

Computationally Efficient Wavefront Reconstruction for Multi-Conjugate Adaptive Optics (MCAO)

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AURA New Initiatives Office

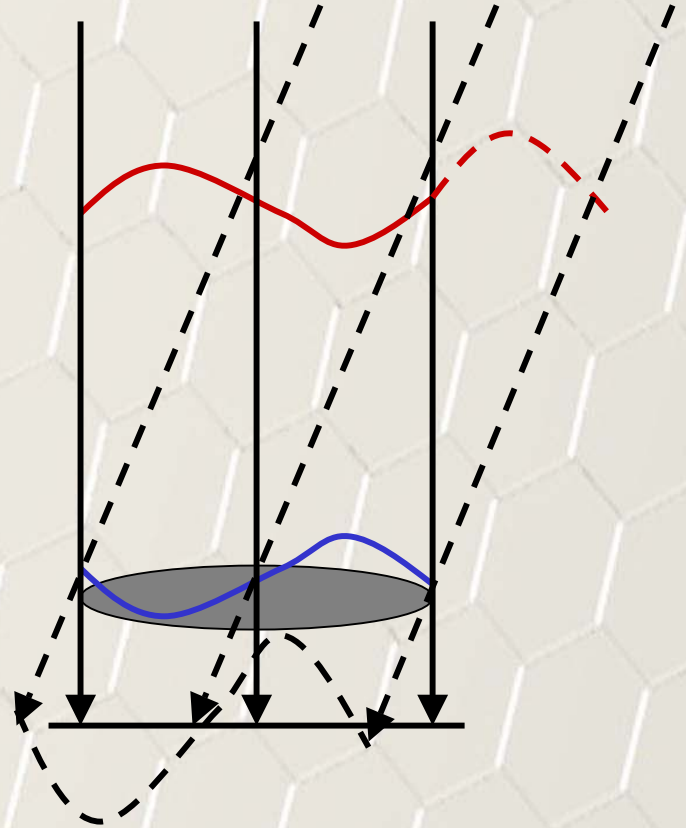
IPAM Workshop on Estimation and Control Problems

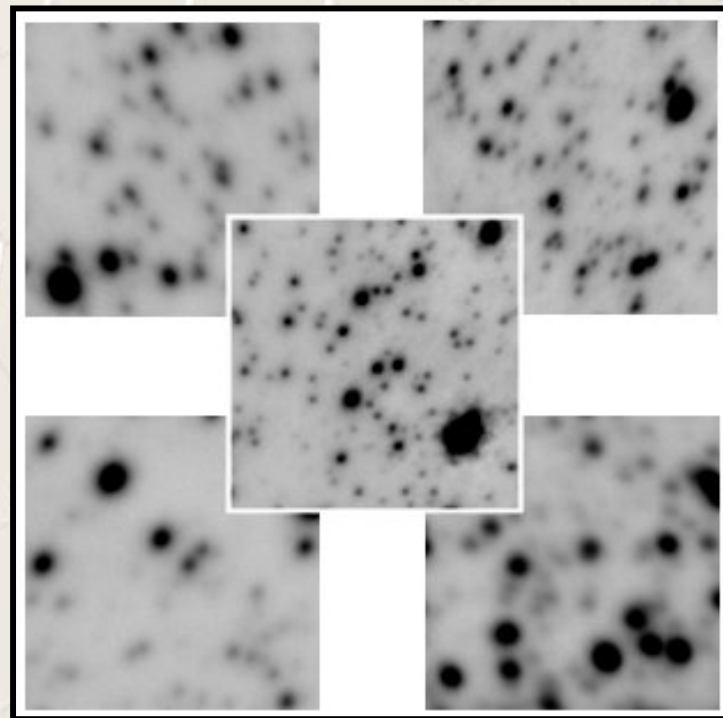
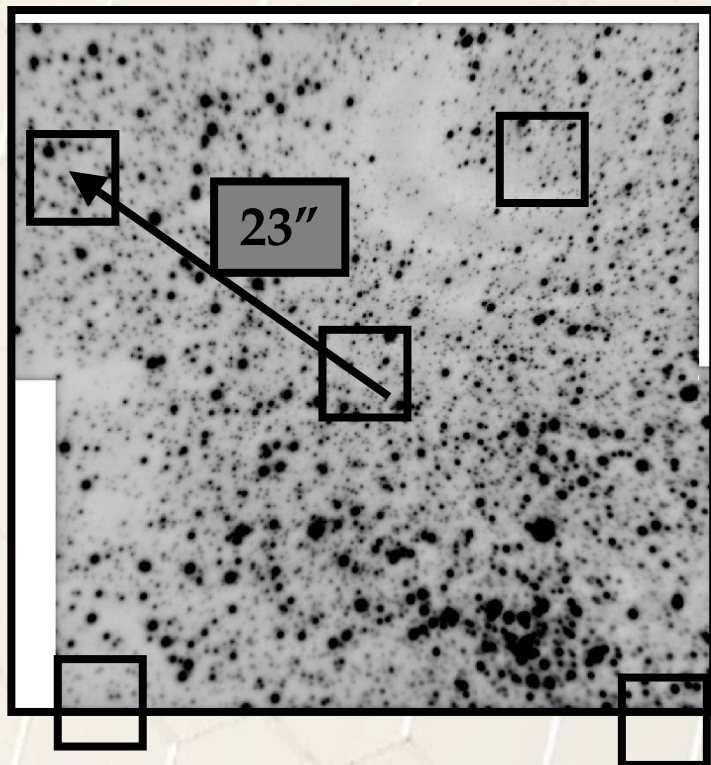
in Adaptive Optics

January 23, 2004

- Anisoplanatism and MCAO
- Minimum variance wavefront reconstruction methods for MCAO
 - Formulation, analytical solution, and scaling issues
- Computationally efficient methods for very high-order MCAO systems
 - Spatial frequency domain modeling (Tokovinin)
 - Sparse matrix techniques
 - Conjugate gradients with multigrid preconditioning
- Sample simulation results
 - MCAO Performance scaling with telescope diameter
- Summary, acknowledgements, references

- Bright **guidestars** are needed for wavefront sensing
 - Not enough bright natural stars for astronomical applications
 - Progress is being made in using **lasers** to generate artificial stars
- Even with lasers, the corrected **field-of-view** is limited
 - Turbulence is 3-dimensional
 - One deformable mirror provides correction in a single direction
 - **Anisoplanatism**

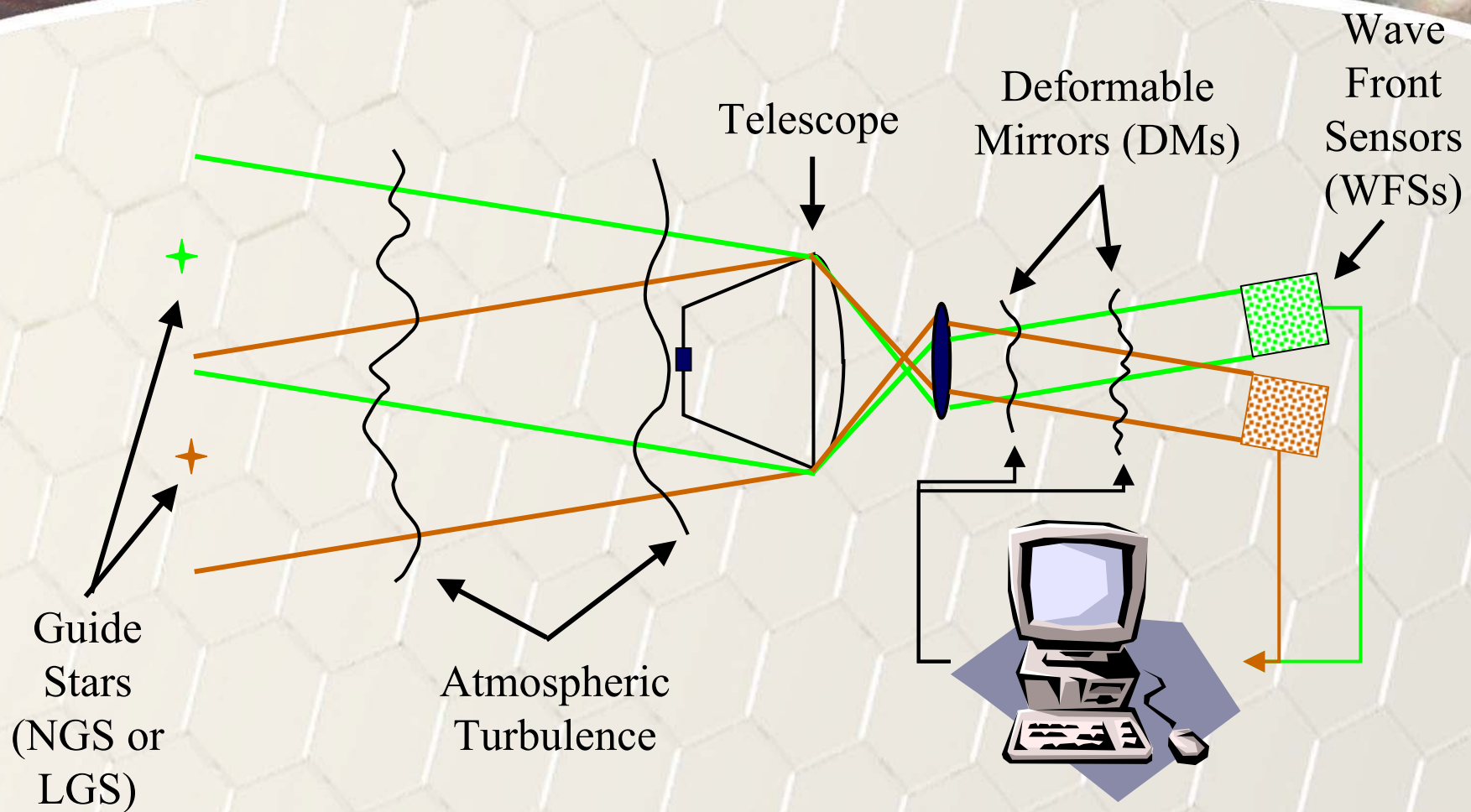




- Low-order AO system on the Gemini-North telescope
- Ambient seeing: $0.9''$
- AO-compensated seeing: $0.12''$ (center of field) to $0.19''$ (corner)
- Impact increases as the quality of correction improves

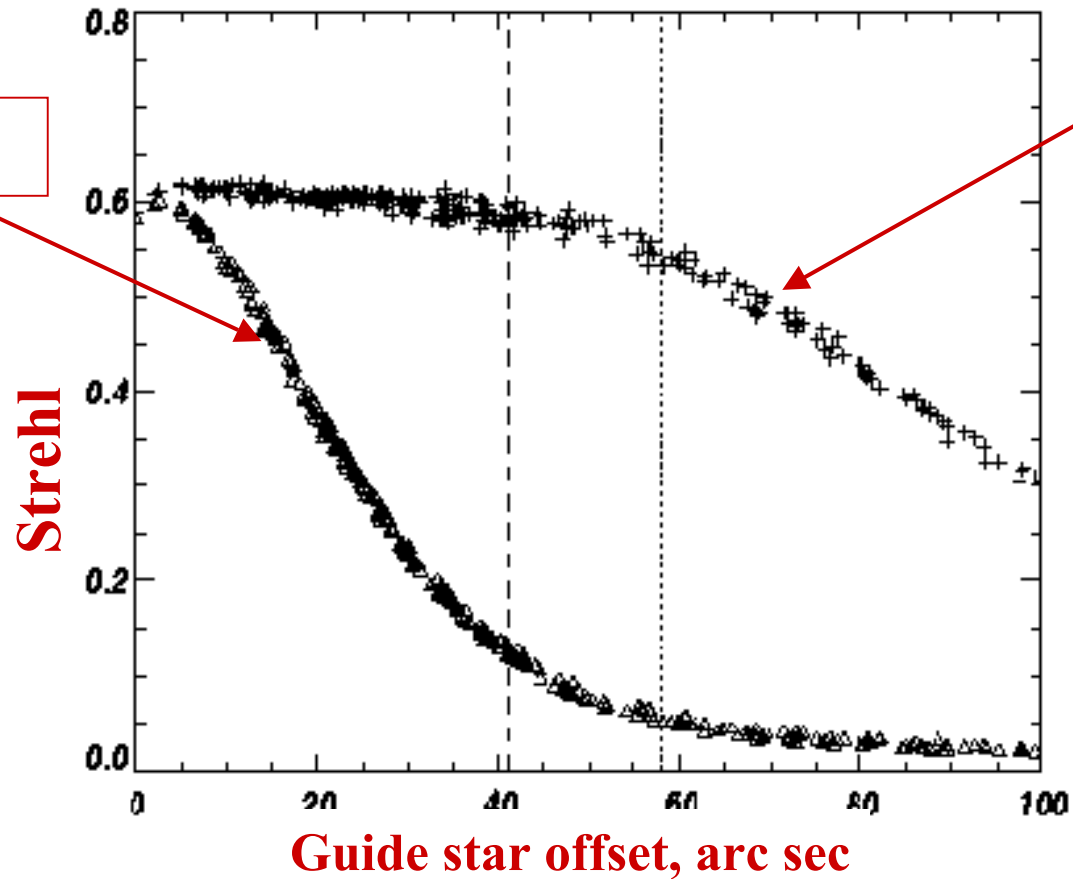


MCAO Compensates Turbulence in Three Dimensions



- An application of limited angle tomography

Processors and Control Algorithms



Classical AO

MCAO

- 8 meter telescope
- 2 deformable mirrors with 13 by 13 actuators
- 5 wavefront sensors with 12 by 12 subapertures



Wavefront Reconstruction for MCAO is Challenging

- **Multiple** turbulence layers, deformable mirrors, wavefront sensors
- Richer **cross-coupling** between variables
- Higher **dimensionality** estimation problem
 - Especially for future extremely large telescopes!
- **Wide-field** performance evaluation and optimization

Wavefront Reconstruction as a Linear Inverse Problem

- Quantities of interest
 - Turbulence profile x ...
 - ...to be corrected by a DM actuator command vector a ...
 - ... using a WFS measurement s with noise component n ...
 - ...leaving a residual phase error ϕ with mean-square value σ^2
- Relationships
 - $s = Gx + n$ (wavefront sensing)
 - $a = Rs$ (wavefront reconstruction)
 - $\phi = H_x x - H_a a$ (residual error computation)
 - $\sigma^2 = \phi^T W \phi$ (variance evaluation)
- Objective: Select R to (in some sense) minimize σ^2



Minimum Variance Wavefront Reconstruction

- Model x , s , and n as zero mean random variables with finite second moments
- Select R to minimize $\langle \sigma^2 \rangle$ (the expected value of σ^2):

$$R_* = \arg \min_R \langle \sigma^2 \rangle$$

$$= \arg \min_R \langle [H_x x - H_a R s]^T W [H_x x - H_a R s] \rangle$$

- Partial derivatives of $\langle \sigma^2 \rangle$ with respect to R_{ij} must vanish at $R=R_*$
- Solution given by $R_* = F_* E_*$, where

$$E_* = \langle x s^T \rangle \langle s s^T \rangle^{-1} = \left(G^T \langle n n^T \rangle^{-1} G + \langle x x^T \rangle^{-1} \right) G^T \langle n n^T \rangle^{-1}$$

$$F_* = \left(H_a^T W H_a \right)^{-1} H_x^T W H_x$$

- Interpretation

- E_* is the “turbulence **E**stimation matrix”

- Minimum variance estimate of profile x from measurement s
 - Depends upon WFS geometry, statistics of x and s
 - **Independent** of the DM geometry

- F_* is the “turbulence **F**itting matrix”

- RMS best fit to estimated value of x using DM degrees of freedom
 - **Independent** of WFS geometry, statistics of x and s
 - Depends upon the DM geometry

- Use

- Once R_* is known, we can estimate performance using

$$\min_R \langle \sigma^2 \rangle = \langle [H_x x - H_a R_* s]^T W [H_x x - H_a R_* s] \rangle$$

- ...or we can use R_* to run simulations (or even systems)

- R_* has complexity $O(N^3)$ to explicitly compute and evaluate, complexity $O(N^2)$ to apply in real time
 - Must be computed/evaluated in a **few hours** for studies
 - Must be applied at rates of **1-2 KHz** for actual use
- Current generation MCAO systems have $N < 1000$
 - Computationally feasible
- Proposed MCAO systems have $N > 10^4$ or 10^5
 - Explicit computations inefficient or outright infeasible
 - How do we analyze and simulate such systems???



Analytical Methods in the Spatial Frequency Domain

- Wavefront propagation, sensing, correction, and reconstruction are all approximately **spatial filtering** operations
- Filtering representation becomes exact in the limit of an **infinite aperture** AO system
- Wavefront reconstruction **decouples** into small independent problems at each spatial frequency
 - Each problem has dimensionality $2 N_{\text{wfs}}$ by N_{dm}
- Overall complexity scales as $O(N_{\text{freq}}) \propto O(N)$
- **Analytical method** only, but very useful



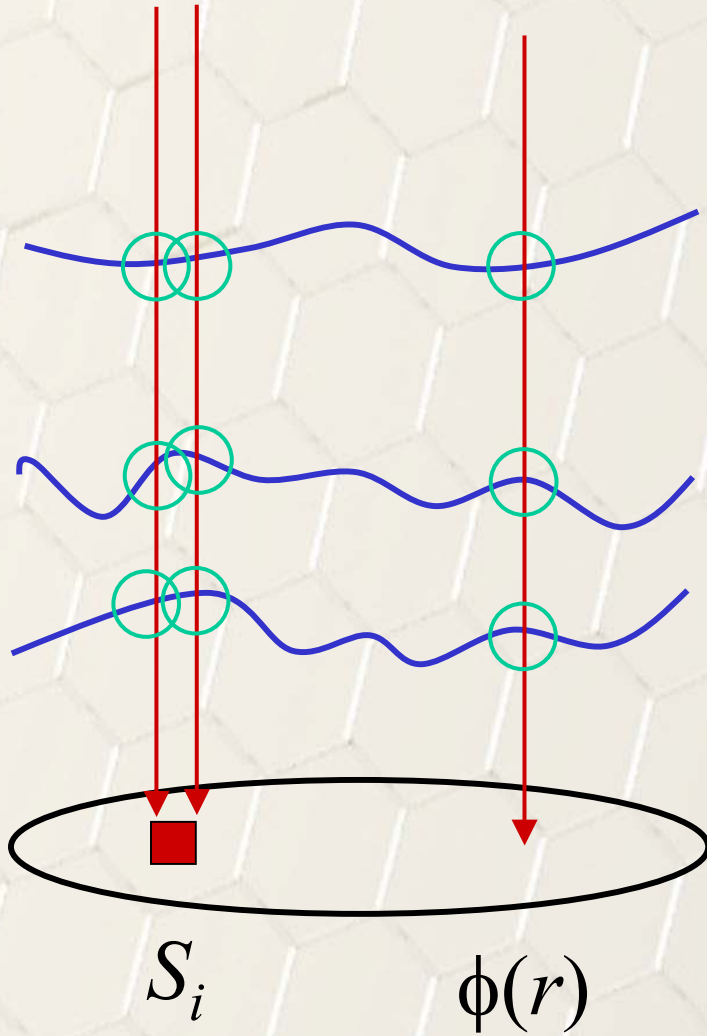
Efficient Approaches for the Spatial Domain

- Must solve $Ax=y$, where

$$A = G^T \langle nn^T \rangle^{-1} G + \langle xx^T \rangle^{-1} \quad \text{or} \quad A = H_a^T W H_a$$

without explicitly computing A^{-1}

- Exploit matrix structure
 - G, H_a, W are sparse
 - $\langle nn^T \rangle$ is diagonal (plus a low-rank perturbation due to laser guide star position uncertainty)
 - $\langle xx^T \rangle^{-1}$ has good approximations that are sparse
- Efficient solutions possible
 - Sparse matrix techniques (close, but not quite)
 - Conjugate gradients with multigrid preconditioning



- Each value of $\phi(r)$ is determined by turbulence values along a single ray path
- Each WFS measurement s_i is determined by values of $\phi(r)$ within a small subaperure

- Suppose A is sparse (with bandwidth $O(N^{1/2})$)

- Factor

$$A = LL^T$$

where L is sparse and lower triangular

- Solve $Ax=y$ in two steps:

$$Lx' = y, \quad \text{followed by} \quad L^T x = x'$$

- Complexity reduced from $O(N^2)$ to $O(N^{3/2})$

- Complexity further reduced by **reordering** rows/columns of A

- For F_* , $A = H_a^T W H_a$ is sparse (at least for conventional AO)

- For E_* , $A = G^T \langle nn^T \rangle^{-1} G + \langle xx^T \rangle^{-1}$ isn't sparse for two reasons:

- The turbulence covariance matrix $\langle xx^T \rangle$ isn't sparse

- For laser guidestars, $\langle nn^T \rangle$ is the sum of sparse and low rank terms



Sparse Approximation to Turbulence Statistics

- $\langle xx^T \rangle^{-1}$ is block diagonal, with N_{layer} by N_{layer} blocks
 - Each diagonal block is full rank!
- We approximate block j as $\alpha_i^{-1} D^T D$
 - α_i proportional to layer strength
 - D is a discrete (and sparse) approximation to ∇^2
- Heuristic justification #1:
 - Both $\langle xx^T \rangle^{-1}$ and $D^T D$ suppress high spatial frequencies
- Heuristic justification #2:
 - In the spatial frequency domain

$$\langle \hat{x}(\kappa) \hat{x}^*(\kappa') \rangle \propto \delta(\kappa - \kappa') \kappa^{-11/3} \approx \delta(\kappa - \kappa') \kappa^{-4}$$

$$\langle \hat{x}(\kappa) \hat{x}^*(\kappa) \rangle^{-1} \propto \kappa^4 = \kappa^2 \kappa^2 \propto [\text{FT}(\nabla^2)]^T [\text{FT}(\nabla^2)]$$

- For a LGS WFS, n is determined by two effects:
 - Detector readout noise and photon statistics (uncorrelated)
 - LGS position uncertainty on the sky
 - Two dimensions of uncertainty per guidestar, **correlated** between subapertures
- More formally

$$n = n_r + n_t$$

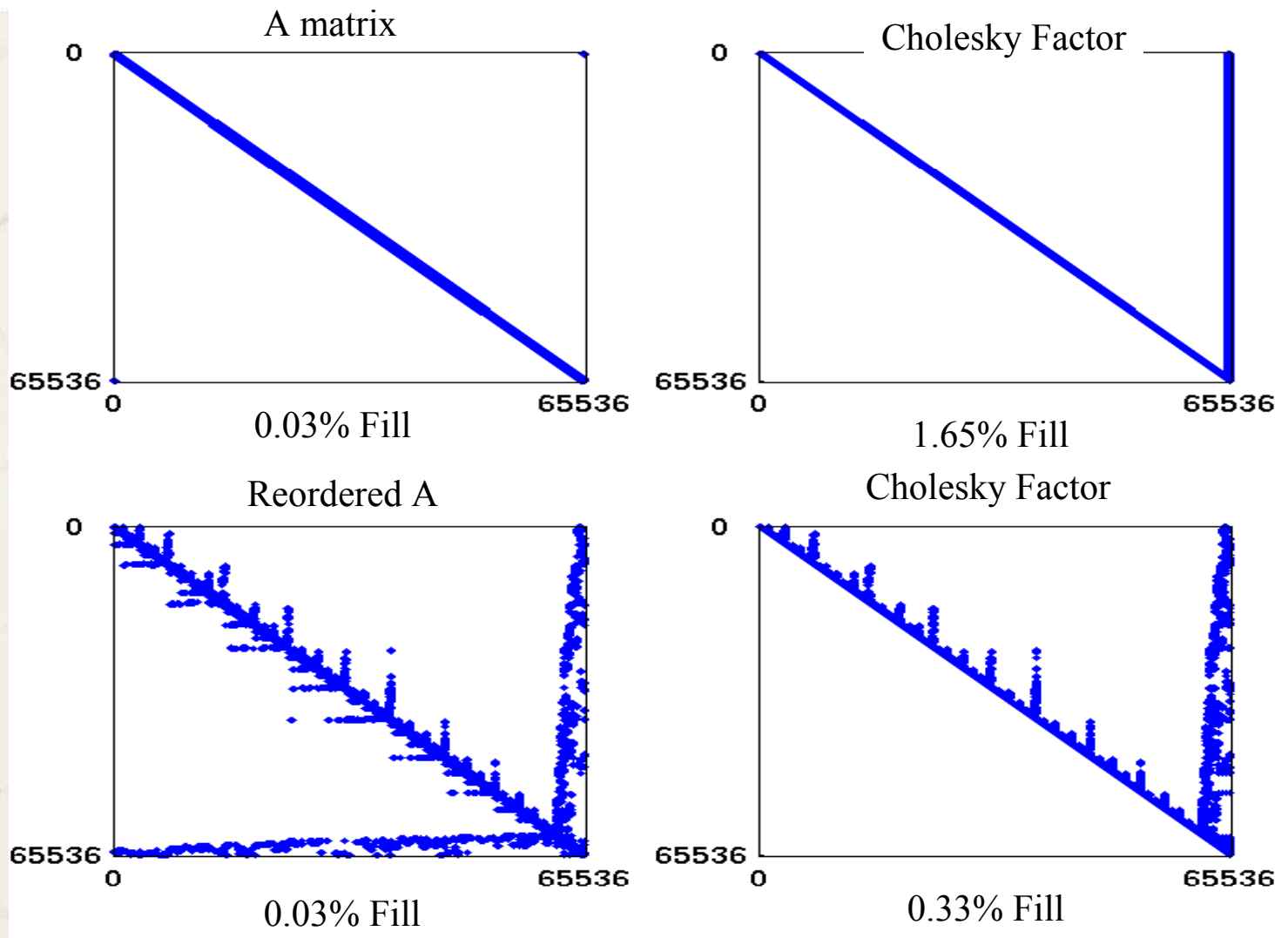
$$\langle nn^T \rangle = \langle n_r n_r^T \rangle + \langle n_t n_t^T \rangle = \text{diag}(\sigma_i^2) + \sigma_t^2 UU^T$$

- UU^T is a non-sparse matrix of rank $2 N_{\text{LGS}}$
- Sparse matrix methods are not immediately applicable

$$\left(M - UV^T\right)^{-1} = M^{-1} + \left(M^{-1}U\right)\left(I - V^T M^{-1}U\right)^{-1}\left(M^{-1}V\right)^T$$

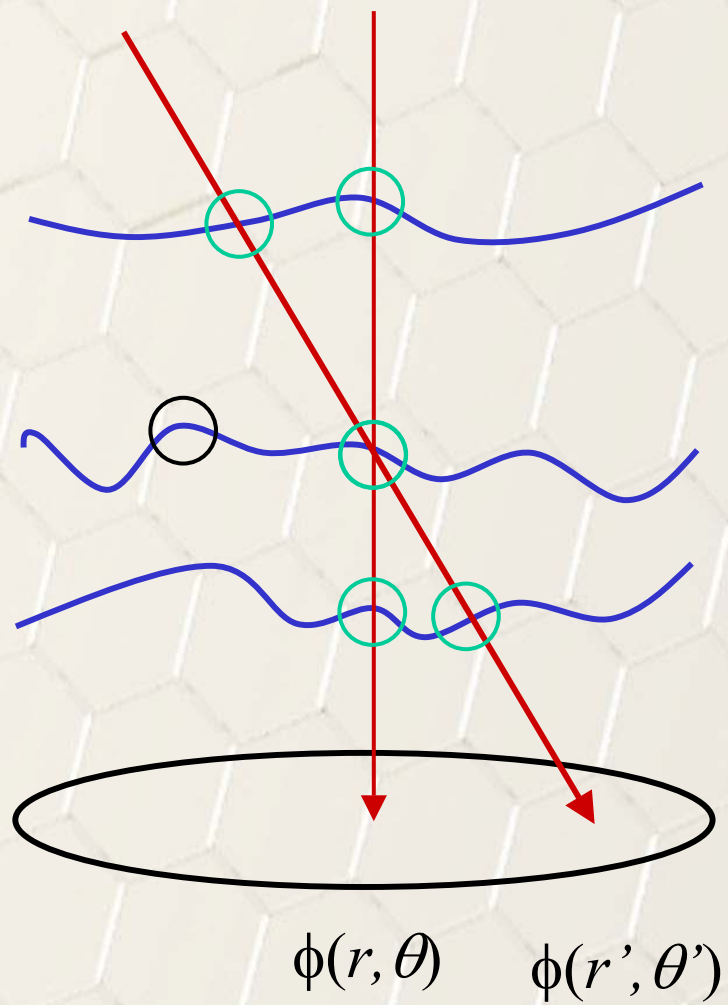
- $\langle nn^T \rangle^{-1} = \langle \text{diag}(\sigma_i^2) + \sigma_T^2 U U^T \rangle^{-1}$ is the sum of $\text{diag}(\sigma_i^{-2})$ and a low rank term $U U^T$
- $G^T \langle nn^T \rangle^{-1} G + \langle xx^T \rangle^{-1} = \underbrace{G^T \text{diag}(\sigma_i^{-2}) G + \langle xx^T \rangle^{-1}}_{\text{Sparse}} + \underbrace{(G U') (G U')^T}_{\text{Low Rank}}$
- Can solve $\left(G^T \langle nn^T \rangle^{-1} G + \langle xx^T \rangle^{-1}\right)^{-1} x = y$
by solving $\left(G^T \text{diag}(\sigma_i^2) G + \langle xx^T \rangle^{-1}\right)^{-1} x = y$
and adding a perturbation term depending upon $\left(G^T \text{diag}(\sigma_i^2) G + \langle xx^T \rangle^{-1}\right)^{-1} (G U')$

Sample Matrix Factorizations for E_*



- Conventional AO with 1 DM and 1 WFS!

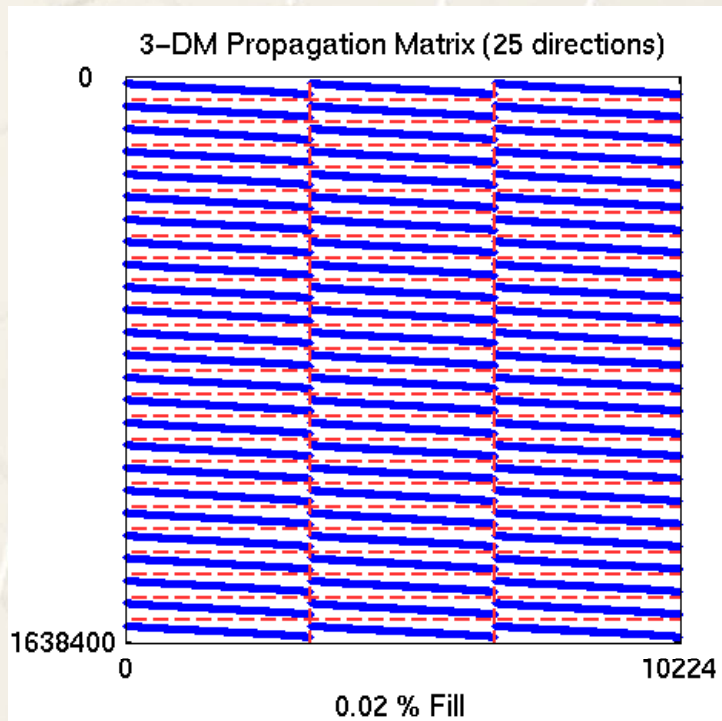
MCAO Increases Coupling between Turbulence Layers



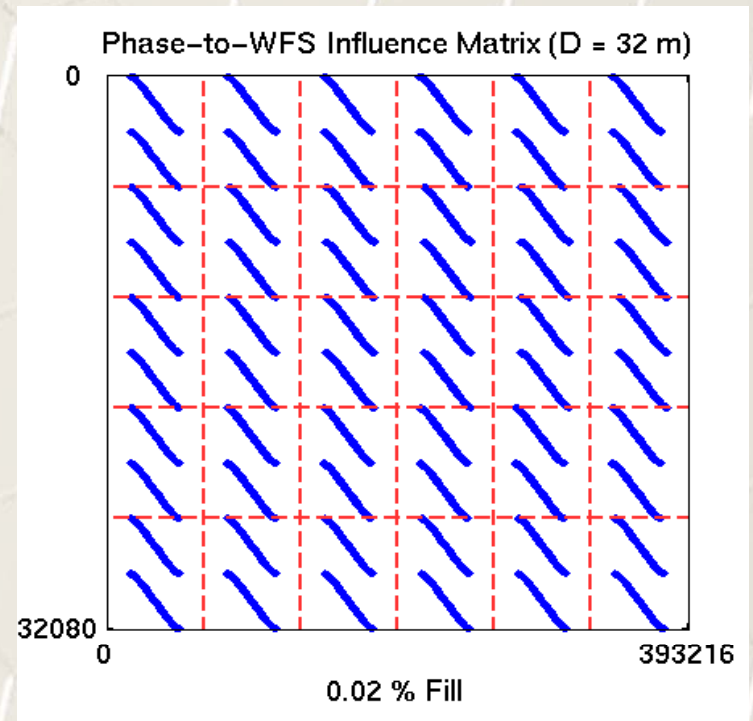
- However, the coupling within a single layer is no greater than before

G, H Matrices Are Block Structured for MCAO

- Column block structure due to multiple atmospheric layers
- Row block structure due to multiple stars/guidestars



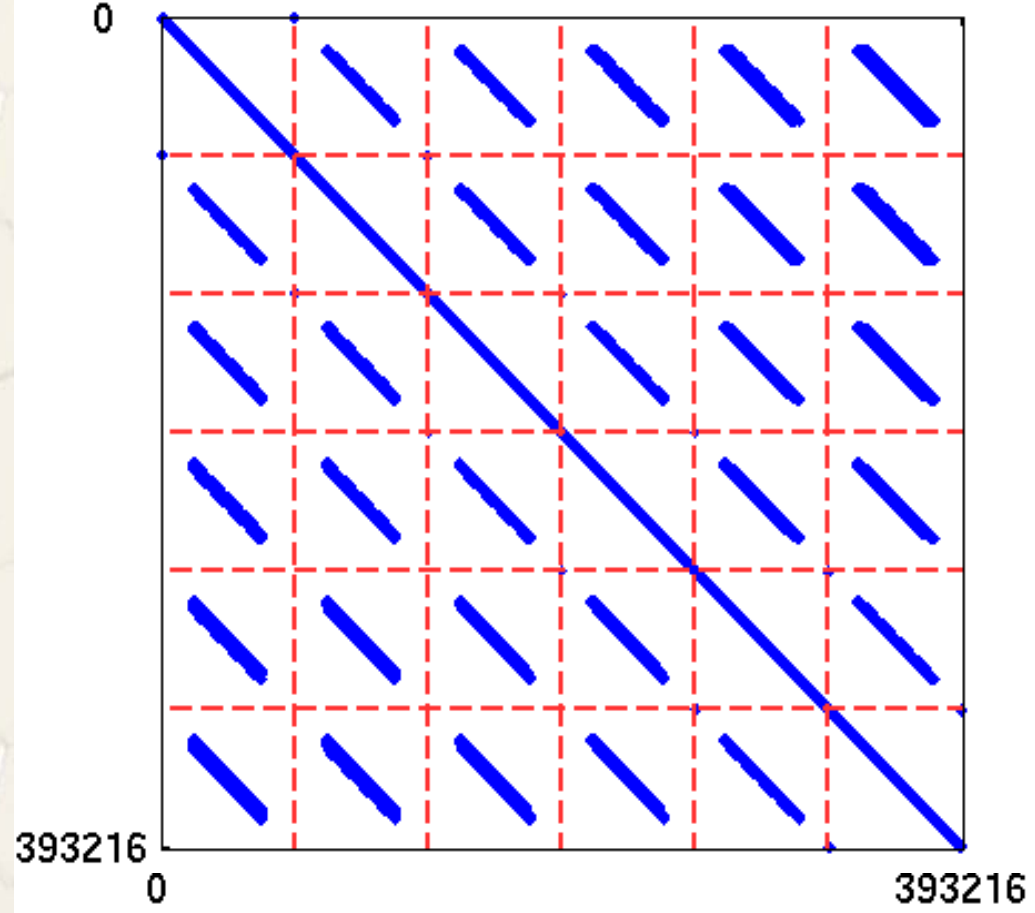
H_a (3 mirrors, 25 stars)



G (5 guidestars, 6 atmospheric layers)

Cross-Coupling of Atmospheric Layers for MCAO

Matrix to be inverted in the estimation step ($D = 32$ m)



- Fill-in of “sparse” Cholesky factorization exceeds 10%
- Cannot factor matrices for a 32m diameter system in a 2 Gbyte address space

An “Efficient” MCAO Reconstruction Algorithm

- Biggest challenge is solving $Ax=y$ with
$$A = G^T \langle nn^T \rangle^{-1} G + \langle \delta\delta^T \rangle^{-1}$$
- Minimize $\|Ax-y\|^2$ using **conjugate gradients**
- Use **multigrid preconditioning** to accelerate convergence
 - **Preconditioning**: Solve an approximate system $A'x=y$ once per conjugate gradient cycle
 - **Multigrid**: Solution to $A'x=y$ determined on multiple spatial scales to accelerate convergence at all spatial frequencies
- Solution on each multigrid scale is determined using a customized (new?) technique:
 - **Block** symmetric Gauss-Seidel iterations on $Ax=y$
 - Block structure derived from atmospheric layers
 - **Sparse matrix factorization** of diagonal blocks

Block Symmetric Gauss-Seidel Iterations

- Blocks of A , x , y denoted as A_{ij} , x_i , y_j

- Decompose

$$A = L + D + U$$

into a sum of lower triangular, diagonal, and upper triangular blocks

- Iterative solution to $Ax = (L+D+U)x = y$ given by

$$(L+D)x'(n) = y - Ux(n)$$

$$(U+D)x(n+1) = y - Lx'(n)$$

- Solve for $x'(n)$ and $x(n+1)$ one block at a time:

$$D_i x_i'(n) = y_i - \sum_{j>i} A_{ij} x_j(n) - \sum_{j<i} A_{ij} x_j'(n)$$

$$D_i x_i(n+1) = y_i - \sum_{j<i} A_{ij} x_j'(n) - \sum_{j>i} A_{ij} x_j(n+1)$$

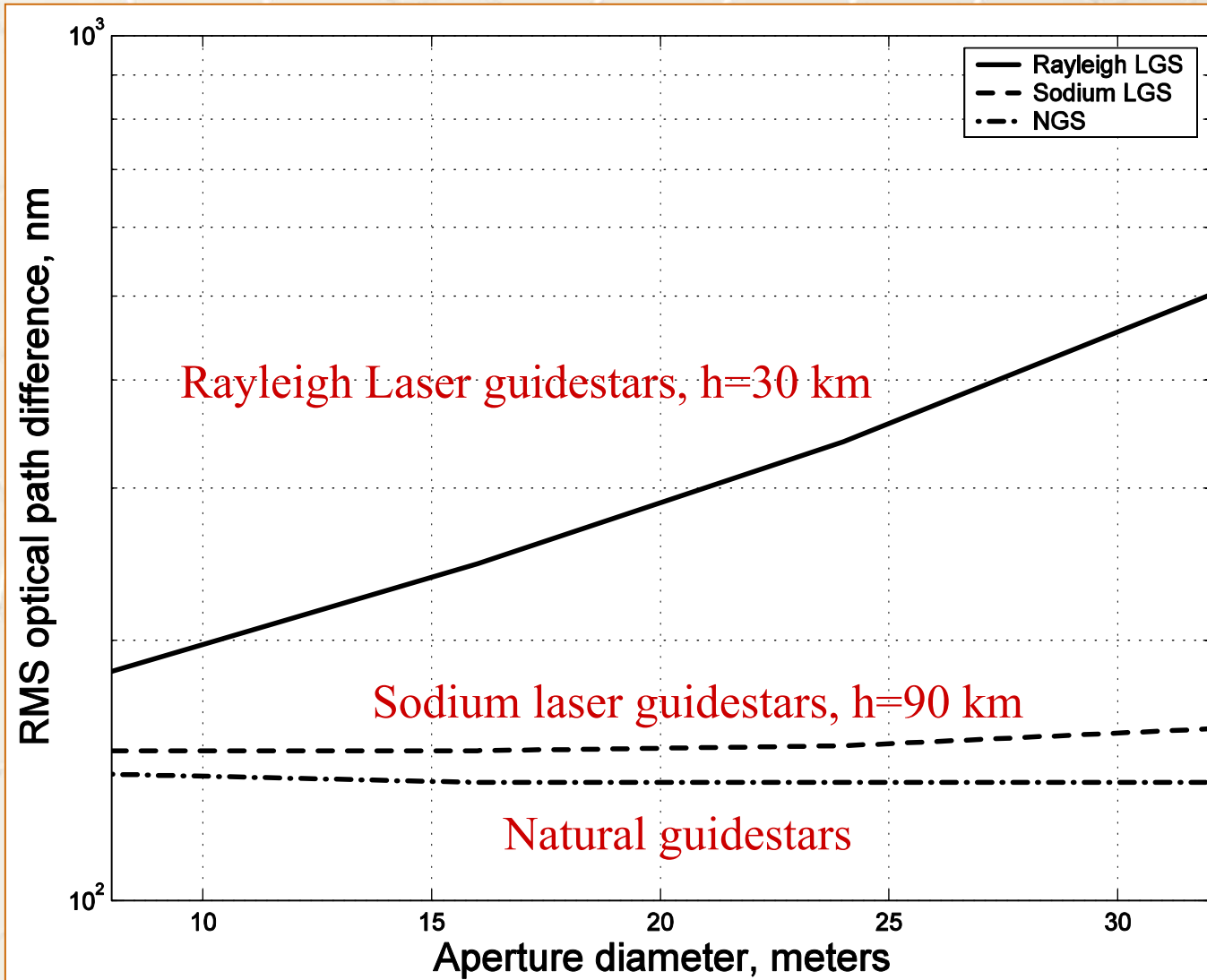
- Solve systems $D_i u = v$ using sparse Cholesky factorizations

TMT MCAO Simulations for Future Telescopes

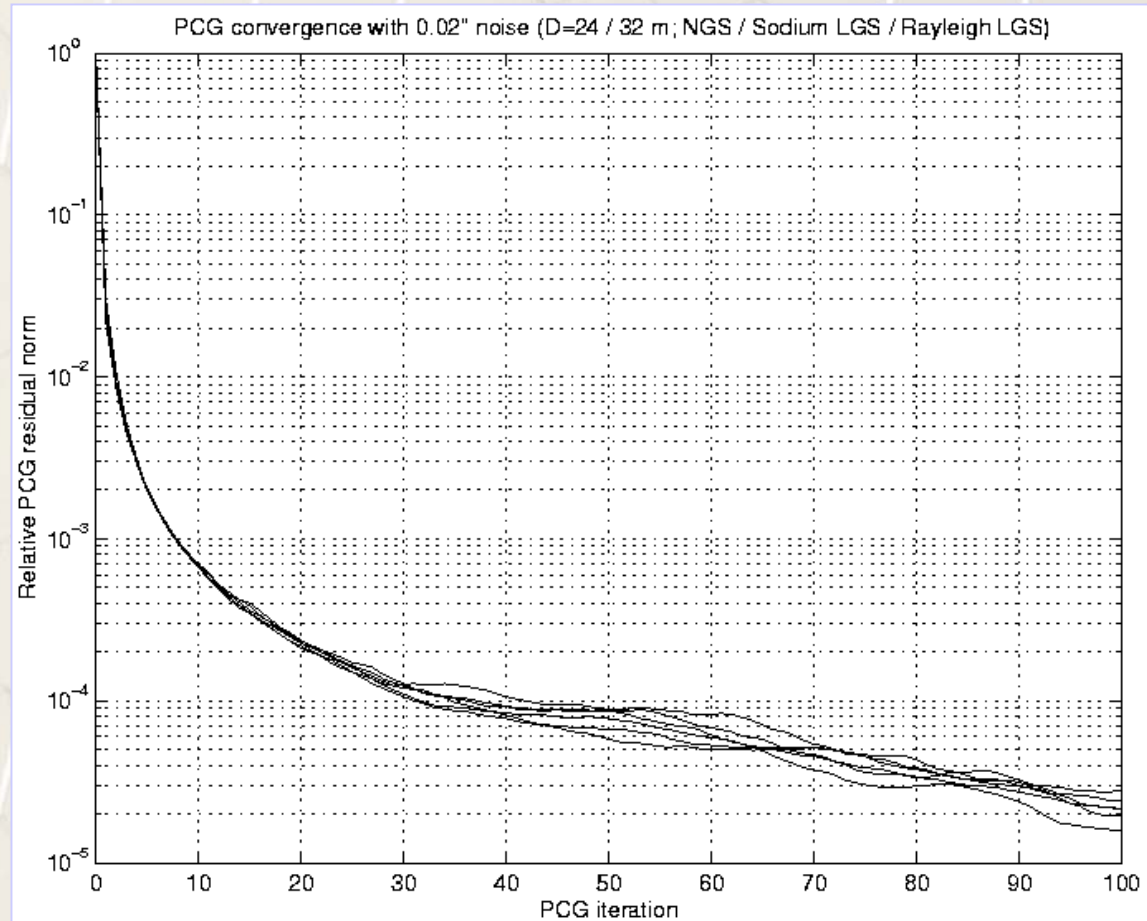
- Goal: Evaluate MCAO performance **scaling with aperture diameter D** from $D=8\text{m}$ to $D=32\text{m}$
- Consider Natural, Sodium, and Rayleigh guidestars
- Other simulation parameters:
 - Cerro Pachon turbulence profile with **6 layers**
 - 1 arc minute square field-of-view
 - **3 DM's** conjugate to 0, 5.15, and 10.30 km
 - Actuator pitches of 0.5, 0.5, and 1.0 m
 - **5 higher order guidestars** at corners and center of 1' field
 - 0.5 m subapertures
 - 4 tip/tilt NGS WFS for laser guide star cases
 - 10 simulation trials per case using 64 m turbulence screens with 1/32m pitch

Aperture, m	8	16	24	32
WFS measurements	2240	8560	18840	33320
Phase points estimated (E_*)	7270	21226	42334	70838
DM actuators fit (F_*)	789	2417	4957	8449

Sample Numerical Results



- Rapid convergence for first 20 iterations
- Convergence then slows due to poor conditioning of A
- Not an issue for practical simulations
- Results effectively independent of aperture diameter and guide star type



- MCAO compensates anisoplanatism and corrects for the effects of atmospheric turbulence across extended fields-of-view
- Minimum variance estimation is a viable approach to MCAO wavefront reconstruction
- Computationally efficient methods needed for the very high order systems proposed for future extremely large telescopes
- Conjugate gradient wavefront reconstruction using multigrid preconditioning and block symmetric Gauss-Seidel iterations enables simulations of 32 meter MCAO systems with 30k sensor measurements and 8k mirror actuators
- Challenging problems remain
 - Closed-loop wavefront reconstruction and control
 - Hardware and software for real-time implementation

- Luc Gilles and Curt Vogel
 - Ongoing collaboration on efficient methods
 - Matrix sparsity plots
- Francois Rigaut
 - MCAO figure and performance plot
- Gemini Observatory
 - Sample AO results
- Support from AFOSR, NSF, and CfAO

- Adaptive optics websites
 - CfAO, <http://cfao.ucolick.org>
 - Gemini AO web pages at <http://www.gemini.edu>
- Minimum variance wavefront reconstruction
 - Wallner, JOSA 73, 1771 (1983)
 - Ellerbroek, JOSA A 11, 783 (1994)
 - Fusco et al., JOSA A 18, 2527 (2001)
- Efficient implementations
 - Ellerbroek, JOSA A 19, 1803 (2002)
 - Ellerbroek, Gilles, Vogel, SPIE Proc. 4839, 989 (2002)
 - Gilles, Ellerbroek, Vogel, Appl. Opt. 42, 5233 (2003)