INTELLIGENT DATA SAMPLING PROMOTES ACCELERATED MEDICAL IMAGING: SHARPER POSITRON EMISSION TOMOGRAPHY

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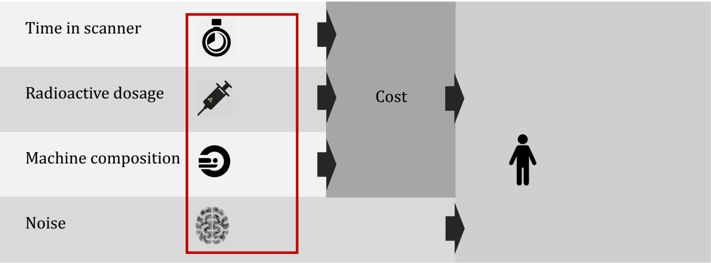
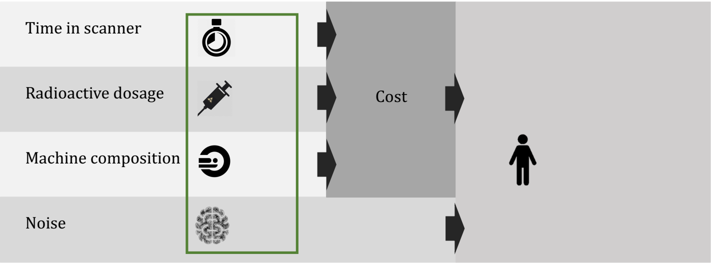
Positron Emission Tomography



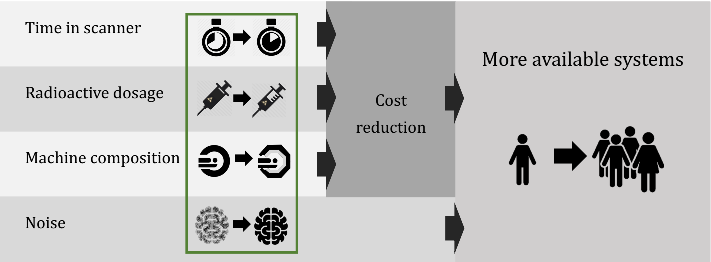
Intelligent data sampling

Positron Emission Tomography



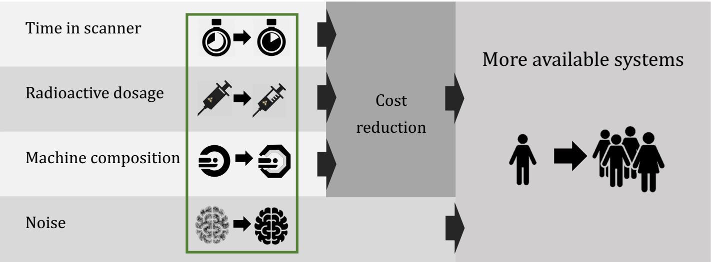
Intelligent data sampling

Positron Emission Tomography



Intelligent data sampling

Positron Emission Tomography



Intelligent data sampling

Inspiration

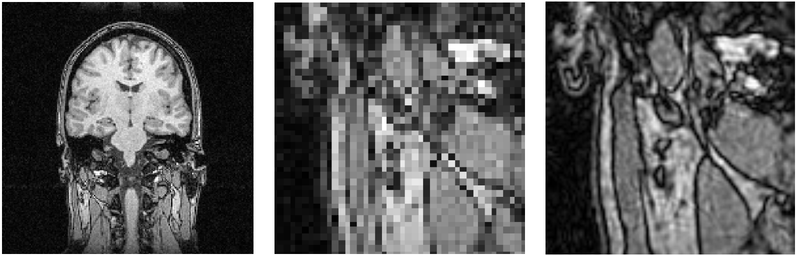


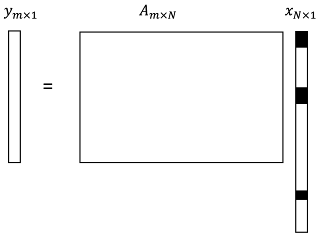
Figure: Left: Full standard 3D Magnetic Resonance Imaging headscan. Middle: Zoom of lower left area. Right: Structured compressed sensing approaches to resolution enhancing.[1]

[1]Figures from "Undersampling improves fidelity of physical imaging and the benefits grow with resolution", B. Roman, R. Calderbank, B. Adcock D. Nietlispach, M. Bostock, I. Calvo-Almazn, M. Graves A. Hansen, PNAS (in revision).

Compressed Sensing

Solve underdetermined linear systems.

$$[\text{measurements}] = [\text{sensing matrix}] \times [\text{signal}]$$



Two types of compressed sensing problems:

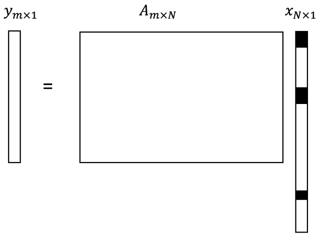
I. Physical devices impose the sampling operator.

II. Sensing mechanism offers freedom to design the sampling operator.

Compressed Sensing

Solve underdetermined linear systems.

$$[\text{measurements}] = [\text{sensing matrix}] \times [\text{image}]$$



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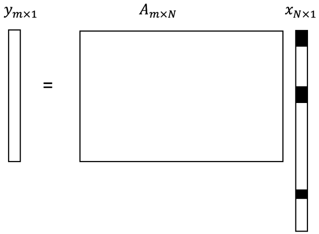
Compressed Sensing

Solve underdetermined linear systems.

$$[\text{measurements}] = [\text{sensing matrix}] \times \underbrace{[\text{image}]}_{\textit{sparse}?}$$



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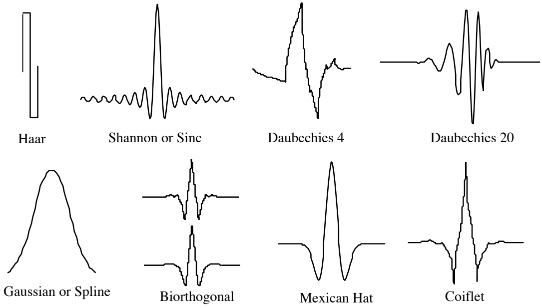
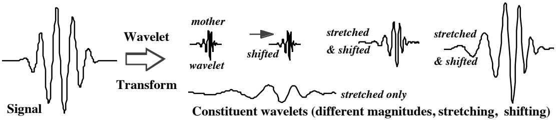
Wavelets





[1] Figures from "Conceptual Wavelets in Digital Signal Processing", D. Lee Fugal (2009).

Wavelets

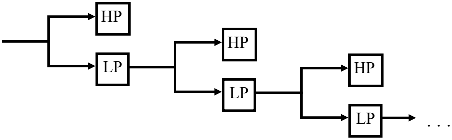
Wavelet transform of image: multiscale representation

- coarse scale – low-resolution components
- fine scale – high-resolution components

$$[\text{image}] = \text{sum } [\text{coefficients}] \times [\text{wavelet functions}]$$

Only few of the coefficients are important.

Sparse representation: keep only the important ones and set the rest to zero.



Simplified Example for Positron Emission Tomography

Unknown image x_0.

Sampling equipment samples radon transform Rx_0.

x_0 may not be sparse itself, but its wavelet transform $\tilde{x} = \Phi_{dwt} x_0$ may be.

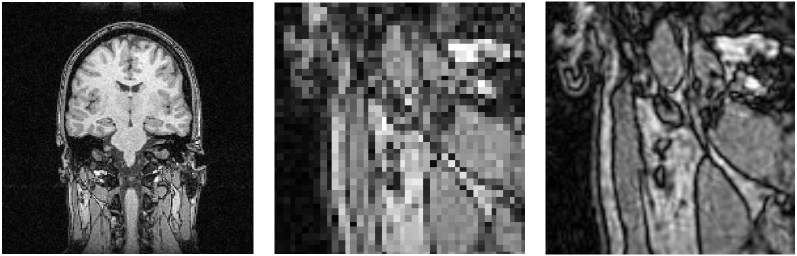
Subsample $\Omega = \{1, \ldots, N\}$ with $m = |\Omega|$ and solve

$$\min \|z\|_1 \quad \text{subject to} \quad P_\Omega R \Phi_{dwt}^{-1} z = P_\Omega R \Phi_{dwt}^{-1} \tilde{x}.$$

Notes:

- Subsampling scheme Ω.
- Minimum number of measurements m.
- Radon transform.
- Choice of wavelets.

Possibilities



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Thanks for listening!

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