such that separate AO and LC  $\chi^2$ s are acceptable
- ◆ e.g.: (9) Metis with a strong smoothness constraint to suppress too many artificial details
- ◆ But one AO image suggests a large crater/spot: let's just add it and see what happens...



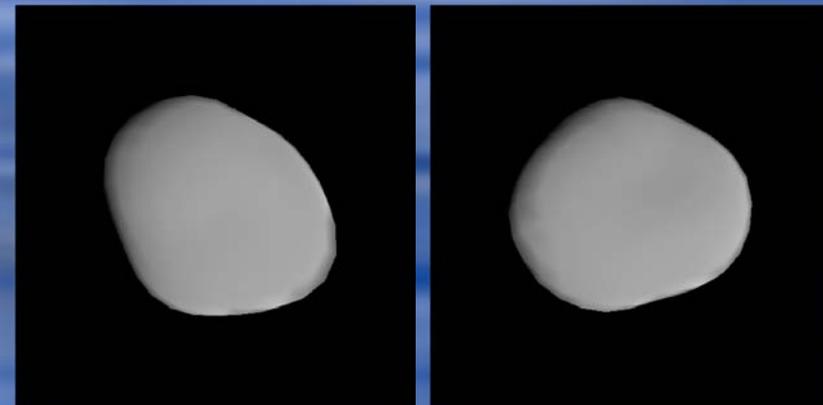
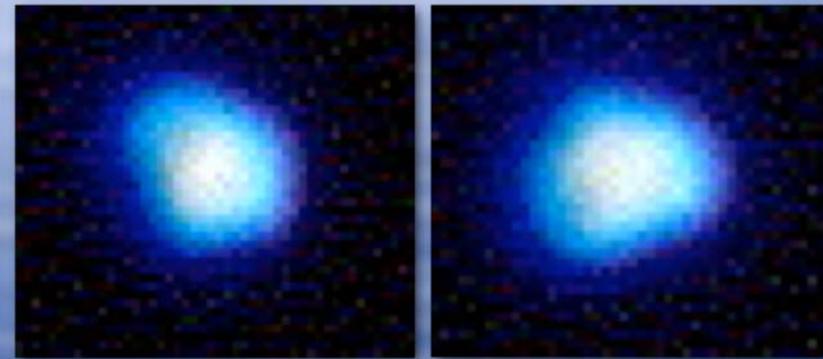
# Is it there...

- ◆ The AO spot can be reproduced with a suitable crater (left)...
- ◆ ...but then it should also be seen in other images (right)!
- ◆ AO post-processing tends to produce exaggerated contrasts and spurious "features"



## ...or not?

- ◆ No spot seen in original basic-processed AO images -- better to err on the safe side
- ◆ Post-processing (from basic image and estimated PSF) is always nonunique: it uses selected a priori constraints not necessarily mutually consistent with the full shape/spin model



# The art of a priori info

- ◆ In principle, the 3-D model should enter already at the post-processing stage: we could invert basic AO+PSF+LC data
- ◆ But post-processing seems to produce very good/sharp edges (silhouette), so we should invert post-proc edges+LC data...
- ◆ ...work in progress: how to get maximal reliable info and separate true details from artificial ones, and how to keep "only" those details in the model

# 1 Profiles, TCBs, uniqueness

- Volumes of projections: unique solution for convex bodies  $\mathcal{C}$
- Profiles (silhouettes): unique for tangent-covered bodies  $\mathcal{T}$
- Generalized profiles (shadows included): unique for a larger class  $\mathcal{G}$

$$\mathcal{C} \subset \mathcal{T} \subset \mathcal{G}.$$

Profile of  $\mathcal{B}$  in direction  $\omega \in S^2$ :

$$\mathcal{P}_\partial(\omega, \mathcal{B}) = \partial\mathcal{P}(\omega, \mathcal{B})$$

*Cylinder continuation* of a set of points  $\mathcal{S}$  in direction  $\omega$ :

$$\mathcal{C}(\omega, \mathcal{S}) = \left\{ x + s\omega \mid x \in \mathcal{S}; -\infty < s < \infty \right\}. \quad (1)$$

*Profile hull* is formed by several profiles:

$$\mathcal{H}(\{\mathcal{P}_\partial(\omega_i) \mid_{i=1}^N\}) = \partial \bigcap_i \mathcal{C}(\omega_i, \mathcal{S}_i), \quad \mathcal{S}_i = \left\{ x_{\varkappa(\omega_i)} \mid \varkappa \in \mathcal{P}(\omega_i) \right\}. \quad (2)$$

Condition for correct profile offsets: the profiles of the constructed  $\mathcal{H}$  must be identical to the observed ones.

$$\mathcal{P}_\partial[\omega_i, \mathcal{H}(\{\mathcal{P}_\partial(\omega_j) \mid_{j=1}^N\})] = \mathcal{P}_\partial(\omega_i)$$

*Tangent-covered bodies* (TCBs) are bodies that are their own complete profile hulls:  $\mathcal{B} = \mathcal{H}_C(\mathcal{B})$ . Thus, each surface point  $x \in \mathcal{B}$  of a TCB is mapped at least to one  $\mathcal{P}_\partial(\omega)$ .

Generalized profiles: illumination and viewing directions  $(\omega_0, \omega) \in S^2 \times S^2$  define the region

$$\mathcal{A}_+(\omega, \omega_0; \mathcal{B}) = \mathcal{A}_+(\omega; \mathcal{B}) \cap \mathcal{A}_+(\omega_0; \mathcal{B}), \quad (3)$$

where

$$\mathcal{A}_+(\omega; \mathcal{B}) = \left\{ x \in \mathcal{B} \mid \langle \nu(x), \omega \rangle \geq 0; \forall s > 0 : x + s\omega \notin \mathcal{B} \right\}, \quad (4)$$

where  $\nu(x)$  is the unit surface normal at  $x$ . The projection  $\mathcal{P}$  of the boundary  $\partial\mathcal{A}_+$  is now the generalized profile:

The *generalized profile* of the body  $\mathcal{B}$  in the direction  $\omega$  and at illumination direction  $\omega_0$  is

$$\partial\mathcal{P}[\omega, \mathcal{A}_+(\omega, \omega_0; \mathcal{B})] = \mathcal{P}[\omega, \partial\mathcal{A}_+(\omega, \omega_0; \mathcal{B})]. \quad (5)$$

Uniqueness theorems for reconstructions from generalized profiles can be shown for various configurations; e.g., shadow contours of a known part  $\mathcal{K}$  of  $\mathcal{B}$  on an unknown part  $\mathcal{U}$ , or shadow contours of  $\mathcal{U}$  on  $\mathcal{K}$ .

## 2 Combined data modes

Full  $\chi^2$ :

$$\chi_{\text{tot}}^2 = \chi_L^2 + \lambda_{\partial}\chi_{\partial}^2 + \lambda_R g(P), \quad (6)$$

Volume of generalized projection:

$$L(\omega_0, \omega) = \int \int_{\mathcal{A}_+} R(x; \omega_0, \omega) \langle \omega, \nu(x) \rangle d\sigma(x) \equiv \int \int_{\mathcal{P}(\omega, \mathcal{A}_+)} R[P^{-1}(\omega, \mathcal{A}_+, \boldsymbol{\varkappa}); \omega_0, \omega] d^2 \boldsymbol{\varkappa}, \quad (7)$$

( $R$  surface scattering model,  $P^{-1}$  backprojection  $\mathbb{R}^2 \rightarrow \mathbb{R}^3$ ) and its  $\chi^2$ :

$$\chi_L^2 = \sum_i [L^{(\text{obs})}(\omega_{0i}, \omega_i) - L^{(\text{mod})}(\omega_{0i}, \omega_i)]^2 \quad (8)$$

For starlike profiles:

$$\chi_{\partial}^2 = \sum_{ij} [r_{\text{max}}^{(\text{obs})}(\alpha_{ij}) - r_{\text{max}}^{(\text{mod})}(\alpha_{ij})]^2. \quad (9)$$

In general:

$$\chi_{\partial}^2 = \sum_{ij} \inf_s \left\{ \|\partial\mathcal{O}_i(s) - \boldsymbol{\varkappa}_{ij}\|^2 \right\}, \quad (10)$$

$\boldsymbol{\varkappa}_{ij}$  observed profile points,  $\partial\mathcal{O}$  modelled profile.

Regularization by, e.g., smoothness:

simple one for low regularization weight:

$$g_S = \int_{\mathcal{B}} [r - \langle r \rangle]^2 d\sigma, \quad (11)$$

For higher weights, suppress local concavities:

$$\mathcal{C} = \frac{1}{\sum_i A_i} \sum_{ij} A_{ij} (1 - \langle \nu_i, \nu_{ij} \rangle), \quad (12)$$

where  $A_i$  denotes the area of the facet  $i$ , and  $A_{ij}$  the areas of those facets around it that are tilted above its plane.

Physical constraint: principal axis rotation

$$g_I = (1 - \cos^2 \tau)^2 = [1 - I_3(\mathcal{B})^2]^2, \quad (13)$$

where  $\tau$  is the angle between the  $z$ -axis of the model and the eigenvector  $I \in \mathbb{R}^3$  (normalized  $\langle I, I \rangle = 1$ ) corresponding to the largest eigenvalue of the inertia matrix  $I$  of the model shape  $\mathcal{B}$ .

Also, we can augment (10) by

$$\lambda \sum_i \frac{1}{C_i} \oint_{\partial \mathcal{O}_i} \inf_{\mathcal{X} \in \{\mathcal{X}_{ij}\}} \left\{ \|\partial \mathcal{O}_i(s) - \mathcal{X}\|^2 \right\} ds, \quad (14)$$

where  $C_i = \oint_{\partial \mathcal{O}_i} ds$ . This suppresses irregularity on surface parts not projected near the observed profile points.

### 3 Maximum compatibility estimate

$P$  parameters,  $D_i$  data sources

$$\chi_{\text{tot}}^2(P, D) = \chi_1^2(P, D_1) + \sum_{i=2}^n \lambda_{i-1} \chi_i^2(P, D_i) \quad D = \{D_i, i = 1, \dots, n\} \quad (15)$$

with nondegenerate solutions for each data mode:

$$\arg \min \chi_i^2(P) \neq \arg \min \chi_j^2(P), \quad i \neq j$$

Consider first two data sources:

$$\begin{aligned} x(\lambda) &:= \{\chi_1^2 \mid \min \chi_{\text{tot}}^2; \lambda\}, \\ y(\lambda) &:= \{\chi_2^2 \mid \min \chi_{\text{tot}}^2; \lambda\}. \end{aligned} \quad (16)$$

The curve

$$\mathcal{S}(\lambda) := [\log x(\lambda), \log y(\lambda)] \quad (17)$$

is a part of the boundary  $\partial\mathcal{R}$  of the region  $\mathcal{R} \in \mathbb{R}^2$  formed by the mapping  $\chi : \mathbb{R}^p \rightarrow \mathbb{R}^2$  from the parameter space  $\mathbb{P}$  into  $\chi_i^2$ -space:

$$\chi = \{\mathbb{P} \rightarrow (\log \chi_1^2, \log \chi_2^2)\}, \quad \mathcal{R} = \chi(\mathcal{P})$$

Translate the origin:

$$\begin{aligned} \hat{x}_0 &= \log x(\lambda)|_{\lambda=0} = \log \min \chi_1^2 \\ \hat{y}_0 &= \log y(\lambda)|_{\lambda \rightarrow \infty} = \log \min \chi_2^2. \end{aligned} \quad (18)$$

Now we have the optimal point on  $\partial\mathcal{R}$ :

$$P_0 = \arg \min \left( [\log \chi_1^2(P) - \hat{x}_0]^2 + [\log \chi_2^2(P) - \hat{y}_0]^2 \right), \quad (19)$$

so we have, with  $\lambda$  as argument,

$$\lambda_0 = \arg \min \left( [\log x(\lambda) - \hat{x}_0]^2 + [\log y(\lambda) - \hat{y}_0]^2 \right). \quad (20)$$

We call the point  $P_0$  the *maximum compatibility estimate* (MCE), and  $\lambda_0$  the *maximum compatibility weight* (MCW). MCE can be determined without MCW (or  $\lambda$ ).

This approach straightforwardly generalizes to  $n$   $\chi^2$ -functions and  $n - 1$  parameters  $\lambda_i$  describing the position on the  $n - 1$ -dimensional boundary surface  $\partial\mathcal{R}$  of an  $n$ -dimensional domain  $\mathcal{R}$ : the MCE is

$$P_0 = \arg \min \sum_{i=1}^n \left[ \log \frac{\chi_i^2(P)}{\chi_{i0}^2} \right]^2, \quad \chi_{i0}^2 := \min \chi_i^2(P), \quad (21)$$

and the MCW is

$$\lambda \in \mathbb{R}^{n-1} : \quad \lambda_0 = \arg \min \sum_{i=1}^n \left[ \log \frac{\hat{\chi}_{i,\text{tot}}^2(\lambda)}{\chi_{i0}^2} \right]^2, \quad \hat{\chi}_{i,\text{tot}}^2(\lambda) := \left\{ \chi_i^2 \mid \min \chi_{\text{tot}}^2; \lambda \right\}. \quad (22)$$

Another scale invariant version of MCE can be constructed by plotting  $\chi_i^2$  in units of  $\chi_i^2/\chi_{i0}^2$  and shifting the new origin to  $\chi_i^2/\chi_{i0}^2 = 1$ :

$$P_0 = \arg \min \sum_{i=1}^n \left[ \frac{\chi_i^2(P)}{\chi_{i0}^2} - 1 \right]^2, \quad \lambda_0 = \arg \min \sum_{i=1}^n \left[ \frac{\hat{\chi}_{i,\text{tot}}^2(\lambda)}{\chi_{i0}^2} - 1 \right]^2. \quad (23)$$

This, however, is exactly the first-order approximation of (21) and (22)

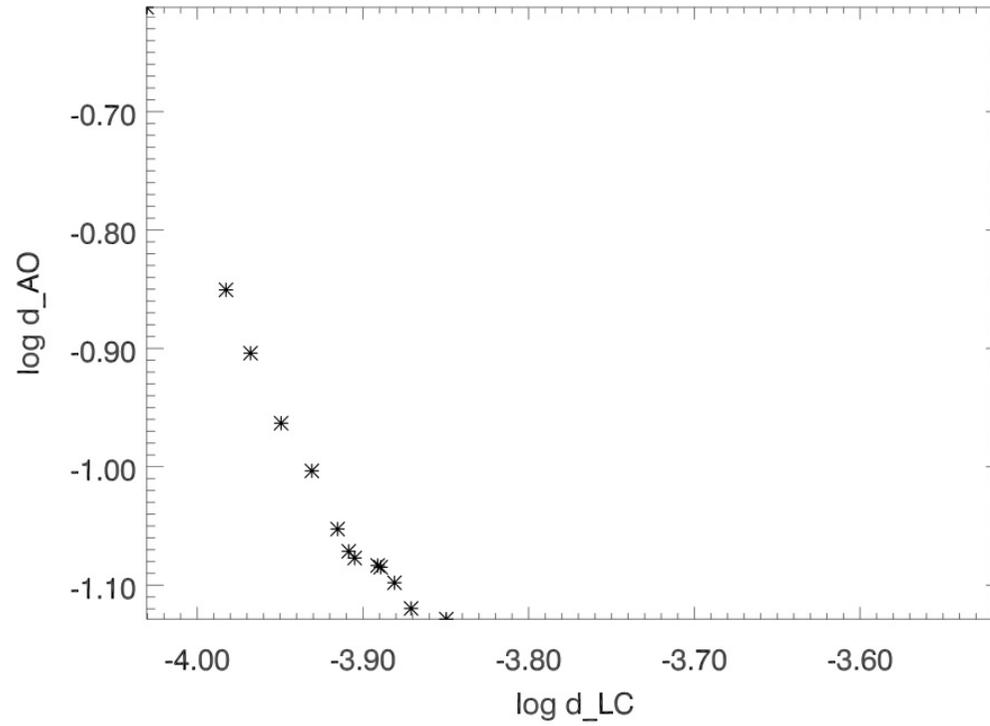


Figure 1:  $S$  curve plotted for 2 Pallas with various weights  $\lambda$  (LC for lightcurves, AO for adaptive optics profiles).

Starlike shapes:

$$r(\theta, \varphi) = \exp \left[ \sum_{lm} c_{lm} Y_l^m(\theta, \varphi) \right], \quad (\theta, \varphi) \in S^2 \quad (24)$$

Other shape types by suitable parametrization/mesh.

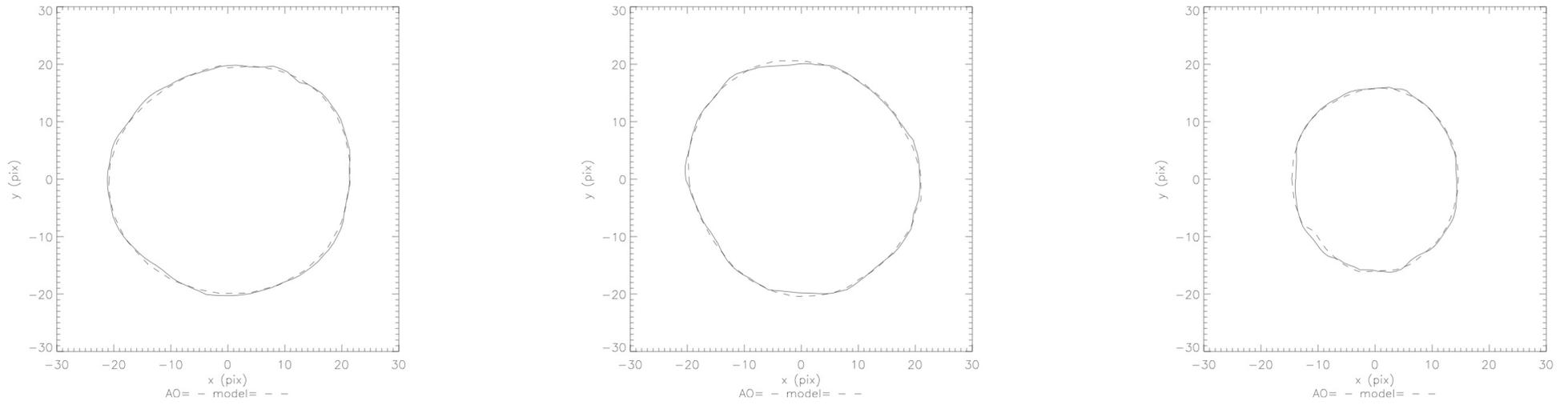


Figure 2: Sample observed (solid lines) vs. modelled (dashed lines) AO contours for 2 Pallas. Coordinates are in pixel units.

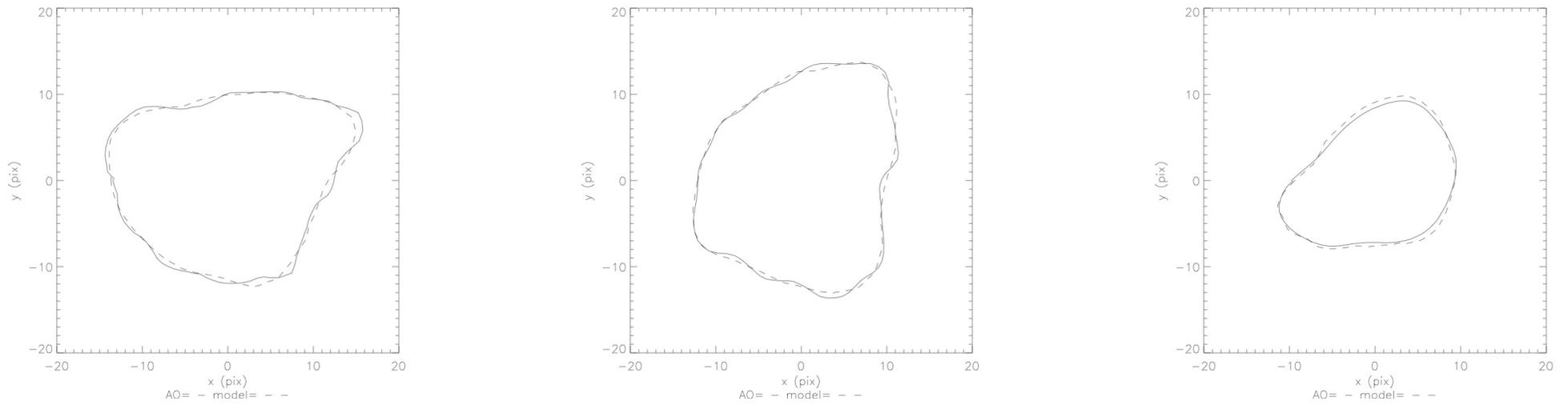


Figure 3: Sample observed (solid lines) vs. modelled (dashed lines) AO contours for 41 Daphne. Coordinates are in pixel units.