

Rigorously simulated vs. optically captured phase fields

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TU Delft

Rigorously simulated vs. optically captured phase fields

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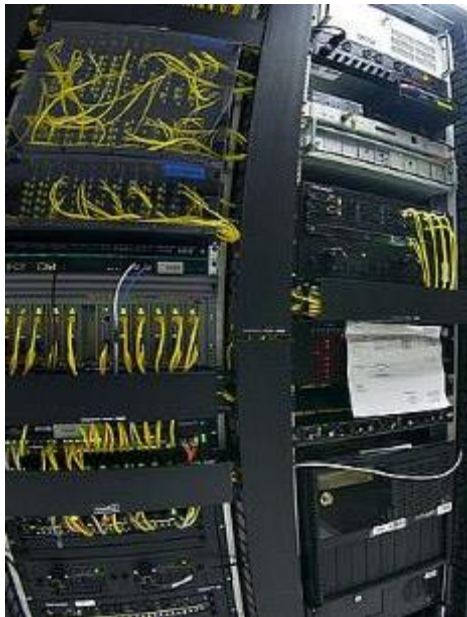
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2 Institute of Applied Optics (Institut für Technische Optik, ITO), University of Stuttgart

Outline

What to expect

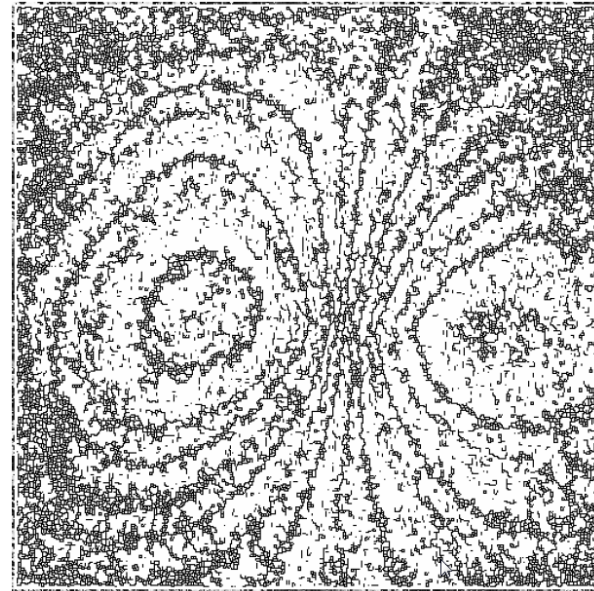
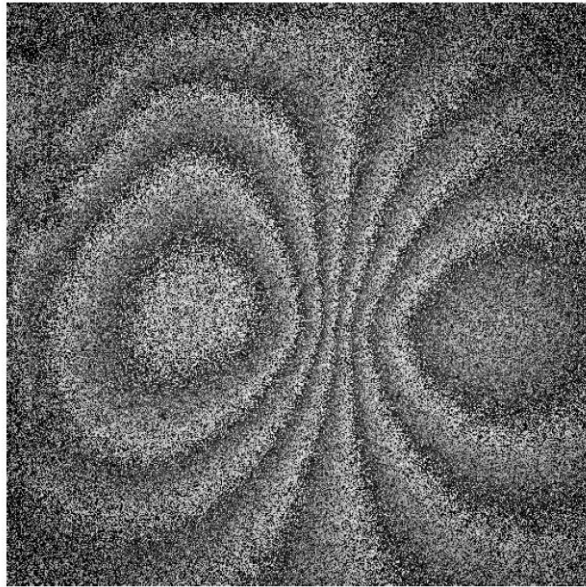


- Machine Learning
- Improving Predictions
- Speckle Simulation



Phase Discontinuity Location

Edge detection



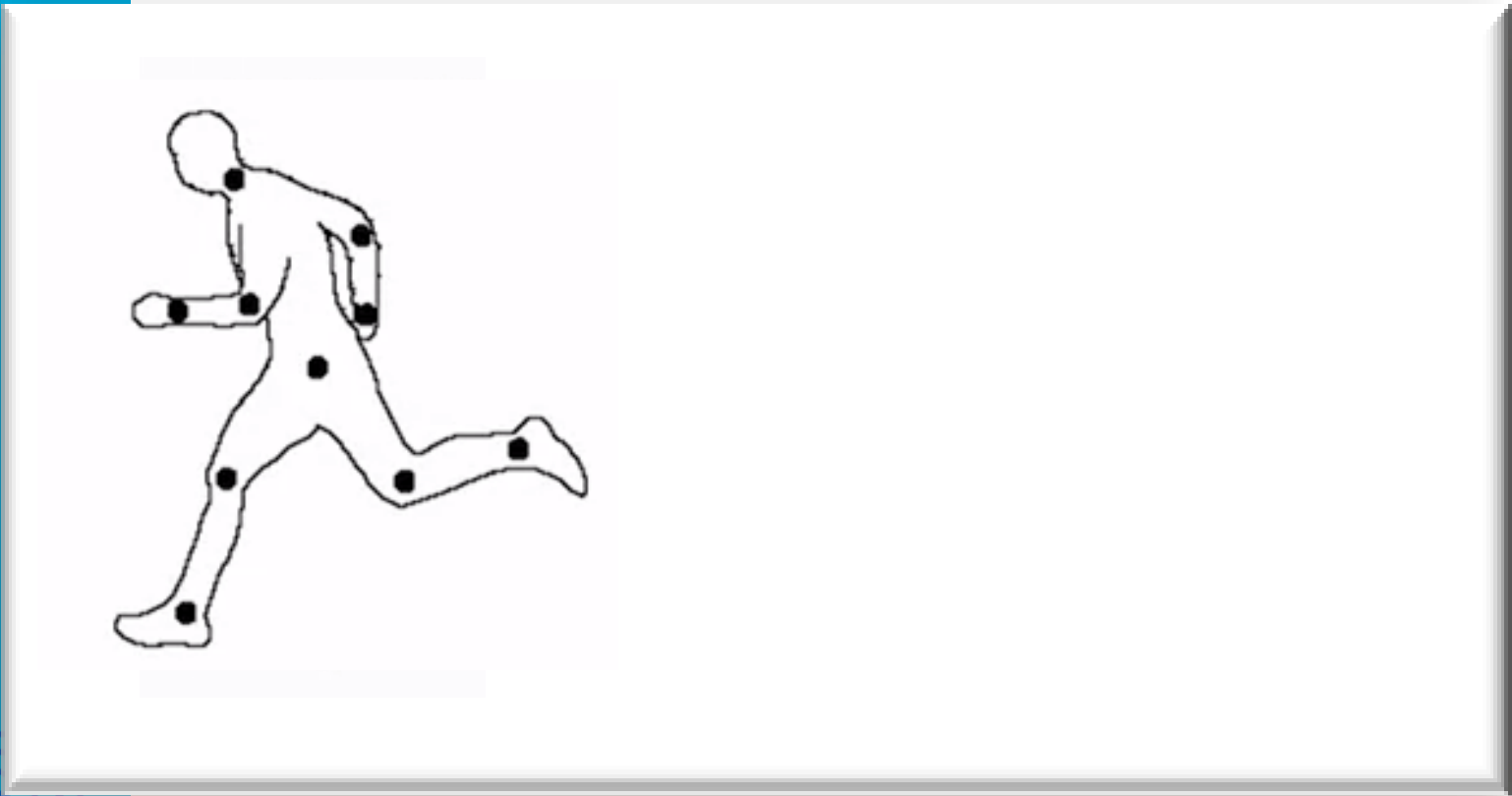
Cognitive Neuroscience

Can you see it?



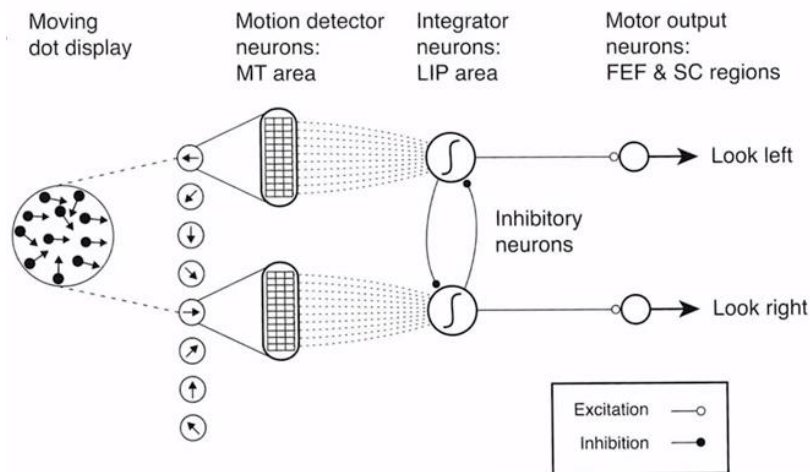
Cognitive Neuroscience

It moves

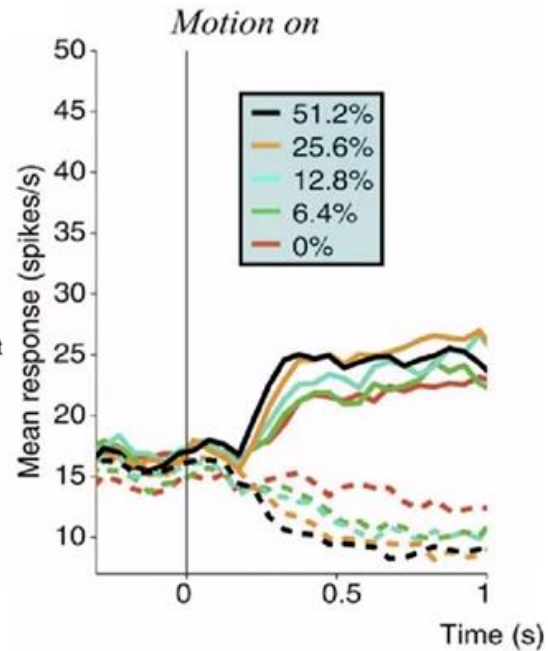


Cognitive Neuroscience

Aggregation

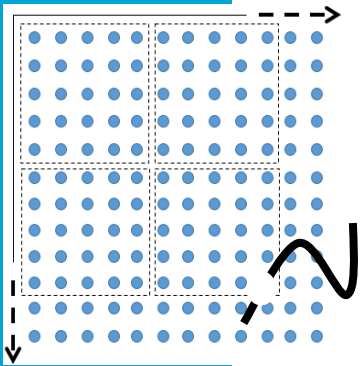


Shadlen and colleagues' (1996) model of a perceptual decision circuit.

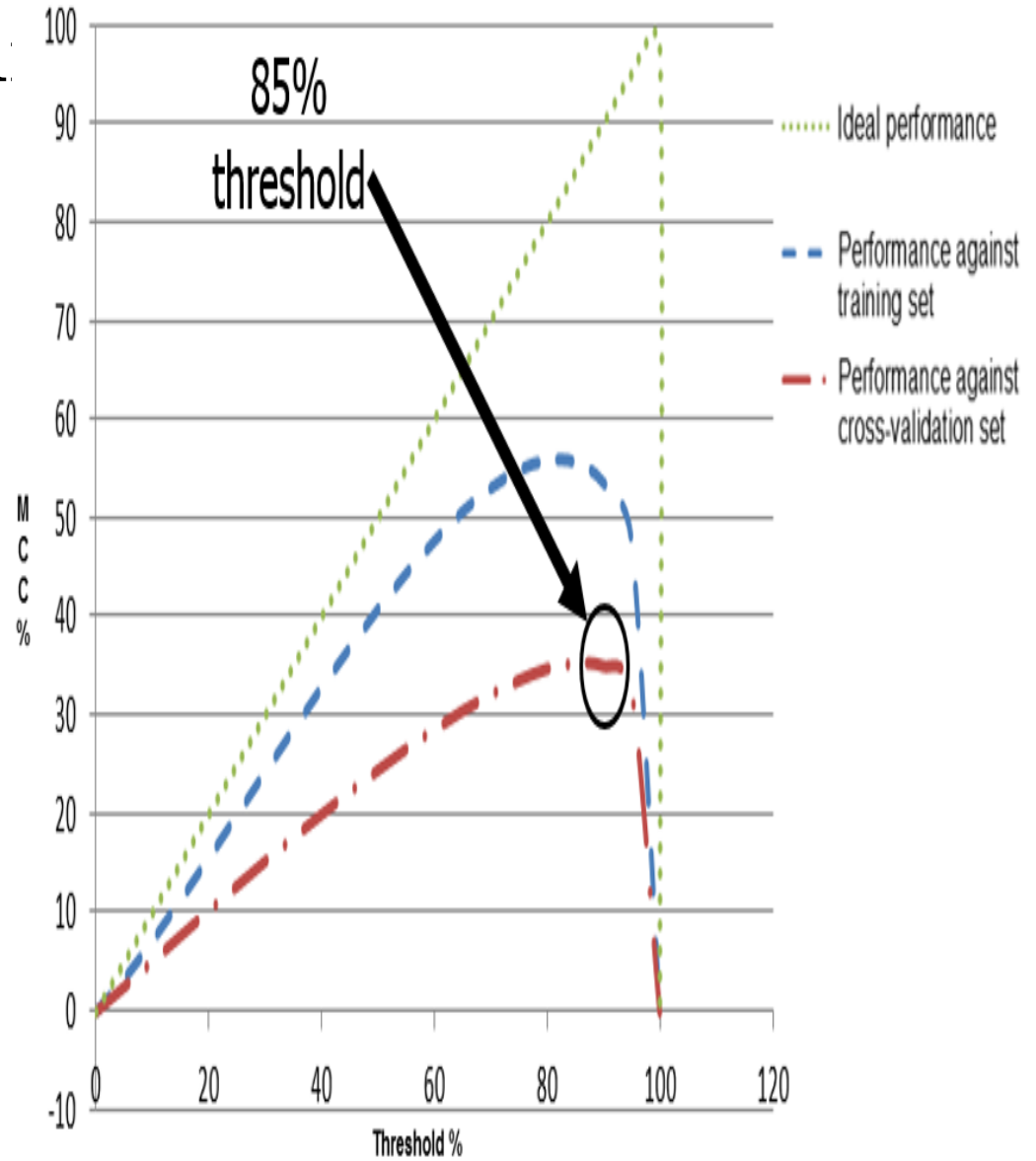


Machine-Learn

We move



NDT



Machine-Learning

How much better?



a. 10x10, 00:253, 1, 1.00



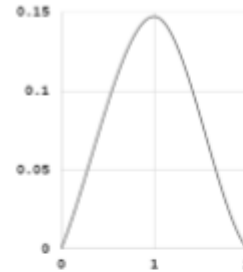
b. 13x13, 00:437, 4, 1.96



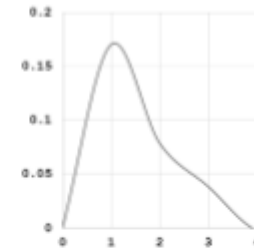
c. 16x16, 1:272, 9, 5.76



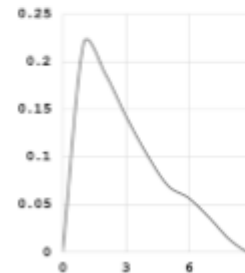
d. 19x19, 19:89, 100, 91.2



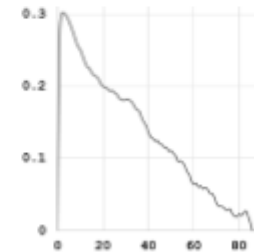
a. 10x10, 0.147



b. 13x13, 0.17



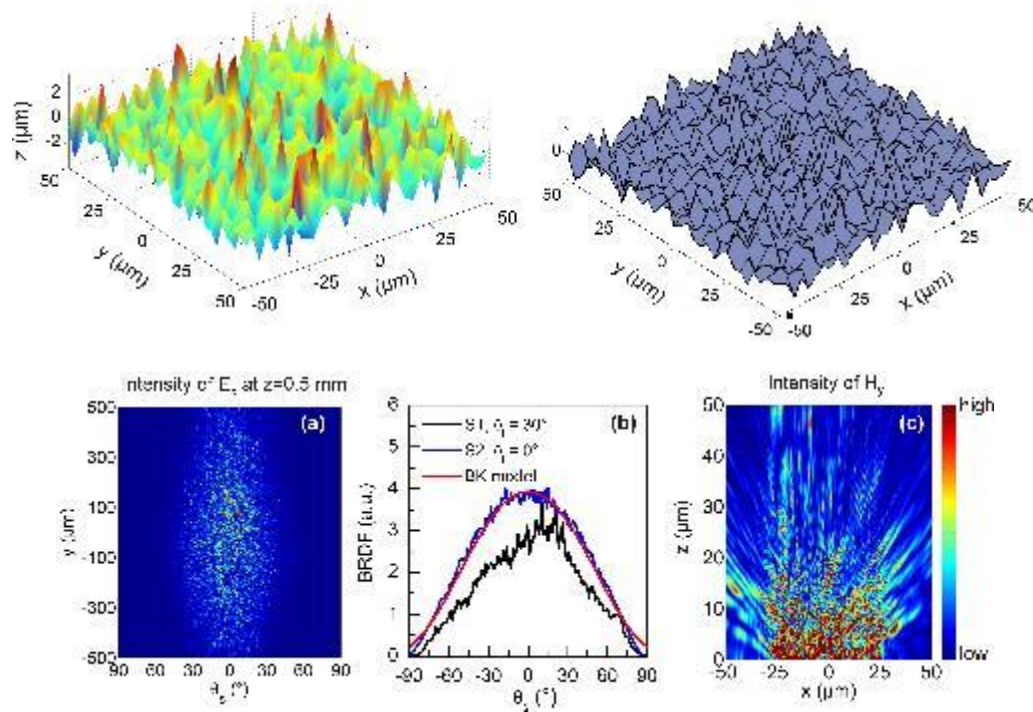
c. 16x16, 0.220



d. 19x19, 0.302

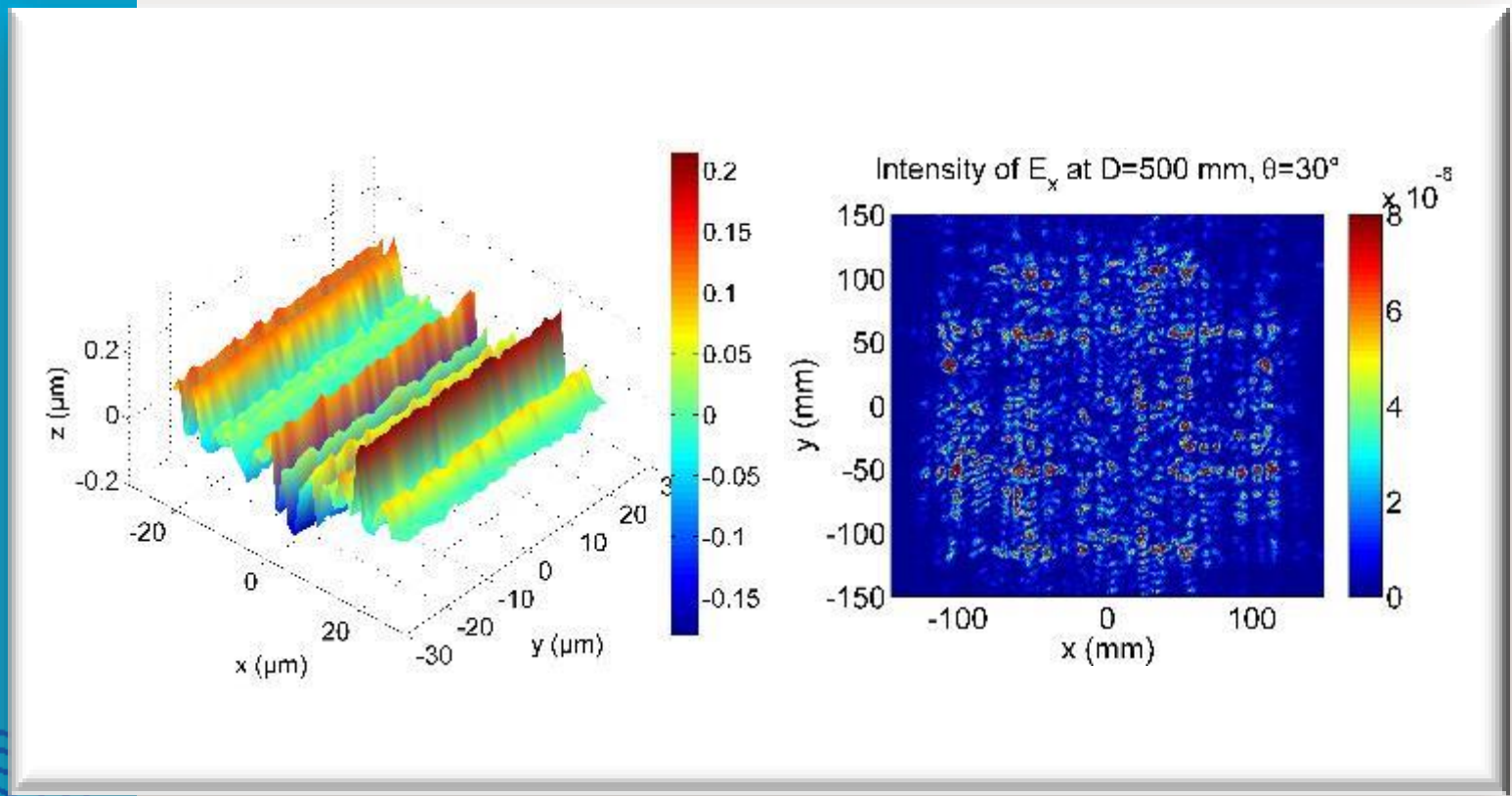
Speckle Simulation

Realistic training



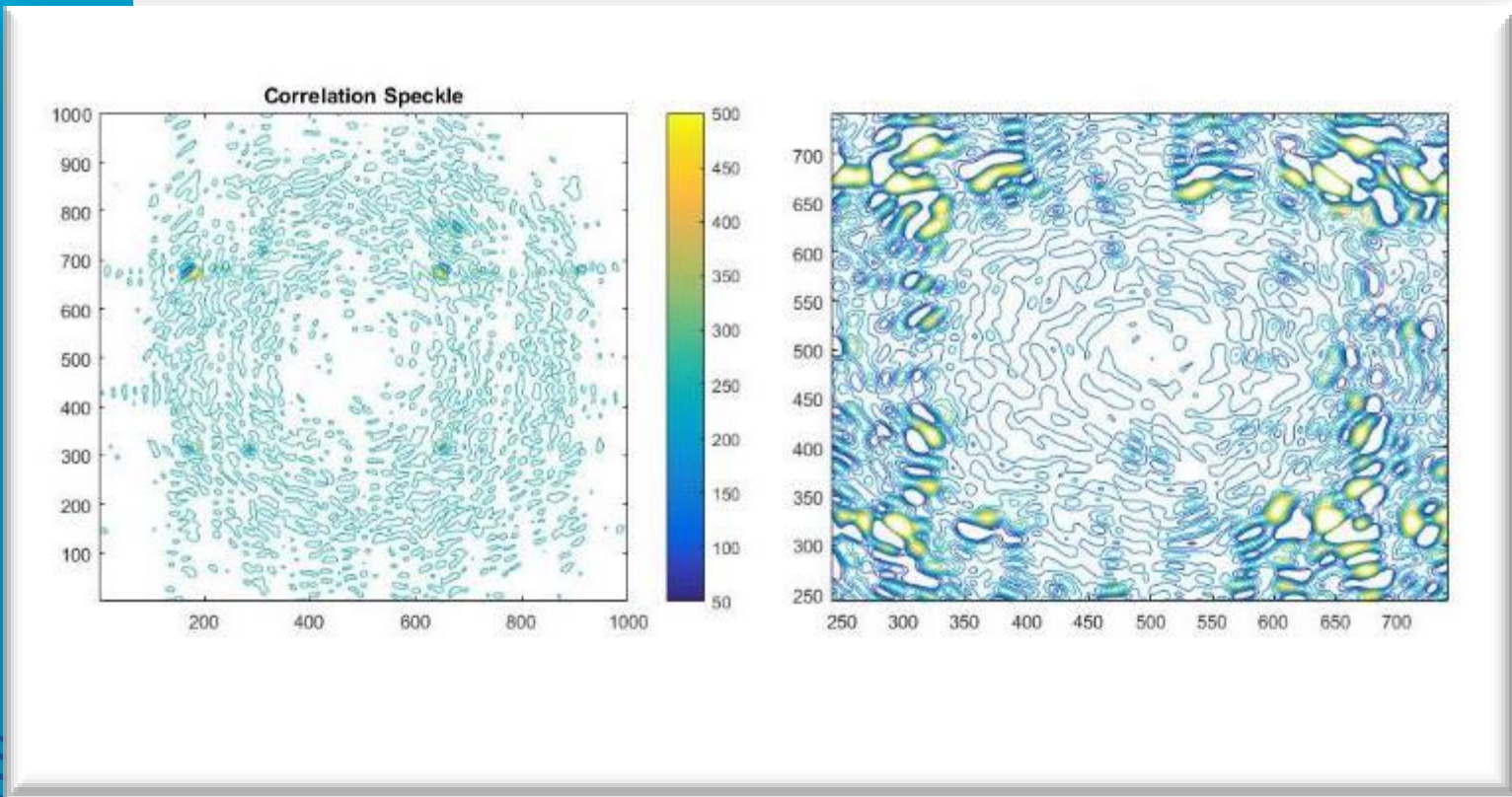
Speckle Simulation

Raw speckle



Speckle Simulation

Correlation



Speckle Simulation

More efficiency

1965	Fast Fourier transform	Gauss, Cooley, Tukey, Sande
1971	Spectral methods for PDE	Chebyshev, Lanczos, Clenshaw
1971	Radial basis functions	Hardy, Askey, Duchon, Micche
1973	Multigrid iterations	Fedorenko, Bakhvalov, Brandt,
1976	EISPACK, LINPACK, LAPACK	Moler, Stewart, Smith, Dongarr
1976	Nonsymmetric Krylov iterations	Vinsome, Saad, van der Vorst,
1977	Preconditioned matrix iterations	van der Vorst, Meijerink
1977	MATLAB	Moler
1977	IEEE arithmetic	Kahan
1982	Wavelets	Morlet, Grossmann, Meyer, Dai
1984	Interior methods in optimization	Fiacco, McCormick, Karmarkar
1987	Fast multipole method	Rokhlin, Greengard
1991	Automatic differentiation	Iri, Bischof, Carle, Griewank

Machine-Learning

Any questions?

Traditional Programing

- F. Sawaf and R. P. Tatam, "Finding minimum spanning trees more efficiently for tile-based phase unwrapping," Meas. Sci. Technol. 17, 1428 (2006).

Machine Learning

- F. Sawaf and R. M. Groves, "Statistically guided improvements in speckle phase discontinuity predictions by machine learning systems," Opt. Eng. 52, 101907 (2013).
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Speckle Simulation

- L. Fu, K. Frenner, and W. Osten, "Rigorous speckle simulation using surface integral equations and higher order boundary element method," Opt. Lett. 39, 4104 (2014).

