Friction: Wet and Dry
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Commonality: Rough surface

• Honed vs. random
• What is random surface?
  – Not white noise
  – Wavy vs. asperity
• Simulation Effort \[ E = (MC)^2 \] for FM

\[ \text{PBC + } \Delta p \]

rough walls
(represented by double Fourier
with pink coefficients)  

Plus “random IC
My problem with MC

• For easy problem (calculate $\pi$) we might do $10^8$ realizations and calculate error bars

• For hard problem (rough surface) we do 1 realization and calculate no error bars

• To a lesser extent this is a problem in experiments as well.
“People Hearing Without Listening:”
An Introduction To Compressive Sampling

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Abstract

Current data acquisition protocols are often extremely wasteful. Indeed, consider that many protocols acquire massive amounts of data which are then - in large part - discarded by a subsequent compression stage, which is usually necessary for storage and transmission purposes. Why then spend so much time and/or money to acquire all these data when we know that most of it can be thrown away anyway? This paper surveys a novel sampling or sensing theory now known as “Compressed Sensing” or “Compressive Sampling” which allows the faithful recovery of signals and images from far fewer measurements or data bits than traditional methods use.
Data Compression

Fig. 1. Original megapixel image with pixel values in the range [0, 255] and its wavelet transform coefficients (arranged in a random order for enhanced visibility). Relatively few wavelet coefficients capture most of the signal energy. Many such images are highly compressible and the rightmost image shows the reconstruction obtained by zeroing out all the coefficients in the wavelet expansion but the 25,000 largest (pixel values below 0 and above 255 are set to 0 and 255 respectively). The difference with the original picture is hardly noticeable.
Underdetermined sparse system minimized by $\ell_1$ norm

Fig. 2. A sparse real valued signal (left) and its reconstruction from 60 (complex) valued Fourier coefficients by $\ell_1$ minimization (middle). The reconstruction is exact. The rightmost plot shows the minimum energy reconstruction obtained by substituting the $\ell_1$ norm with the $\ell_2$ norm; $\ell_1$ and $\ell_2$ give wildly different answers. The $\ell_2$ solution does not provide a reasonable approximation to the original signal.
Figure 10: Image recovery from reweighted TV minimization. (a) Original $256 \times 256$ phantom image. (b) Fourier-domain sampling pattern. (c) Minimum-TV reconstruction; total variation $= 1336$. (d) Reweighted TV reconstruction; total variation (unweighted) $= 1464$. 
(a) Original MR angiogram. (b) Fourier sampling pattern. (c) Backprojection, PSNR = 29.00dB. (d) Minimum TV reconstruction, PSNR = 34.23dB. (e) $\ell_1$ analysis reconstruction, PSNR = 34.37dB. (f) Reweighted $\ell_1$ analysis reconstruction, PSNR = 34.78dB.
One pixel camera

- Expense/pixel: IR, MRI, … solid/fluid feature
- Rice University
- Pixels taken sequentially, randomly
- \( O(1/1000) \) pixel input
- 3% of Nyquist sampling rate
These are time intensive problems!

- Well, perhaps experiments and simulations can be simplified by $1/1000(?)$, resolution increased sequentially
- But now we should repeat these MC simulations $O(10^5)$ times!?
- Let’s get on a Petaflop machine
  - Problem is elliptic -- challenging to parallelize
  - Do one realization on each machine
  - Time dependence can be handled by mpeg techniques