TAOS Photometry with the Expectation-Maximization Algorithm

Matthew J. Lehner
Harvard-Smithsonian Center for Astrophysics
University of Pennsylvania

Penn
University of Pennsylvania

The TAOS Collaboration:

C. Alcock (CfA)
T. Axelrod (Arizona)
F. Bianco (UPenn)
Y.-I. Byun (Yonsei)
W.-P. Chen (NCU)
K. Cook (LLNL)
R. Dave (UPenn)
J. Giammarco (Upenn)
D.-W. Kim (Yonsei)
S.-K. King (ASIAA)
T. Lee (ASIAA)
M. Lehner (CfA/UPenn)
J. Lissauer (NASA Ames)
S. L. Marshall (KIPAC/SLAC)
T. Nihei (UPenn)
I. de Pater (UC Berkeley)
J. Rice (UC Berkeley)
M. Schwamb (UPenn)
A. Wang (ASIAA)
S.-Y. Wang (ASIAA)
C.-Y. Wen (ASIAA)
Z.-W. Zhang (NCU)

Plan of the talk:

- Background, Motivation
- EM Algorithm and Stellar Photometry
- Current Status
- Future Plans

University of Pennsylvania

TAOS:

- Discover small/distant KBOs by searching for occultations of distant stars
- Event durations ~200 ms, sample at 5 Hz
- Events extremely rare, monitor 1000's of stars
- Limit false positives, use multiple (4) telescopes

TAOS:

- Reduce data in real time for follow-up
- 4 telescopes $\times$ 3000 stars $\times$ 5 Hz = 60,000 photometric reductions/second, 100 GB/night
- Read out all stars in 64 $\times$ 2048 subimage, extremely crowded
- Low bandwidth network, low power budget
- Rare events, weak signature: accuracy important

$$\frac{\partial \log L(\Psi)}{\partial f_l} = \sum_{j=1}^{N_p} \left[n_j \frac{F(\vec{x}_j;\Theta_l) - 1}{\sum_{i=1}^{N_*} f_i F(\vec{x}_j;\Theta_i) + f_B} \right] = 0$$

f_l depends on all other parameters

→ Non-linear system of $n_p N_*$ eqn's, $n_p N_*$ unknowns

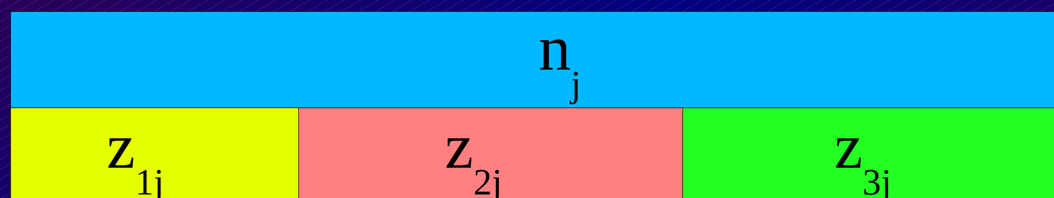
Not a problem if field is sparse: $f_l = \sum_{j=1}^{N_p'} n_j$

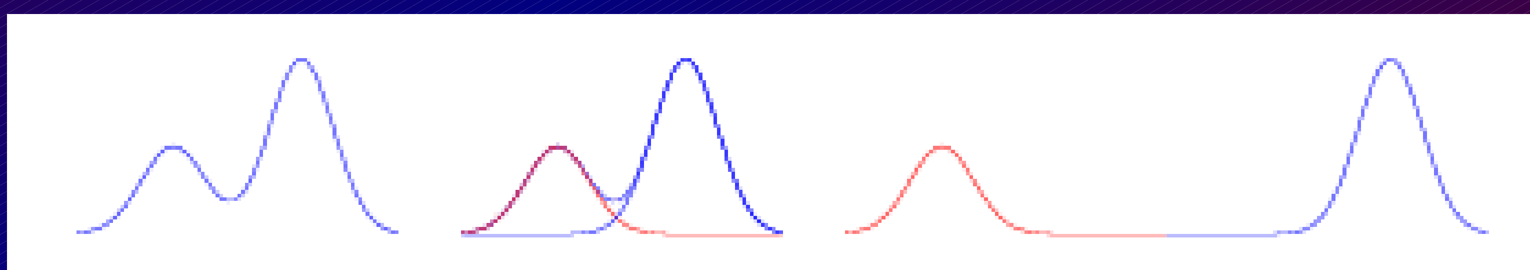
Expectation-Maximization Algorithm

- Some "unobservable data" which simplifies problem

- Calculate "complete log-likelihood" function assuming unobservable data known

- Assume we have CCD which gives number of photons in each pixel from each star, z_{ij}.





Crowded field becomes "sparse"

EM Algorithm

1) Initial guesses $\Psi^{(0)}$

2) Calculate $E\left(z_{ij} \middle| \Psi^{(k)}; n_j\right)$

3) Maximize $\log\left(L_C\left(\Psi^{(k+1)}; \Psi^{(k)}\right)\right)$

4) Repeat until convergence

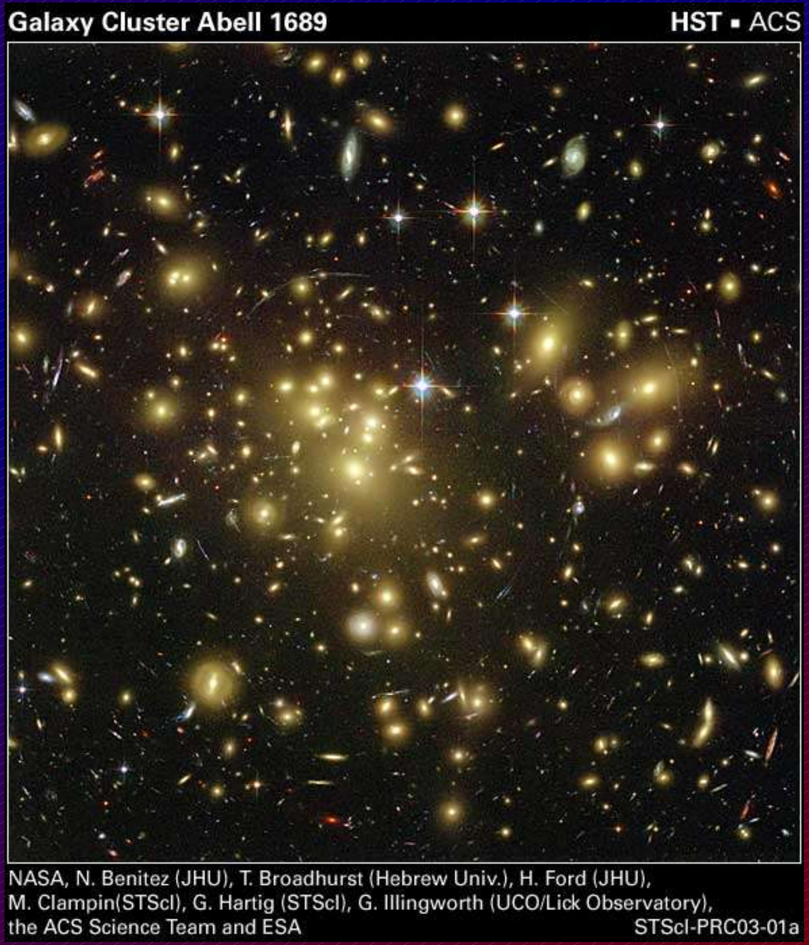
Current Status

- Algorithm works on simulated test images
- Code meets speed requirements (60,000 PSFs/sec)
- Initialization nearly ready for testing
- Currently working on tracking issues to reduce initialization overhead

Penn
UNIVERSITY of PENNSYLVANIA

Future applications

- Fitting galaxies (weak lensing)
- Overlapping galaxies, point sources
- Model galaxies with "shapelet" expansion
- Use EM algorithm for blended fits
- Funded by NASA AISR program



Penn
University of Pennsylvania

Shapelet Expansion

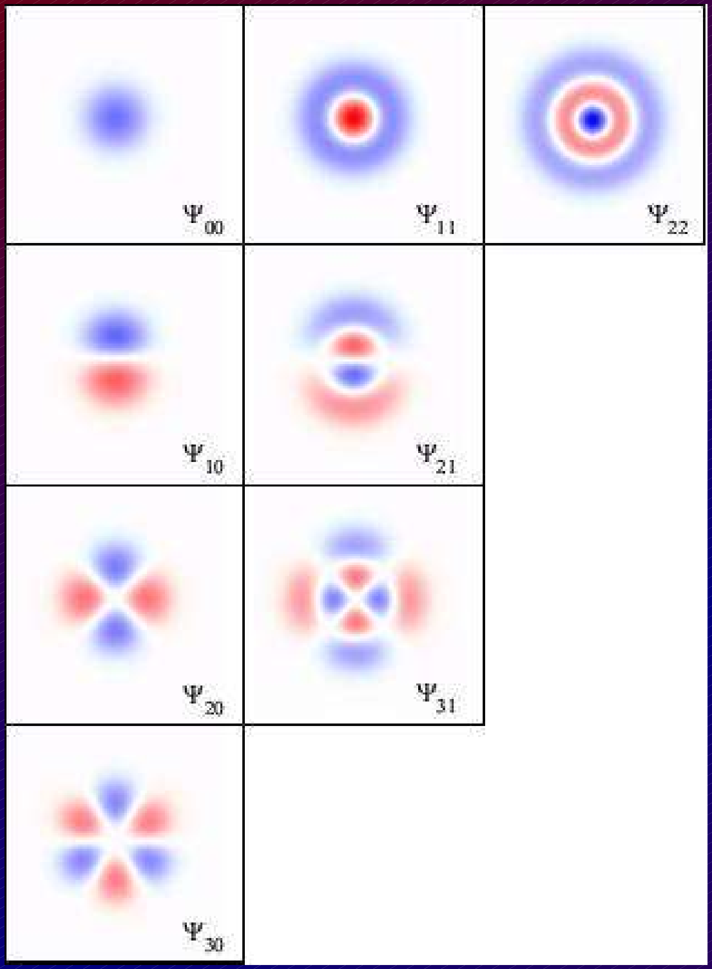
Eigenfunctions of 2-D quantum harmonic quantum oscillator $\left(r^2 - \nabla^2\right)$

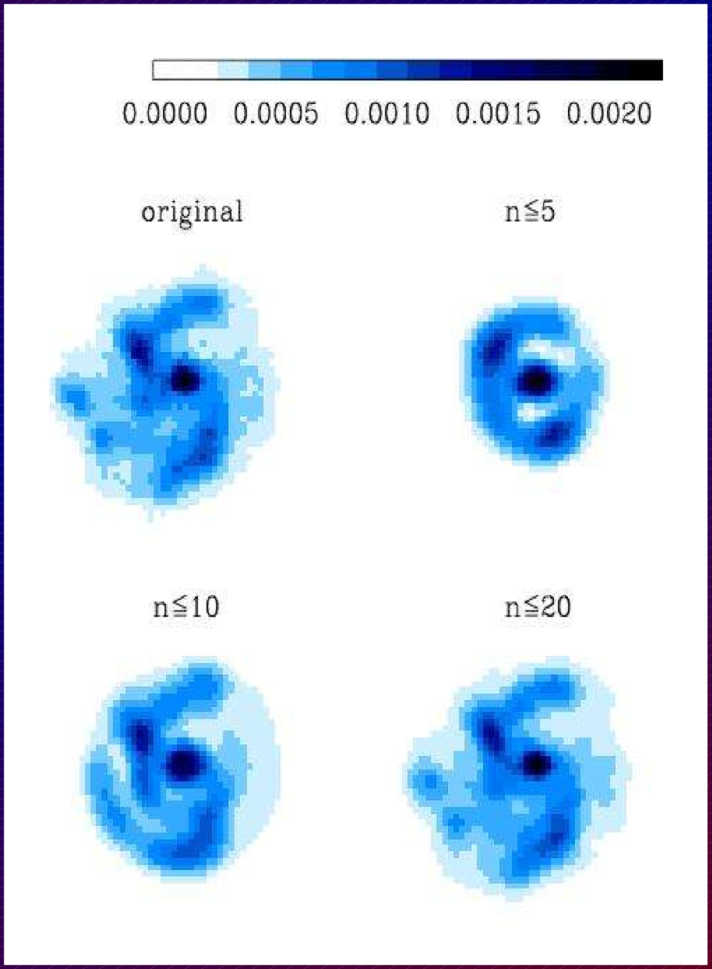
$$I(r,\sigma) = \sum_{p,q\geq 0} b_{pq} \psi^{\sigma}_{pq}(r,\phi)$$

$$\psi^{\sigma}_{pq}(r,\phi) \propto r^m e^{im\phi} e^{-r^2/2\sigma^2} L_q^{(m)}(r^2/\sigma^2)$$

$$m = p - q$$

Shapelet Expansion





Refregier, Chang and Bacon (2002)