Toward an optimal LINEAR sensing and calibration strategy for high contrast imaging

Introduction to ...

Linear Dark Field Control (LDFC)

... and other useful tricks

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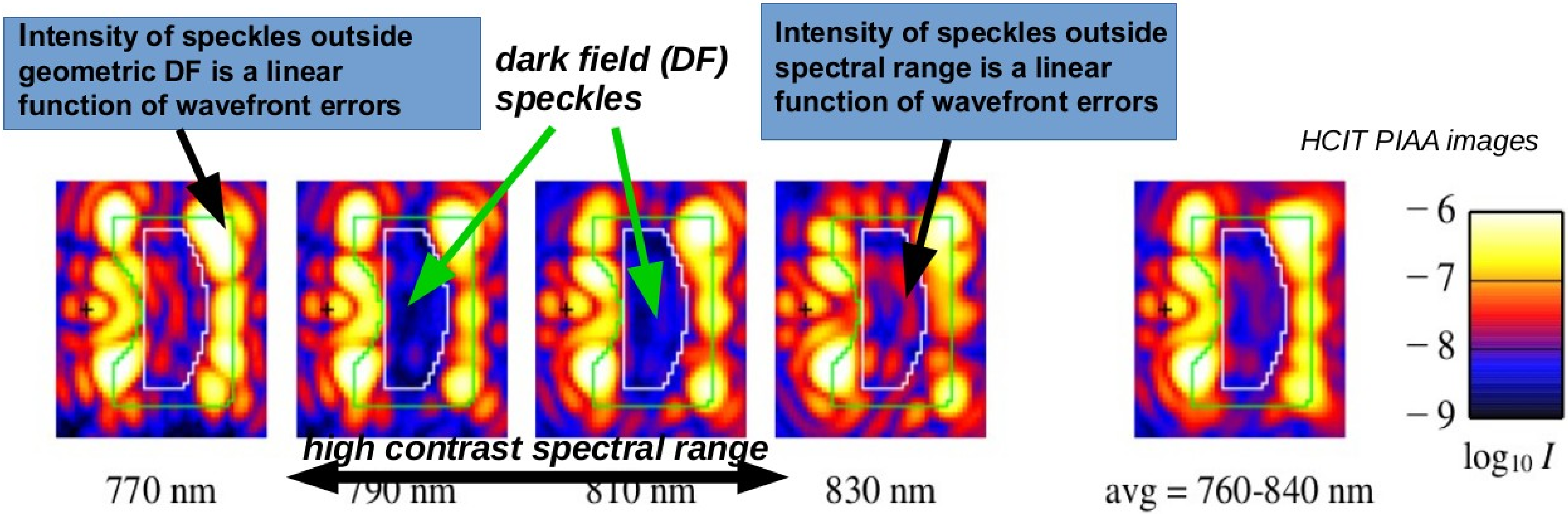
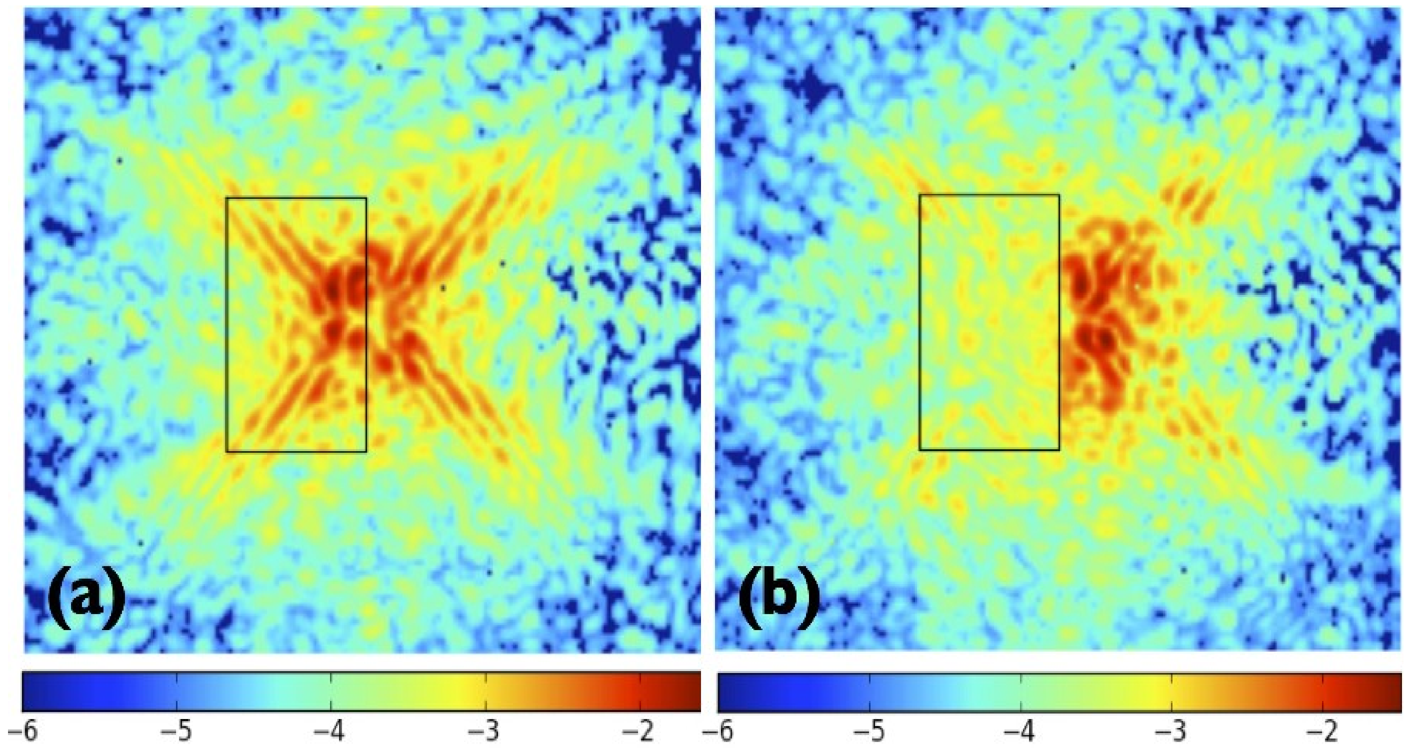
Linear Dark Field Control (LDFC)

Speckle intensity in the DF are a non-linear function of wavefront errors
→ current wavefront control technique uses several images (each obtained with a different DM shape) and a non-linear reconstruction algorithm (for example, Electric Field Conjugation – EFC)

Speckle intensity in the BF are linearly coupled to wavefront errors → we have developed a new control scheme using BF light to freeze the wavefront and therefore prevent light from appearing inside the DF



Bright field speckles in ½ field dark hole



LDFC vs. EFC

LDFC improves wavefront control loop speed by ~20x (more starlight is used for the measurement) and does not require DM modulation.
Linear loop is simpler, more robust that state of the art.

EFC

- Requires $\approx$4 images
- Competes with science measurement: dark field needs to be broken
- Time aliasing effects and confusion between incoherent residual and time-variable coherent residual
- Sensitive to (exo)zodi unless probes are large
- Sensitive to dark current and readout noise unless probes are large
- Sensing relies on DM calibration and system model
- Difficult to measure/verify G-matrix
- Only uses $\approx$15% spectral band
- Only uses dark field area
- Single polarization
- Non-linear loop (convergence, computing power)

LDFC

- Single image
- Maintains dark field during measurement: 100% duty cycle
- More robust against temporal effects: speckle variations have small negative effect on loop
- Insensitive to (exo)zodi
- Robust against dark current and readout noise (photon noise $>$ readout noise)
- Sensing relies on camera calibration
- Response matrix obtained from linear measurements
- Can use $\approx$ 100% spectral band
- Can use whole focal plane (if combined with EFC)
- Dual polarization (if detector(s) allow)
- Linear loop: simple matrix multiplication

Application to NASA missions

We assume here:

- 2.4m telescope, 10% efficiency, 400nm-900nm LDFC bandwidth
- 1e-9 contrast dark field speckle sensing, $m_V = 5$ star
- 1e-8 incoherent background (zodi + exozodi + detector)

0.2 ph/sec/speckle, 2ph/sec for background.

Bright speckle level	Relative modulation	Absolute change	1mn SNR	Camera dynamical range
1e-4 (20000 ph/sec)	0.6%	6.3e-7 (127 ph/sec)	7.0	1e5
1e-5 (2000 ph/sec)	2%	2.01e-7 (40.2 ph/sec)	7.0	1e4
1e-6 (200 ph/sec)	6%	6.43e-8 (12.86 ph/sec)	7.0	1000
1e-7 (20 ph/sec)	21%	2.1e-8 (4.2 ph/sec)	6.9	100
1e-8 (2 ph/sec)	73%	7.3e-9 (1.46 ph/sec)	5.65	10
1e-9 (0.2 ph/sec)	300%	3e-9 (0.6 ph/sec)	3.13	1

Case study for WFIRST:

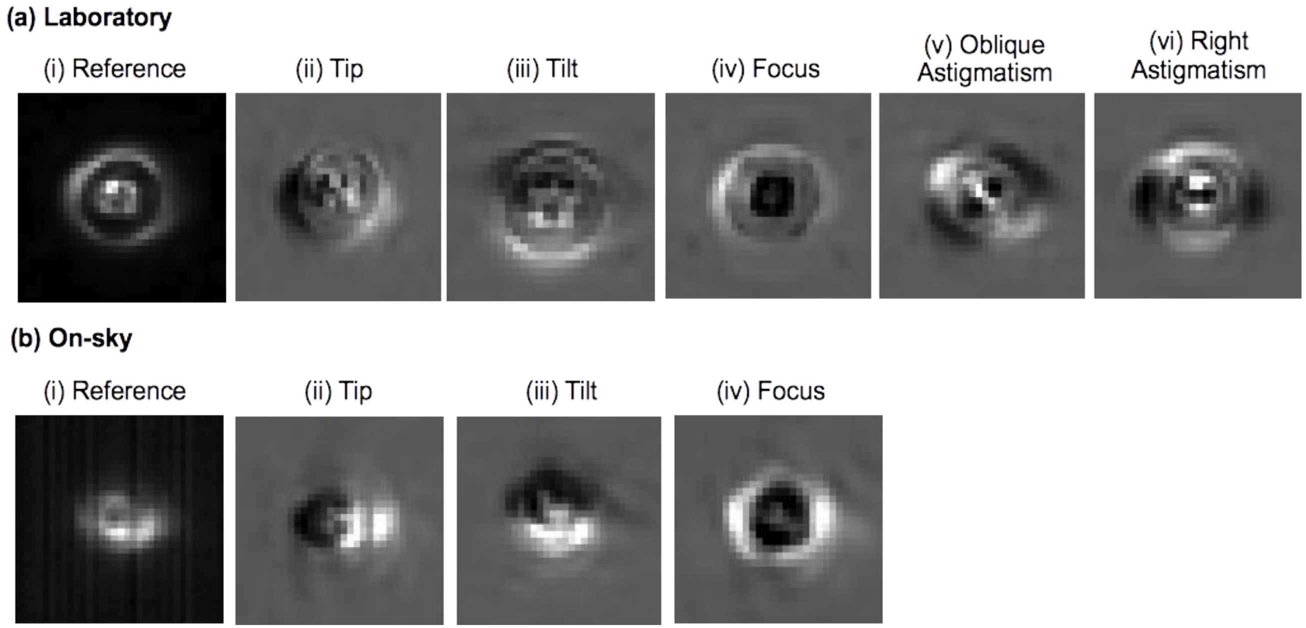
LDFC control bandwidth is 10mn, compared to several hr for state of the art EFC

Key benefits:

- LDFC enables close loop aberration control on science targets, as opposed to the current "set and forget" scheme → deeper contrast can be maintained, and system can be more resilient to small wavefront changes
- LDFC is also a powerful aid to PSF calibration. During science exposures, LDFC images provide live telemetry of wavefront changes.

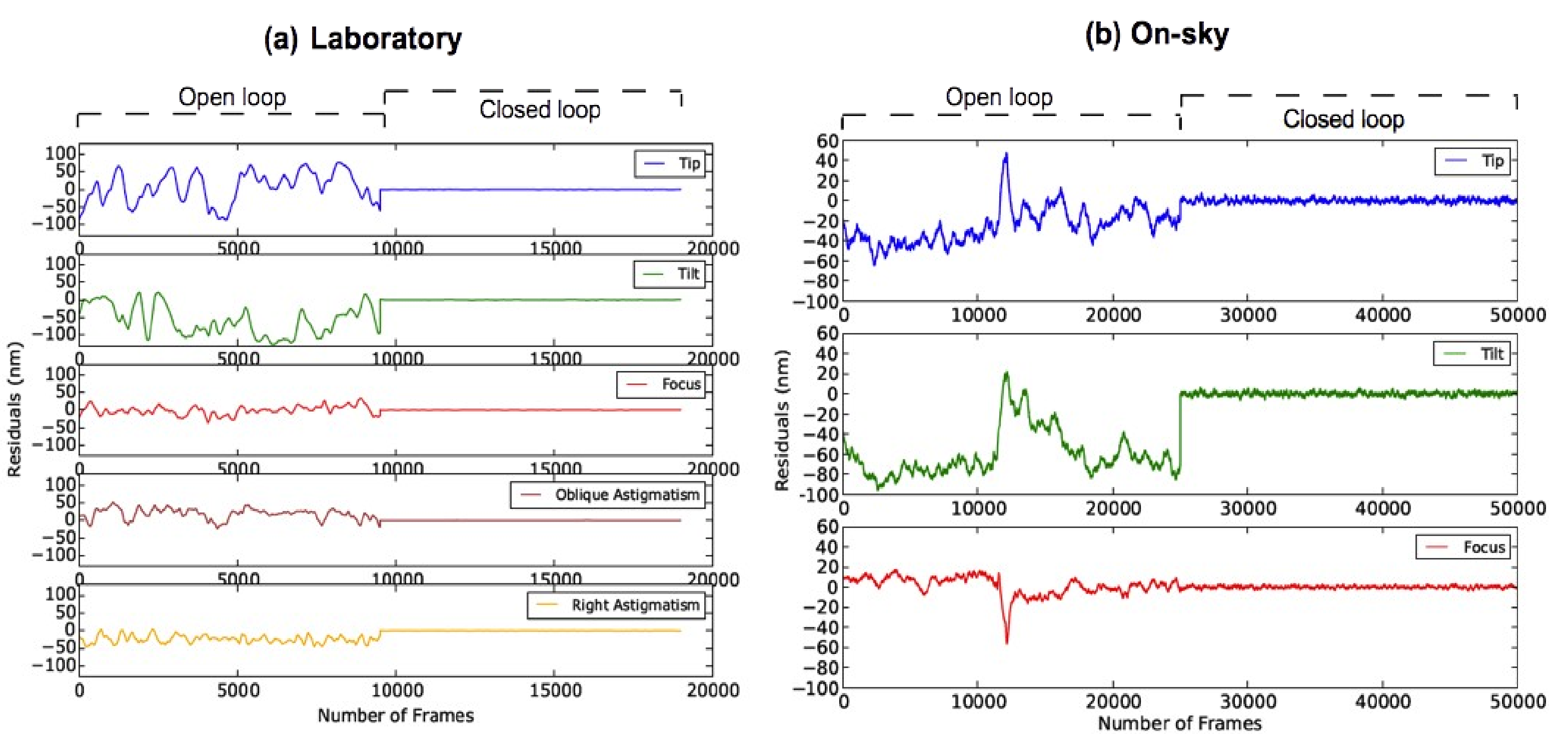
LDFC is particularly well suited to track cophasing errors on a segmented aperture, using diffraction features created by segments

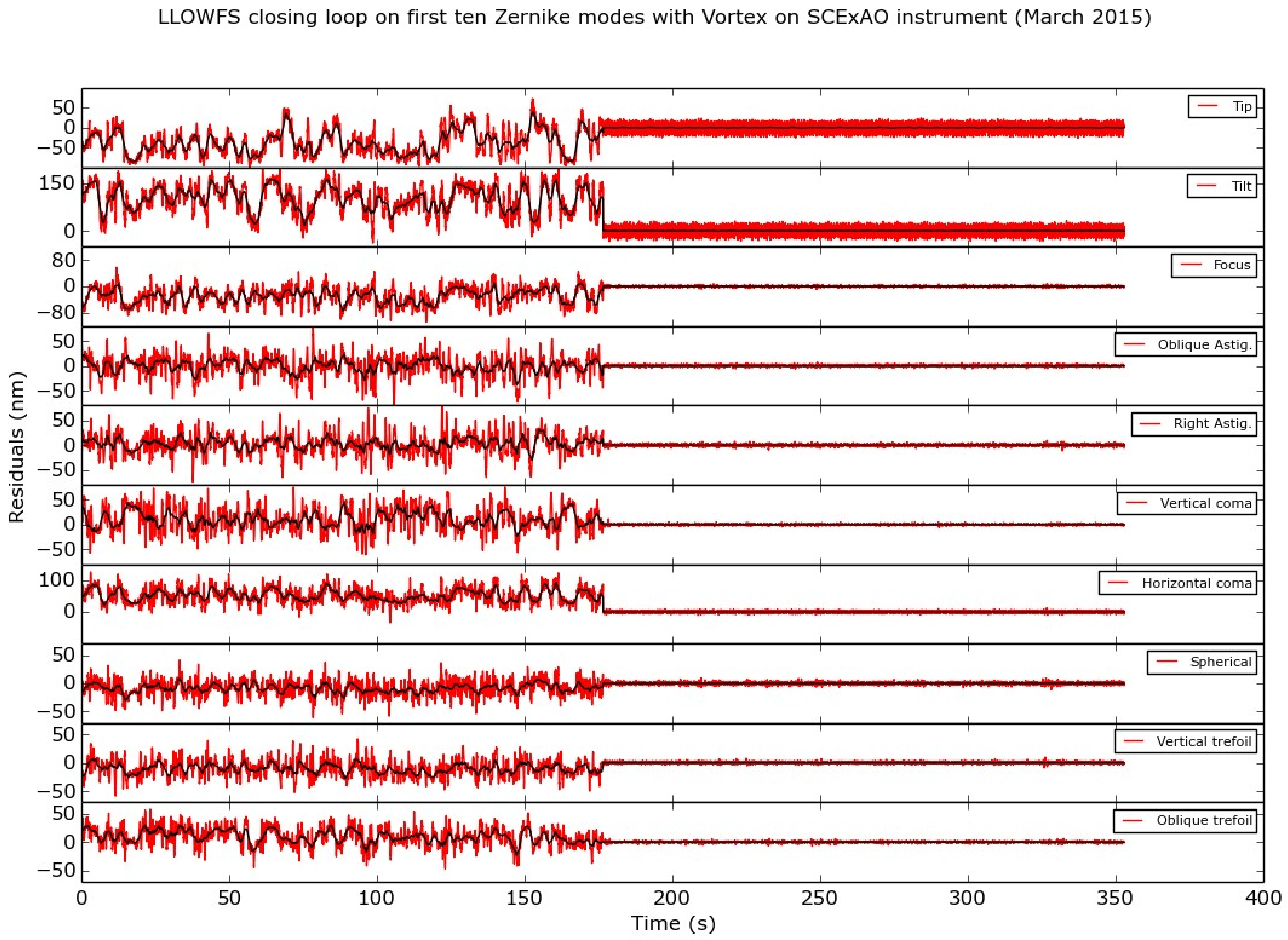
LDFC ↔ LOWFS



Response Matrix

Residuals

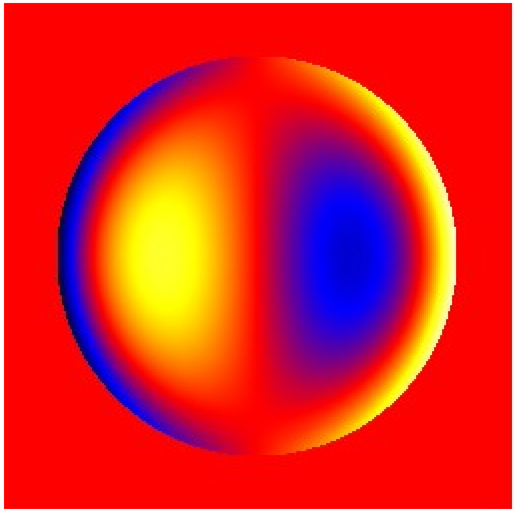




Ref: Singh et al.

Warning !

<u>LOWFS control should NOT use Zernikes</u>…
it should control the modes it can see, and not attempt to control its null space
Knowledge of statistical WF variations should be included



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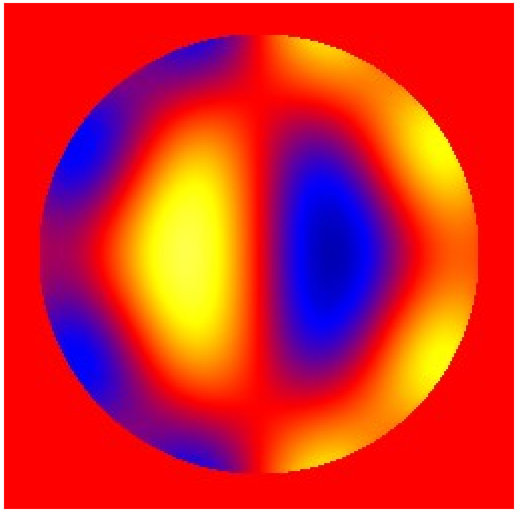

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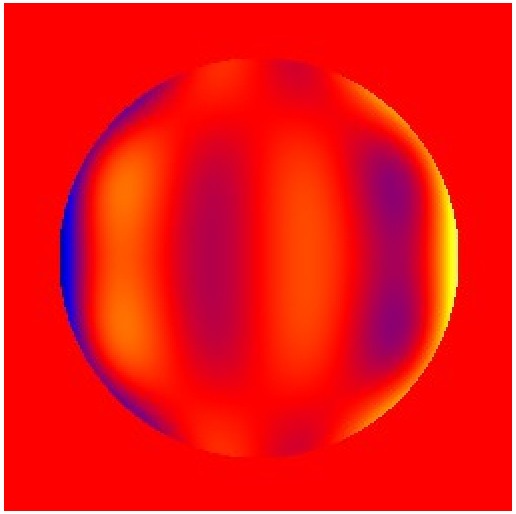


coma

6.9nm RMS

Seen by LOWFS

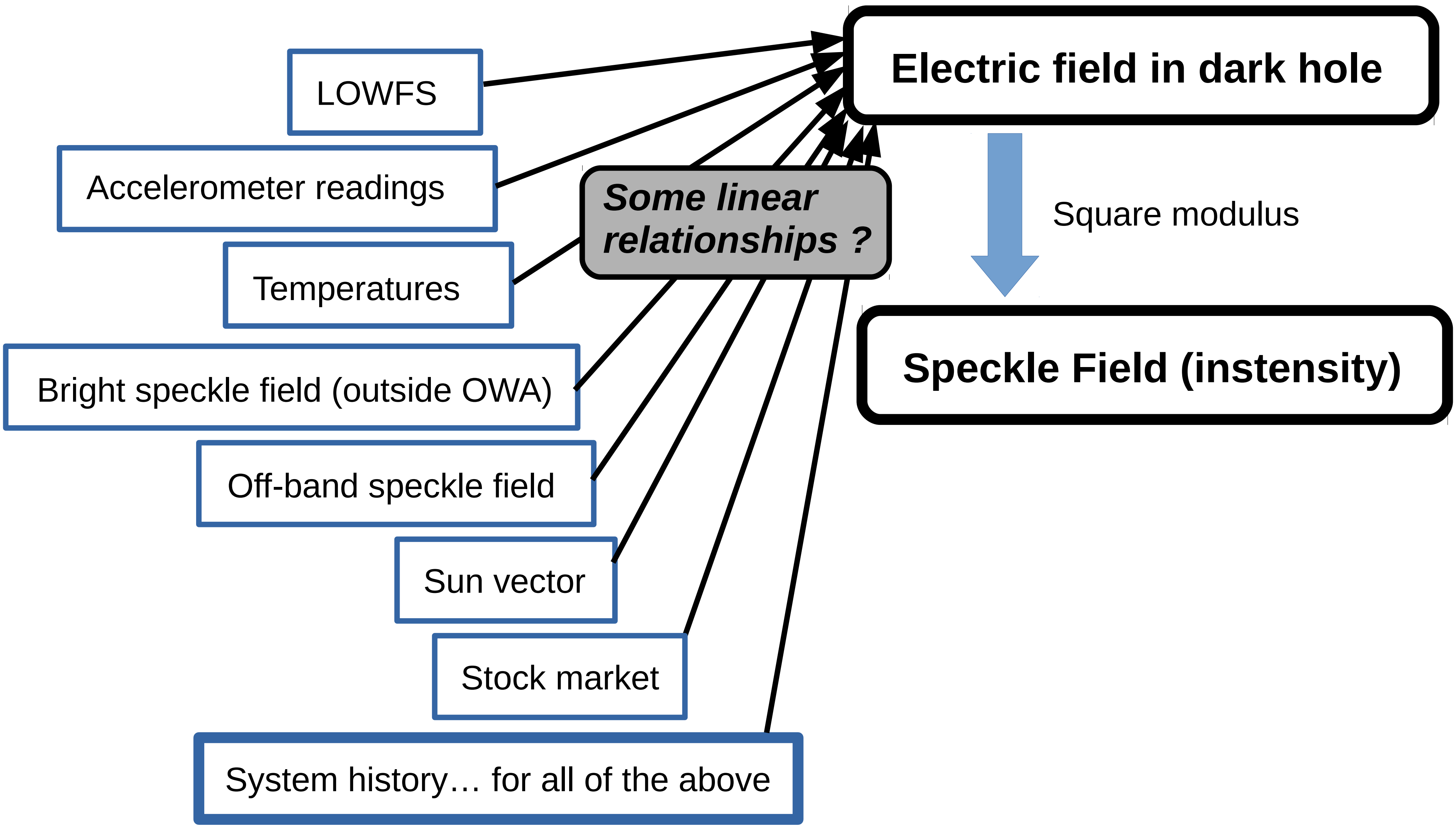
7.1nm RMS

LOWFS null space

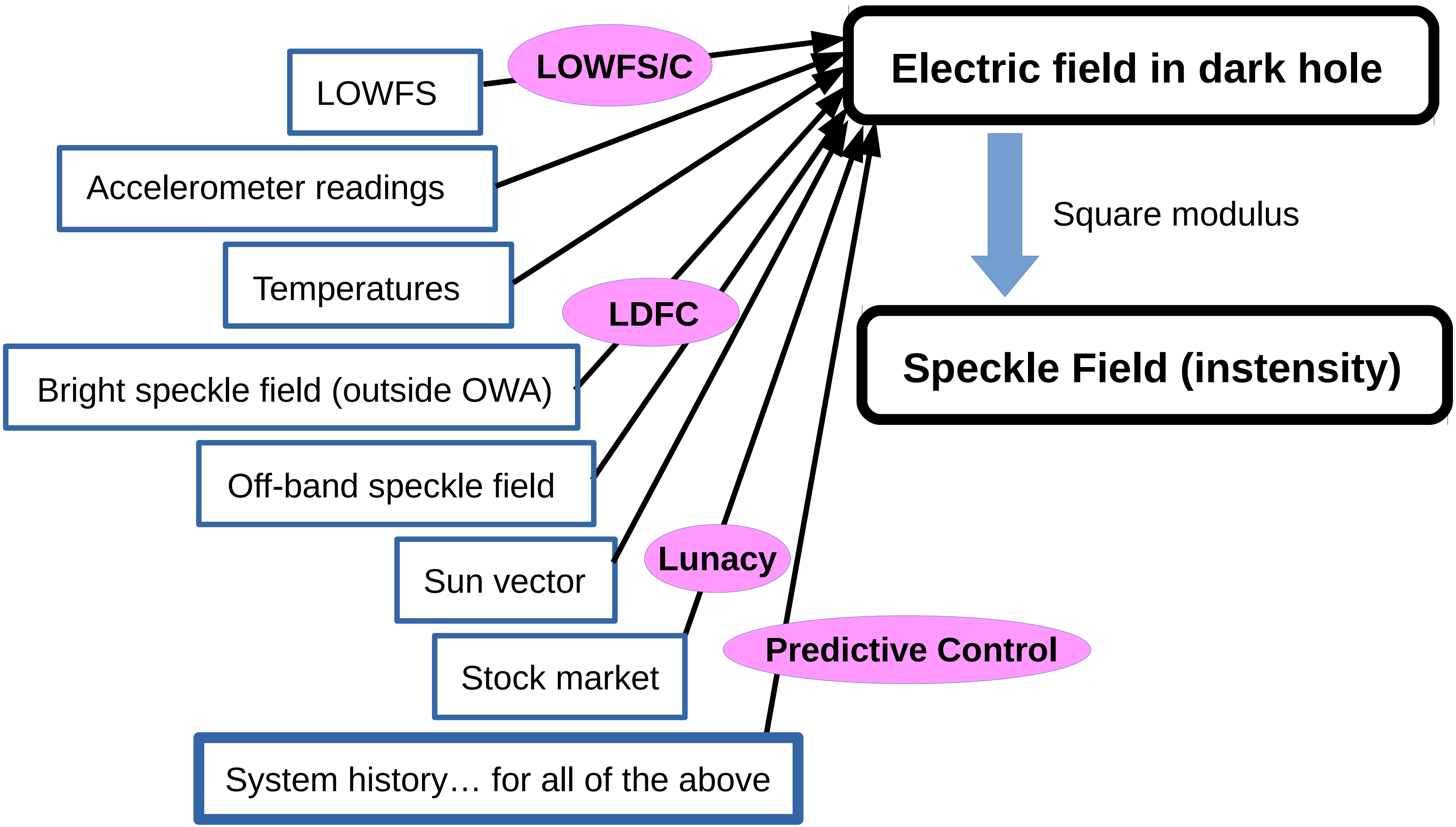
2.8nm RMS

SIGNIFICANT IMPACT ON CONTRAST

Overall challenge: figuring out and exploiting linear relationships



Overall challenge: figuring out and exploiting linear relationships



Problem statement

How do we find the the <u>optimal</u> (least square) linear filter **F** that minimizes:

WF = F x Meas

2 approaches:

- acquire response matrix
- process past measurements (learning)

Do this if you can !

Use previous measurements
Standard least-square problem

Solution: extract linear dependencies from previous measurements

"history" vector H of $n \times m$ coefficients:

$$\mathbf{H}(t) = \begin{bmatrix} \tilde{w_0}(t) \\ \tilde{w_1}(t) \\ \vdots \\ \tilde{w_{m-1}}(t) \\ \tilde{w_0}(t-dt) \\ \vdots \\ \tilde{w_{m-1}}(t-dt) \\ \vdots \\ \tilde{w_{m-1}}(t-(n-1)dt) \end{bmatrix}$$

$$\mathbf{F}^i = \begin{bmatrix} ar^i_{0,0} & ar^i_{1,0} & \dots & ar^i_{m-1,n-1} \end{bmatrix}$$

The predicted value is obtained as an linear sum of previous wavefront sensor measurements :

$$\hat{w}_i(t+\delta t) = \mathbf{F^i H}(t) \tag{3}$$

To find the optimal filter, we first consider a training set, consisting of l vectors $\mathbf{H}$, arranged in a $n \times m$ by l data matrix

$$\mathbf{D} = [\mathbf{H}(t) \quad \mathbf{H}(t-dt) \quad \dots \quad \mathbf{H}(t-(l-1)dt)] \tag{6}$$

and the corresponding a-posteriori measured wavefront variable values arranged in a 1 by l matrix $\tilde{\mathbf{P}}_i$:

$$\tilde{\mathbf{P}}_i = [\tilde{w_i}(t+\delta t) \quad \dots \quad \tilde{w_i}(t+(l-1)dt+\delta t)] \tag{7}$$

The algebraic representation of equation 4 is

$$min_{F^i} ||\mathbf{F^i D} - \tilde{\mathbf{P}}_i||^2 \tag{8}$$

By taking the transpose of the quantity to be minimized, we recognize the classical least-square problem

$$||\mathbf{D}^T \mathbf{F}^{iT} - \tilde{\mathbf{P}_i}^T|| \tag{9}$$

yielding the filter solution

$$F^i = \left((\mathbf{D}^T)^+ \tilde{\mathbf{P}_i}^T \right)^T \tag{10}$$

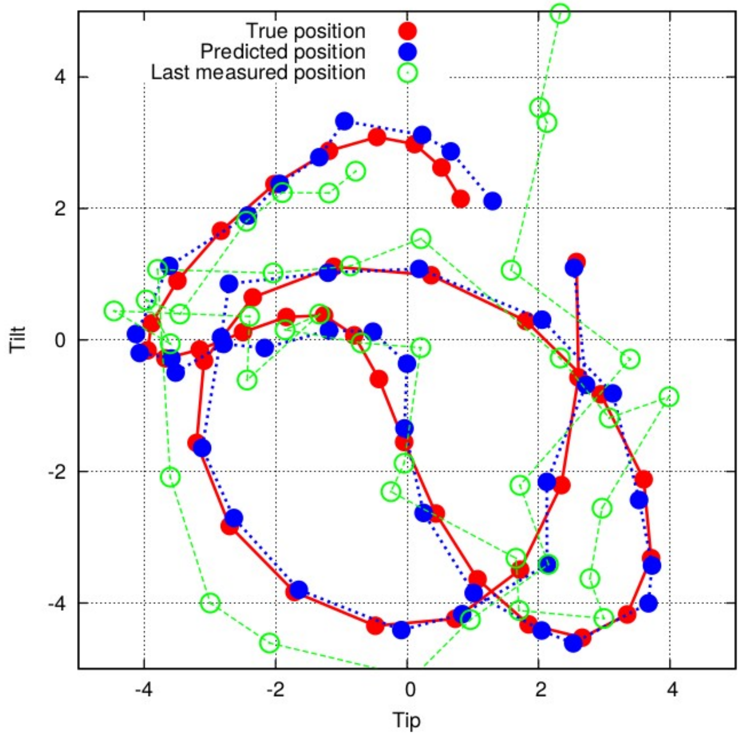
According to equation 10, the regressive filter F can then be written as

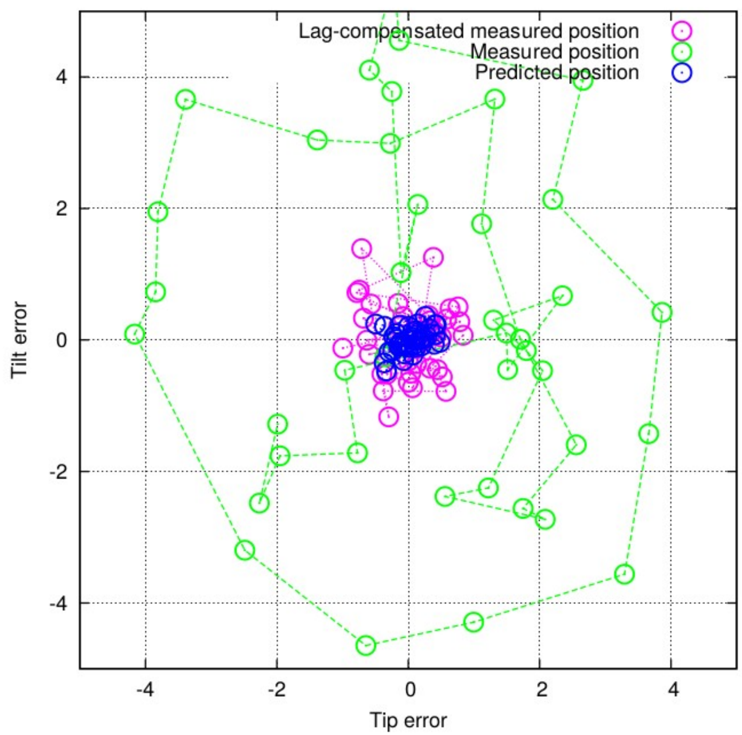
$$\mathbf{F}^i = \tilde{\mathbf{P}}_i \mathbf{U} (\mathbf{\Sigma}^+)^T \mathbf{V}^T \tag{13}$$

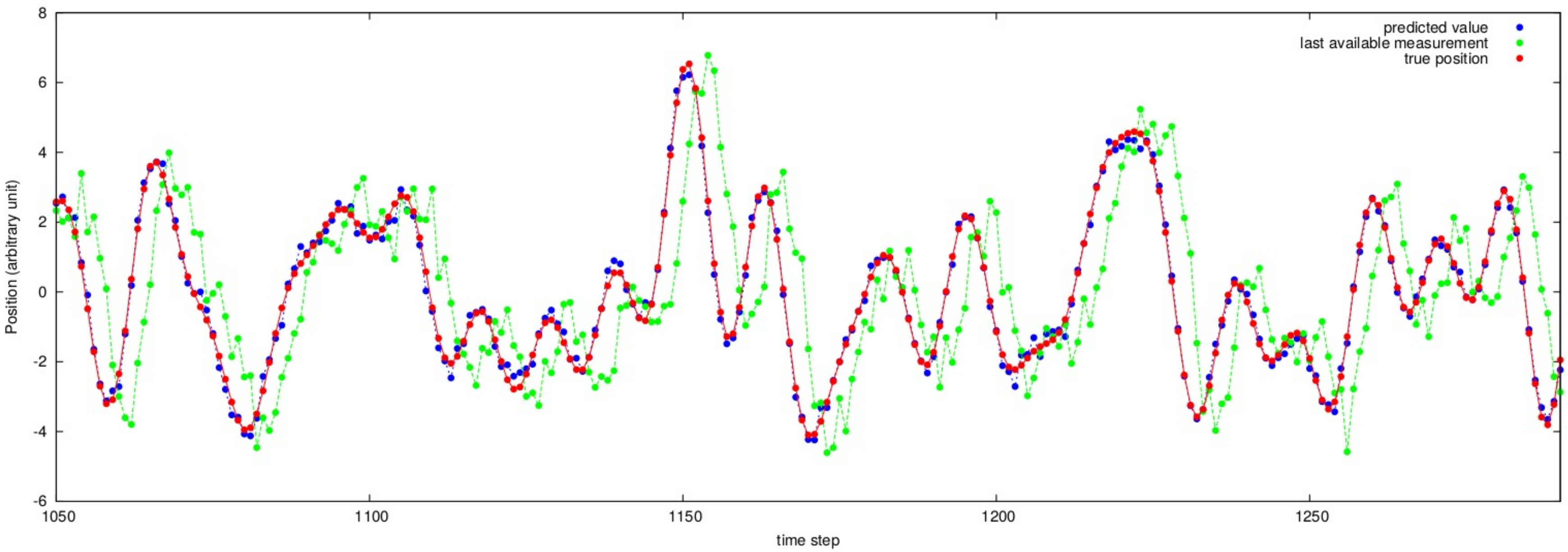
and the predicted value is

$$\hat{w}_i(t+\delta t) = \tilde{\mathbf{P}}_i \mathbf{U} (\mathbf{\Sigma}^+)^T \mathbf{V}^T \mathbf{H}(t). \tag{14}$$

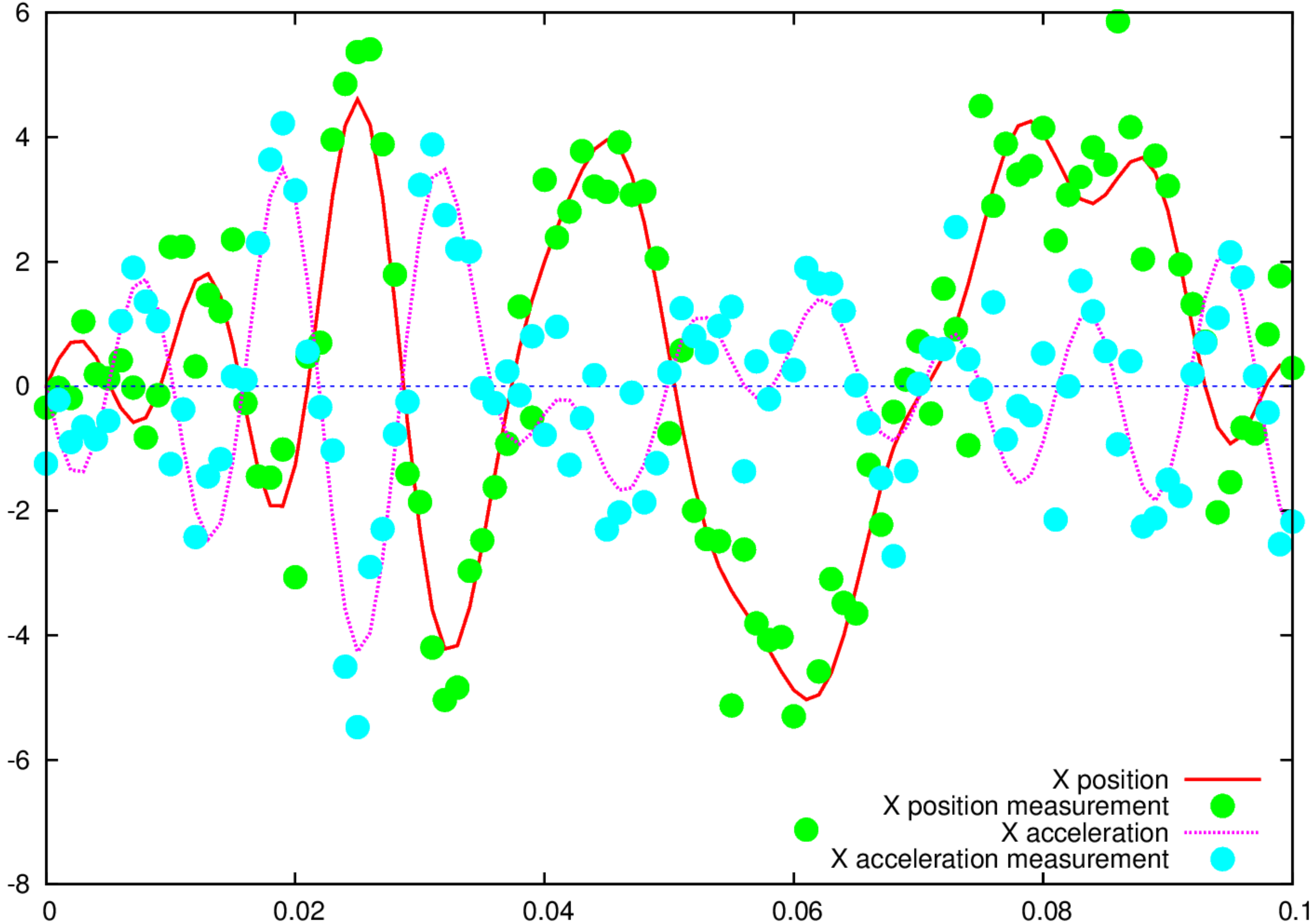
Simple example: TT errors averaging + prediction







Simple example: TT errors averaging + prediction with accelerometer telemetry (3-step lag)



Simple example: TT errors averaging + prediction with accelerometer telemetry (3-step lag)

100x better accelerometer precision