(With Demo)

The Wavefront Sensing Problem

Wavefront sensing is an old yet fundamental problem in optics: Direct phase measurement is not feasible through intensity sensors, and thus requires a joint design of both the hardware and the software.

- Traditional wavefront sensors [1, 2] are limited to using conventional optical components and simple algorithms, suffering a tradeoff between temporal, spatial resolution and the wavefront range.
- We introduce the *Coded Wavefront Sensor*, which is easy to fabricate and calibrate, with high wavefront range and accuracy, and of high temporal-spatial wavefront resolution as well.





Figure: Experimental setup for accuracy validation.

Quantitative Wavefront Measurement: We evaluated the Coded Wavefront Sensor by E using it to measure known wavefronts that are generated by a SLM. A distant point white light source serves as illumination. A telescope system ensures the wavefront sensor and the SLM are in conjugate. Results are shown on the right.

Original

Figure: Selected quantitative experimental results. The original ground truth, our reconstruction, and the errors are shown. All wavefronts are shown in interference fringes where one fringe maps to wavefront difference of $\lambda = 632.8$ nm. Scale bar is 1 mm.

Ultra-High Resolution Coded Wavefront Sensor

Visual Computing Center, King Abdullah University of Science and Technology (KAUST)

The Coded Wavefront Sensor: Principle & Implementation



Calibration (reference)



Measurement



Results



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For small z (e.g. 1.5 mm), one can show using the Rayleigh-Sommerfeld diffraction formula [3]:

$$I(\mathbf{r}) \approx I_0(\mathbf{r} - (z/k)\nabla\phi(\mathbf{r})),$$

where k is the wave number and $\nabla \phi$ is the wavefront gradients. A direct linearization leads to the so-called optical flow method [4]:

$$\frac{z}{k} \nabla \phi(\mathbf{r}) \cdot \nabla I_0(\mathbf{r}) + I(\mathbf{r}) - I_0(\mathbf{r}) = 0.$$

We devise our own reconstruction method, adding a wavefront smoothness regularizer, and solve for the wavefront directly. In linear algebra:

ninimize
$$\|\mathbf{G}\mathbf{M}\nabla\boldsymbol{\phi} + \mathbf{g}_t\|_2^2 + \alpha \|\nabla\boldsymbol{\phi}\|_2^2$$
,

where $\mathbf{G} = [\operatorname{diag}(\mathbf{g}_x) \ \operatorname{diag}(\mathbf{g}_y)]$ is a concatenated diagonal matrix with the image derivatives $((\mathbf{g}_x, \mathbf{g}_y) = \nabla I_0(\mathbf{r}))$ on the diagonal, a "time" derivative $\mathbf{g}_t = I(\mathbf{r}) - I_0(\mathbf{r})$, and \mathbf{M} is a binary diagonal matrix that selects only the visible pixels from the wavefront samples. Our solver employs ADMM [5], and each updating step enjoys closed-form solution and is parallelizable on GPU.

the heat flow and the defocusing. In the

original large version, the scale bar is 2 mm.

Unknown Size	Performance
1024×1024	19.54 ms / 51.18 frames
1024×768	15.24 ms / 65.62 frames
640×480	10.97 ms / 91.16 frames
512×512	5.77 ms / 173.31 frames,
256×256	2.95 ms / 338.98 frames,
128 imes128	2.17 ms / 460.83 frames,

We introduce the Coded Wavefront Sensor, a novel sensor design that is physically implemented by a single binary masked sensor to encode the incoming wavefront, and is numerically implemented by an efficient optimization decoding algorithm, such that high spatio-temporal resolution wavefront reconstruction is achieved within sub-wavelength accuracy.

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Conclusion

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