Processing Weak Biosignals

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Application 1: screening for hearing problems

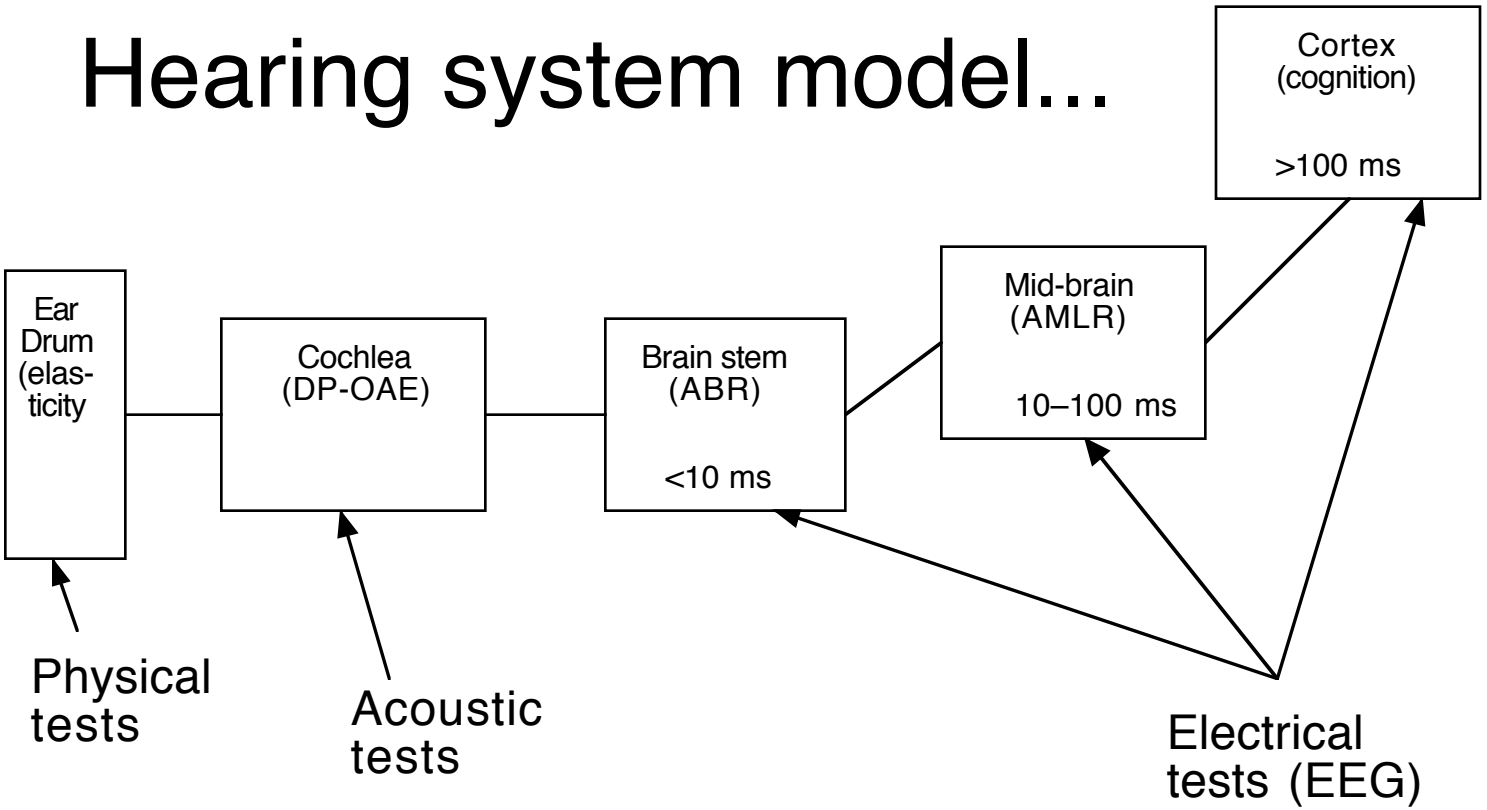
About 3 in 1000 newborns have hearing problems. How can these be detected?

– evoked distortion product otoacoustic emissions (DP-OAE) from the cochlea.

– evoked electroencephalograph potentials (EEG) from auditory system brain activity.

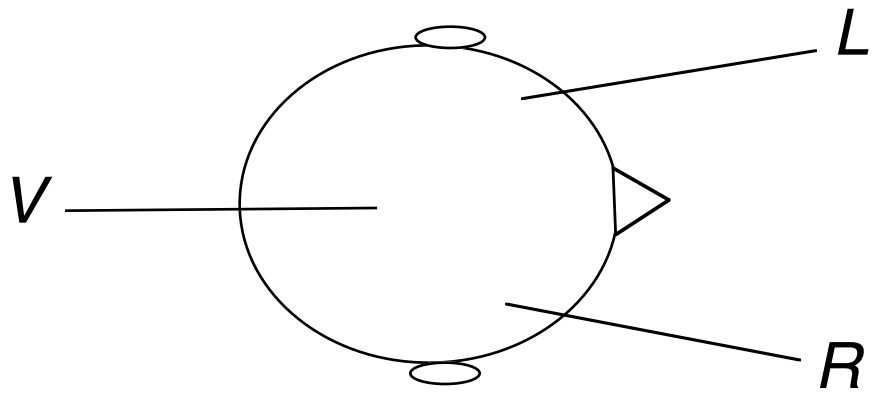
Existing methods are non-invasive and reliable, but not fast.

Hearing system model...



...and screening tests.

Evoked electroencephalograph (EEG) potentials



Left ear:
$x = L - V$

Right ear:
$x = R - V$

– stimulus: click presented in one ear

– differences of 10 μV between scalp electrodes

– differences of 0.1 μV due to brain activity

Measuring auditory evoked EEG potentials

– Auditory stimulus (“click”) produces a reproducible smooth evoked potential (“signal”) from specific regions in the attached brain.

– Measure the electrical potential difference (“instance”) between two points on the scalp.

– Muscles, RF energy, etc. contribute “noise” independently to each instance.

– Instance = signal + noise(instance)

– Assume E(noise) = 0, E(signal) = signal.

– Average many instances to approximate the signal, equivalently to improve SNR.

Auditory Brainstem Response (ABR)

All living patients exhibit brainstem electrical activity in response to sound, regardless of state of consciousness, even *in utero*.

ABR Parameters:

- peak V latency ~ 8 ms
- wait between stimuli ~ 30 ms
- minimum SNR for detection ~ 0 dB
- typical instance SNR ~ –40 dB

ABR Implications:

~ 10,000 independent instances need to be averaged to achieve detection SNR

~ 300 s per ear to achieve detection SNR

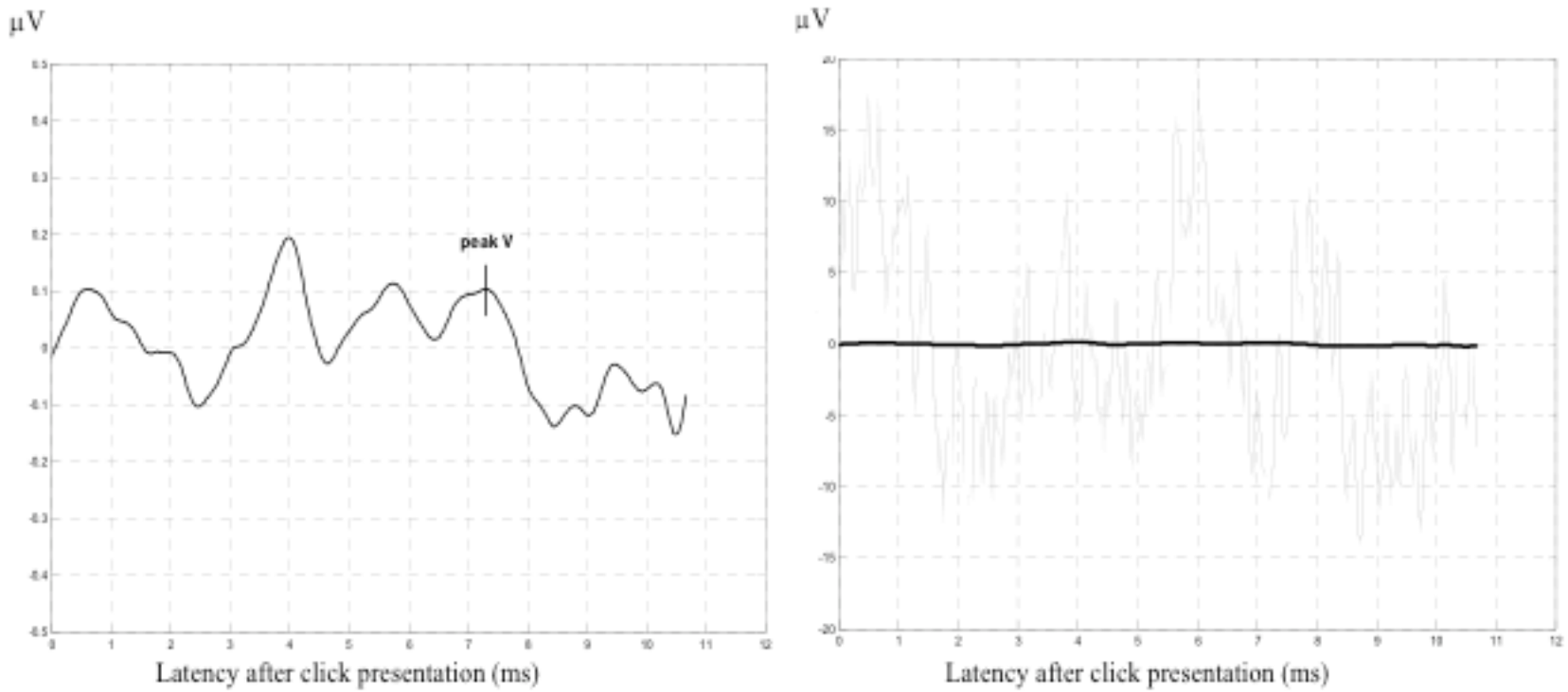


Figure 1: Left: typical ABR waveform averaged over 8,192 frames and filtered by a BP Butterworth filter with linear phase (100-1,500Hz). Right: Typical single frame of ABR data, overlaid on the averaged waveform shown with the darker line. Note the peak-to-peak amplitude of the unaveraged single-frame signal.

Auditory Middle Latency Response (AMLR)

Patients exhibit middle brain and cortical electrical activity in response to sound.

Latency of features depends on level of consciousness.

AMLR parameters:

- Na,Pa,Nb,Pb latency ~ 15,25,40,50 ms
- wait between stimuli ~ 120 ms
- minimum SNR for detection ~ +5 dB
- typical frame SNR ~ –20 dB

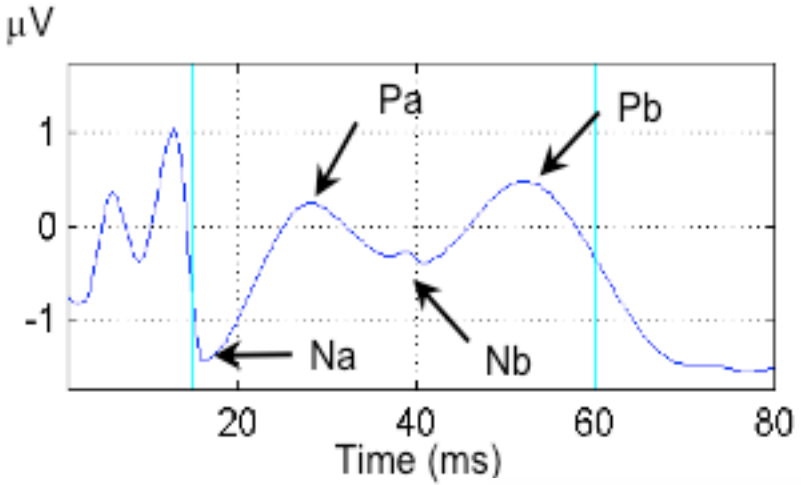
AMLR implications:

~ 250 independent instances need to be averaged to achieve detection SNR

~ 30 s per ear to achieve detection SNR

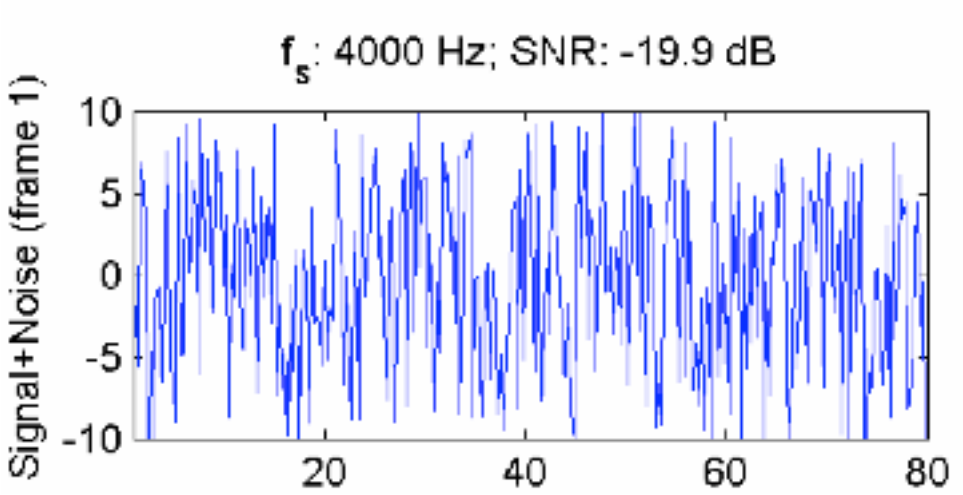
...but *accurate* peak detection needs better

Auditory Middle Latency Response (AMLR)



Signal

Signal+Noise
~ Noise



Problem: averaging works, but takes too long

Idea: Pre-process instances with wavelet threshold denoising, then combine denoised instances to accelerate convergence to the smooth signal.

BUT, a single instance is too noisy for wavelets to improve.

SO, pre-average small sets of instances into “frames” before denoising.

AND, combine denoised frames in various ways and denoise again to exploit nonlinearity of wavelet thresholding.

Cyclic-shift tree denoising (CSTD)

1. Original signal x[n] consisting of N=8 frames of data of n signal samples in each frame

f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8
N							

2. Create a signal x1[1] at level k=1 by averaging frames of x[n] ($f_{12}=(f_1+f_2)/2$), then cyclic shifting frames x[n] to create new cyclic shift averages ($f_{23}=(f_2+f_3)/2$), and denoise with δ_1

fd_{12}	fd_{34}	fd_{56}	fd_{78}	fd_{23}	fd_{45}	fd_{67}	fd_{81}
N/2				N/2			

3. Create a signal x2[1] at level k=2 by averaging frames of x1[n], then cyclic shifting frames x1[n] to create new cyclic shift averages, and denoise with δ_2

fd_{1234}	fd_{5678}	fd_{3456}	fd_{7812}	fd_{2345}	fd_{6781}	fd_{4567}	fd_{8123}
N/4		N/4		N/4		N/4	

4. Create a signal x3[1] at level k=3 by averaging frames of x2[n], then cyclic shifting frames x2[n] to create new cyclic shift averages, and denoise with δ_3

$fd_{12345678}$	$fd_{56781234}$	$fd_{34567812}$	$fd_{78123456}$	$fd_{23456781}$	$fd_{67812345}$	$fd_{45678123}$	$fd_{81234567}$
N/8	N/8	N/8	N/8	N/8	N/8	N/8	N/8

CSTD on noisy sine wave instances

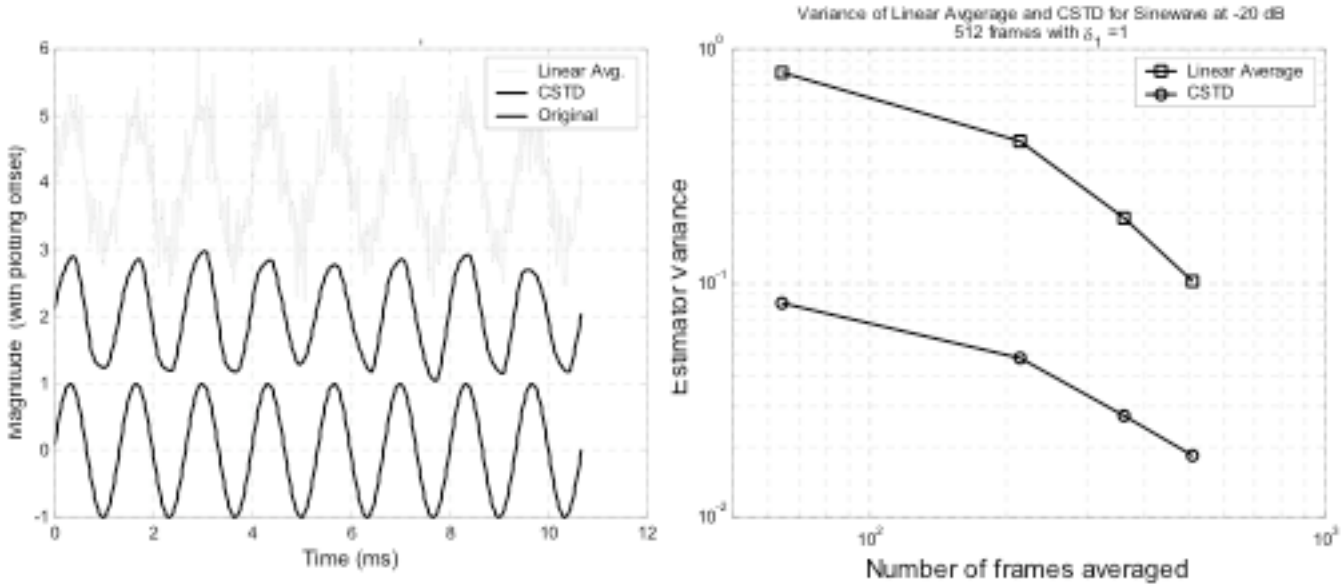


Figure 5: Left: Performance of the novel wavelet algorithm compared to linear averaging 512 data frames (Top: linearly averaged 512 frames, middle: CSTD wavelet denoised 512 frames, bottom: original waveform ("true value")). Right: Variance comparison between linear averaging (top) and novel wavelet algorithm (bottom).

CSTD on simulated noisy AMLR instances

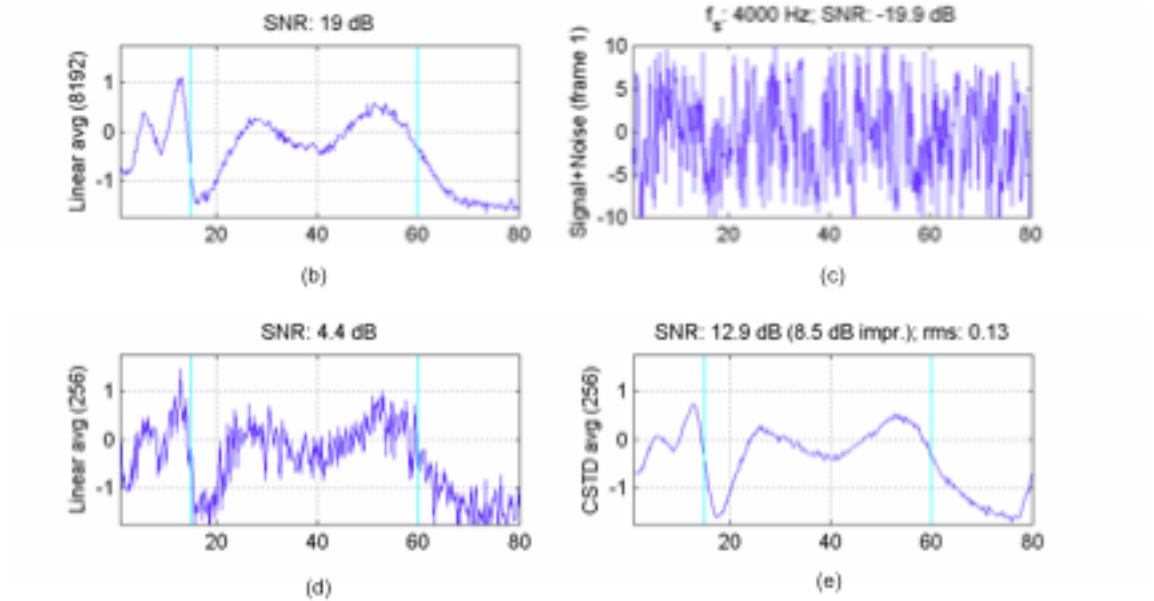


Figure 6: Performance of CSTD algorithm compared to linear averaging 256 data frames. (a): Template of AMLR evoked potential waveform from Spehlmann; (b): linear average of 8192 AMLR frames; (c): Single frame consisting of AMLR model plus WGN; (d): Linear average of 256 frames; (e): Result of CSTD algorithm.

CSTD vs. averaging on actual ABR instances

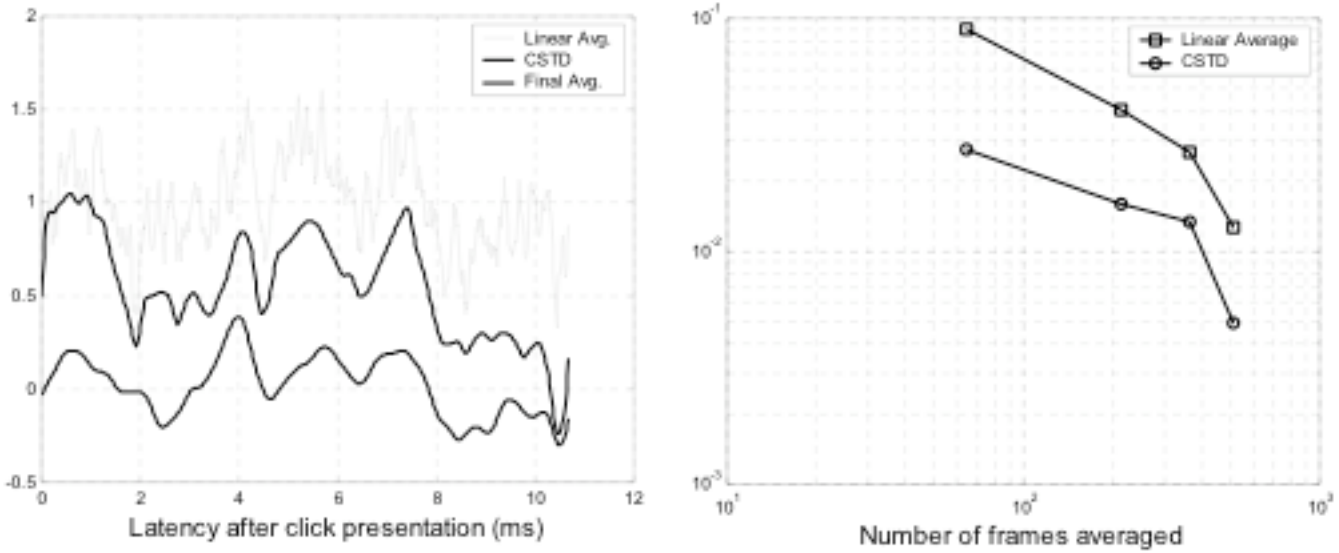


Figure 7: Left: Comparison of Linear Averaging to CSTD for 512 frames of ABR data. (Top: linearly averaged 512 frames, middle: CSTD wavelet denoised 512 frames, bottom: linearly averaged 8,192 frames ("true value")). Right: Variance comparison between linear averaging and CSTD, as a function of number of frames.

Averaging and CSTD on actual AMLR instances

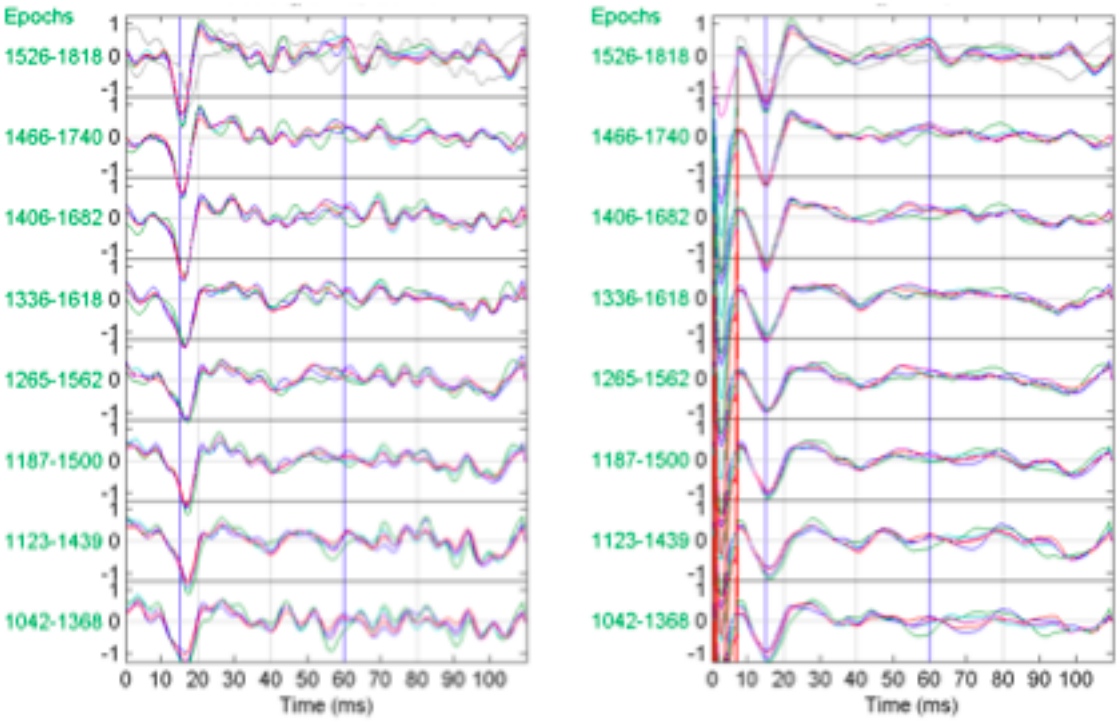
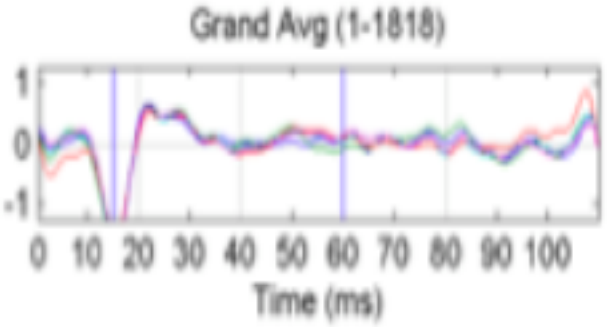
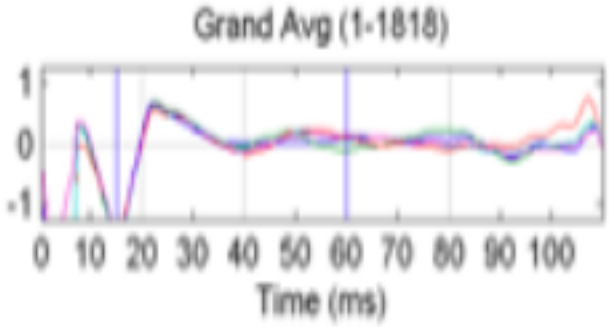


Figure 8: Comparison between linear averaging and CSTD for AMLR. Signal pre-filtered with a passband filter 25-180 Hz in both cases. Left: consecutive averages of 256 frames of 110 ms each. Right: Results of CSTD algorithm applied to EEG frames covering the temporal range [7.5 ms, 110 ms] (Note: In the interval [0, 7.5 ms] the signal displayed is simply the linear average of 256. It is of little importance for AMLR interpretation).

Averaging vs. CSTD on actual AMLR instances



Simple average
of all 1818 instances



Full CSTD with 8 frames
for 1818 instances

Application 2: radiation oncology dose planning

Small differences in radiation dose greatly affect the success of tumor treatment. Stray radiation harms healthy adjacent tissue. How can the dose distribution be controlled?

– By Monte Carlo methods, simulate the dose distribution for the patient.

– use CT or MR images (2-D or 3-D) for tumor location, adjacent tissue characterization, and scattering cross-section.

– adjust the radiation source to optimize the dose distribution; iterate until satisfied.

Radiation oncologists are too expensive for this.

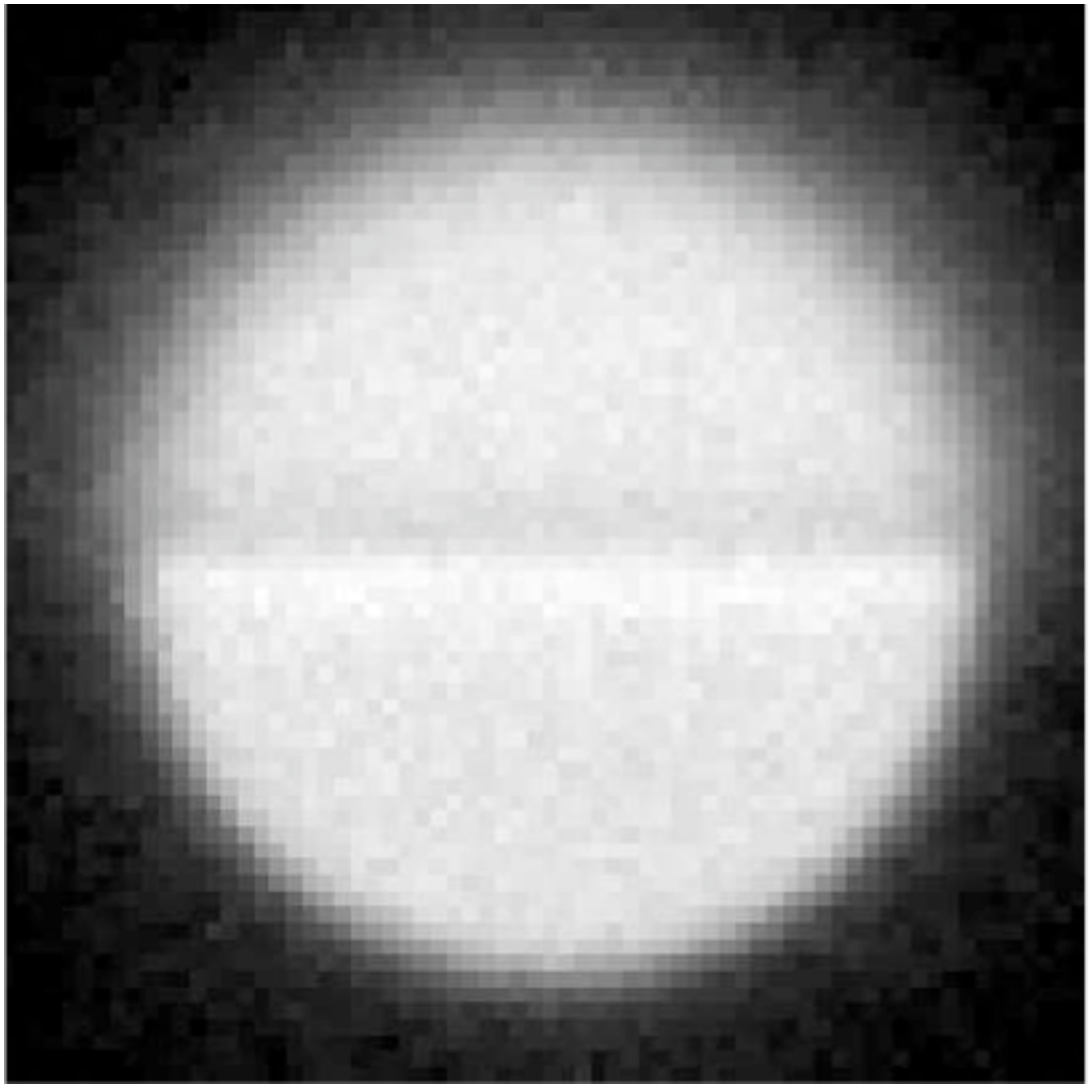
Monte Carlo simulation of radiation dosage

– most accurate technique in common use

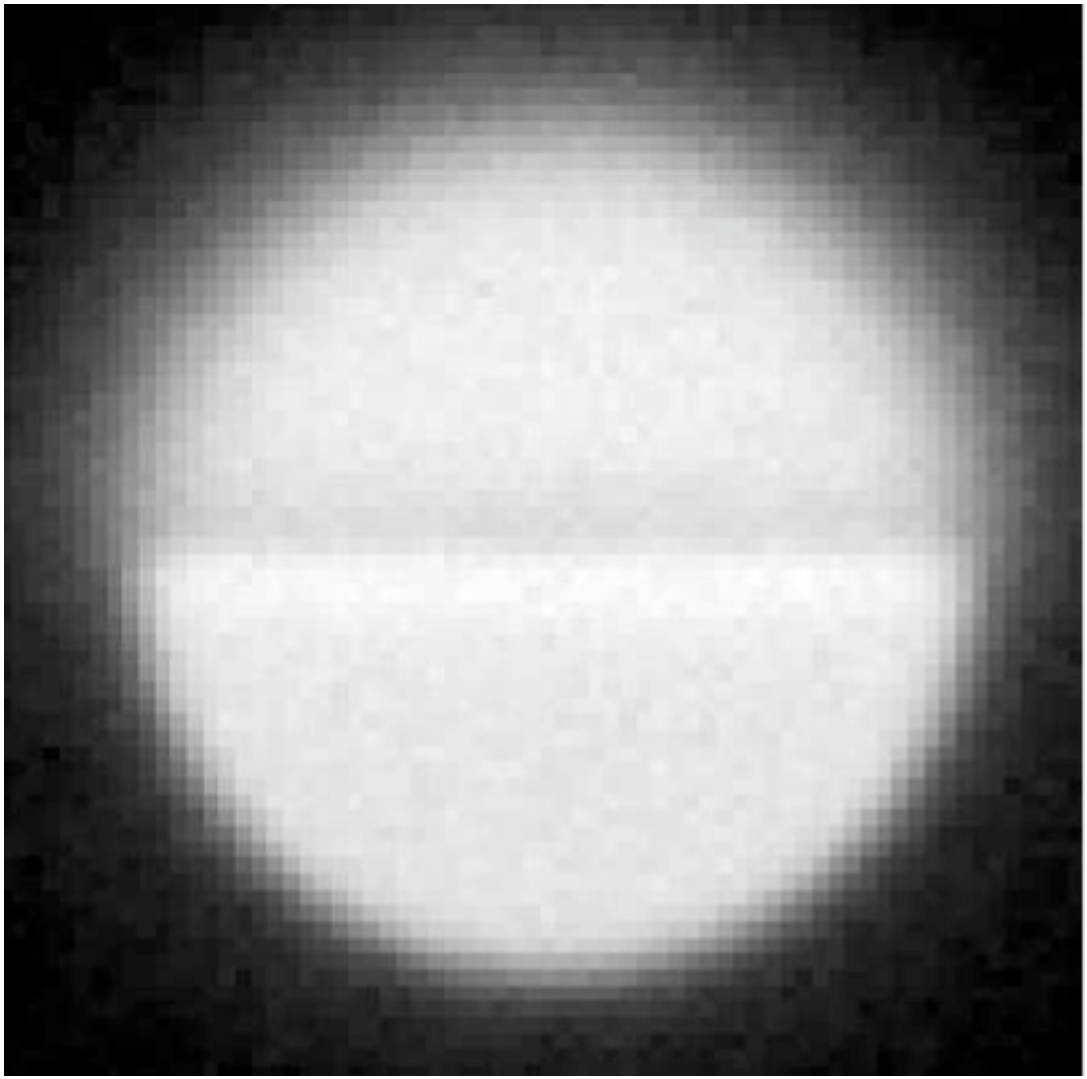
– fully parallel:
  - p processors reduces time by factor p
  - $X = X_1+X_2+...+X_p$ step is very cheap

– electron beam case (β particles):
  - initial trajectory is modeled
  - scattering is computed
  - instance = one β particle dose
  - 100 to 200 million instances are needed

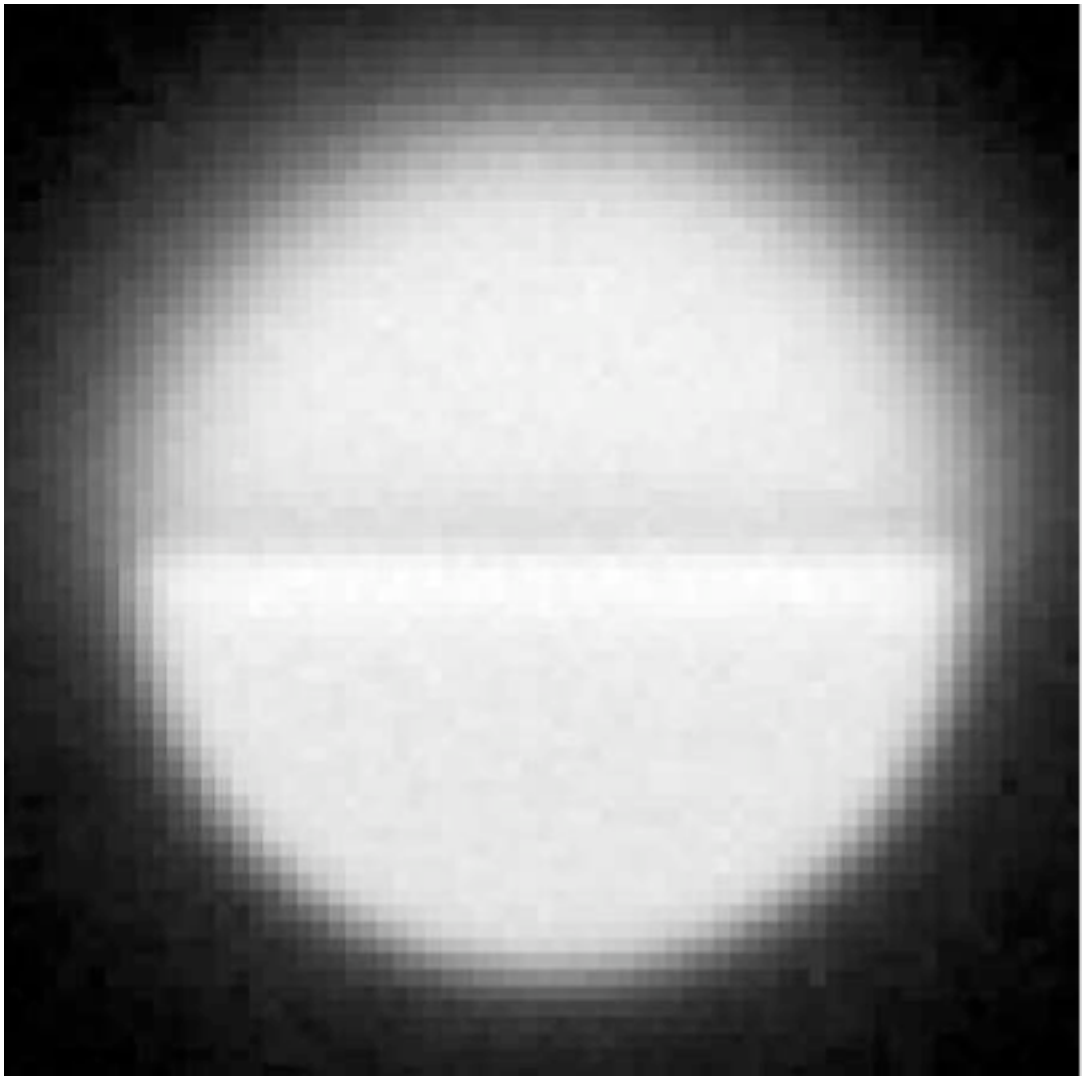
2 million
β particles



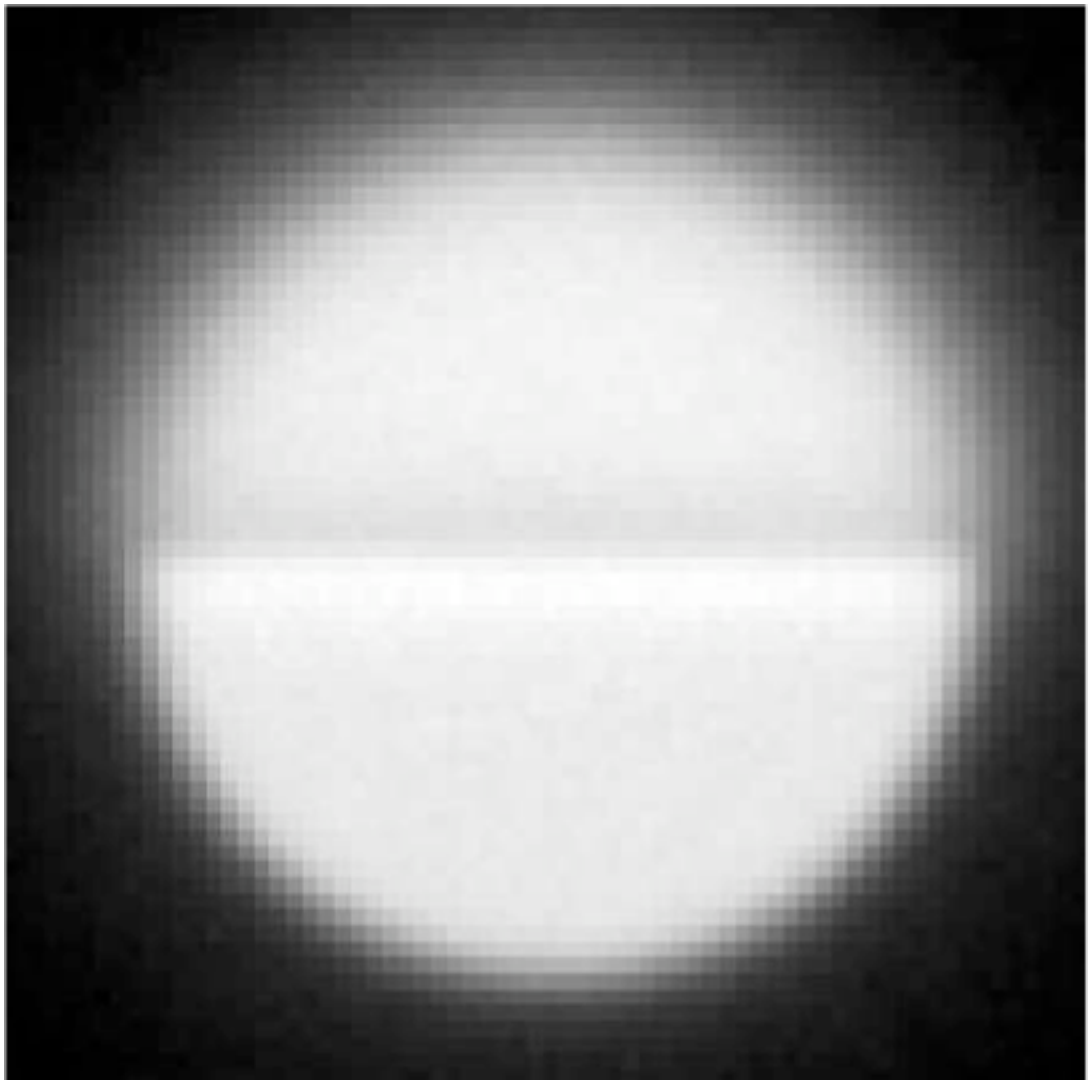
4 million
β particles



8 million
β particles



16 million
β particles



Accelerated convergence of MC simulations

Idea: post-process low-count simulations with wavelet threshold denoising.

Problem: determine the best threshold.

Technical issues:

- instances are too noisy for wavelet methods
  - + pre-average instances to increase SNR
- noise is multiplicative
  - + variance stabilizing transform (sqrt() or log())
- dyadic orthonormal wavelet artifacts
  - + spin cycle averaging

Result: acceptable accuracy with 4 million β particles.

Determining the wavelet denoising threshold

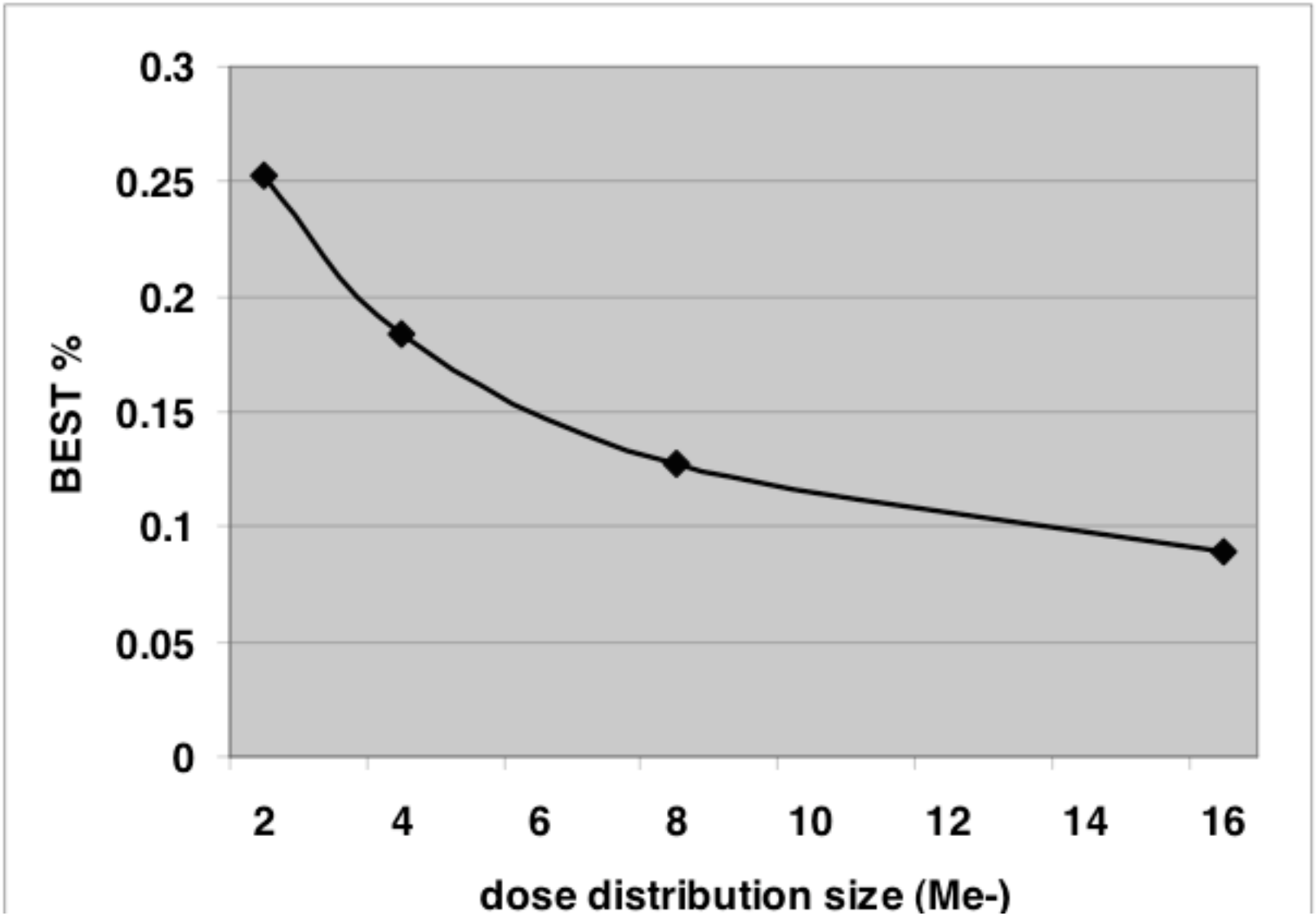
Oracle method:

– obtain approximate limit X for typical phantom
  - same average density and size as patient.
  - 100 million or 200 million β particles.

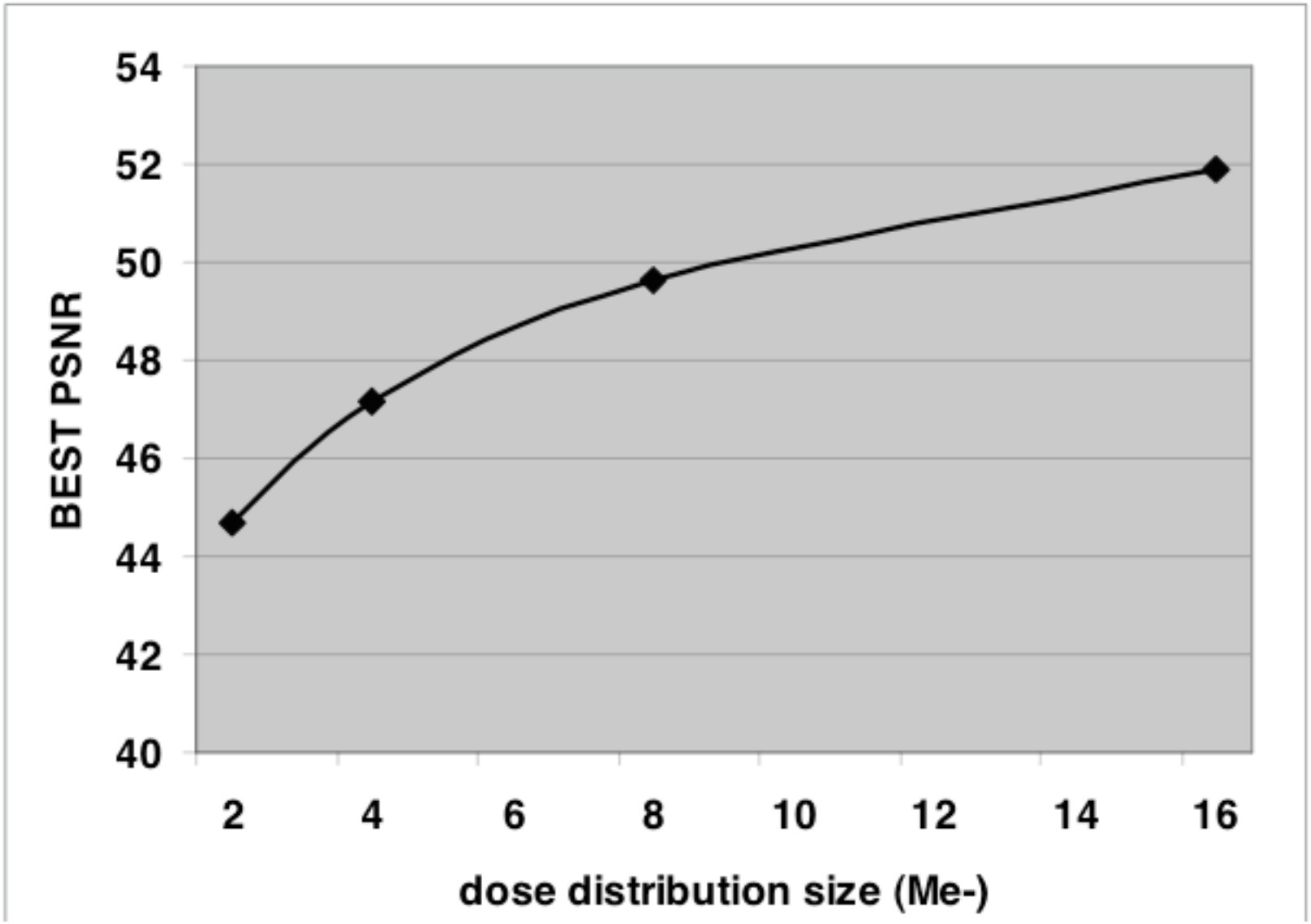
– denoise several independent frames $X_1,...,X_m$
  - each has same number N of β particles
  - N << 100 million
  - Wavelet denoised frame $D(X_j, t)$, threshold t
  - Compute residual error $r_j(t) = \|X - D(X_j,t)\|$
  - Compute average error $e(t) = E(r_j(t))$

– Find argmin $e(t)$ and its standard deviation

Best thresholding % function



Best PSNR function



De-noising process

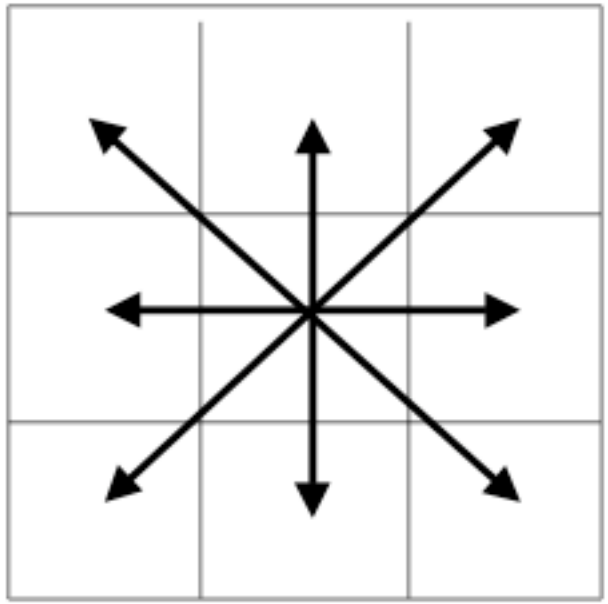
- We start with a 2D dose distribution array $\boldsymbol{p}$
- We apply the square root variance stabilizing transformation : $\boldsymbol{p' = \mathbf{sqrt}(p)}$
- The (9-7) wavelet transform is applied to $\boldsymbol{p'}$: $\boldsymbol{c = \mathbf{Omega}(p')}$
- Wavelet Thresholding : given a percentage $\boldsymbol{T}$, every wavelet coefficient such that $|\boldsymbol{c_{i,j}}| \leq \boldsymbol{T}\ \mathbf{max(c)}$ is set to $\mathbf{0}$

De-noising process

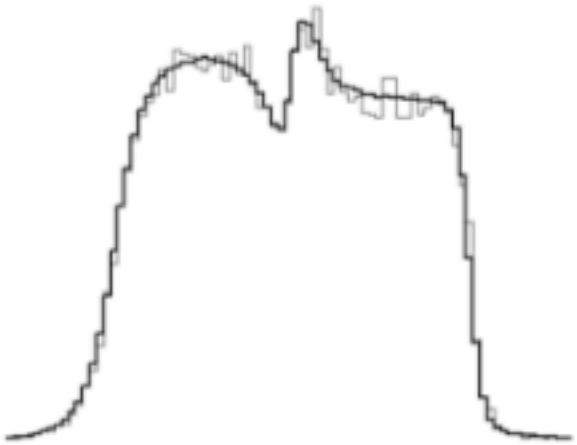
- The inverse (9-7) wavelet transform is applied to the resulting array ***c***
- The new array ***g*** values are truncated if necessary to fit in the [0,max] interval of the original dose distribution ***p'***
- We finally get the de-noised dose distribution ***g'*** by reversing the square root transform : $\boldsymbol{g' = g^2}$

Spin Cycle technique

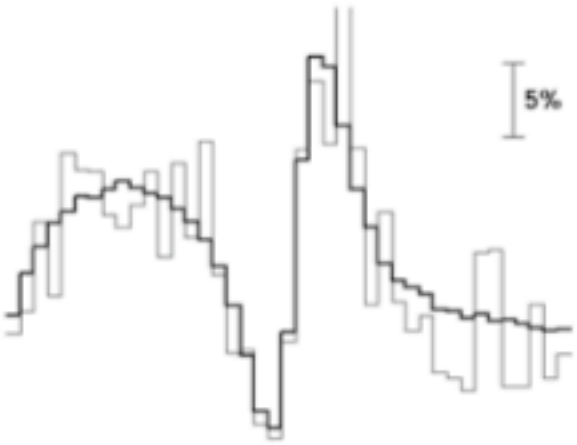
- Wavelet transforms are very sensitive to a shift on the original data
- To reduce these artifacts, one can apply the previous de-noising method to the 9 2D maps resulting from shifts in all directions, shift back and average the de-noised maps



Low density



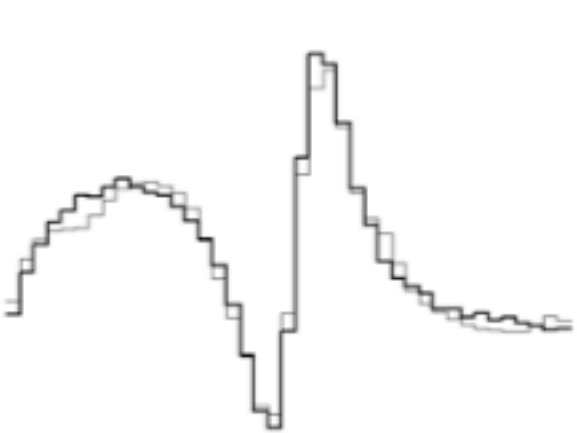
Low density (detail)



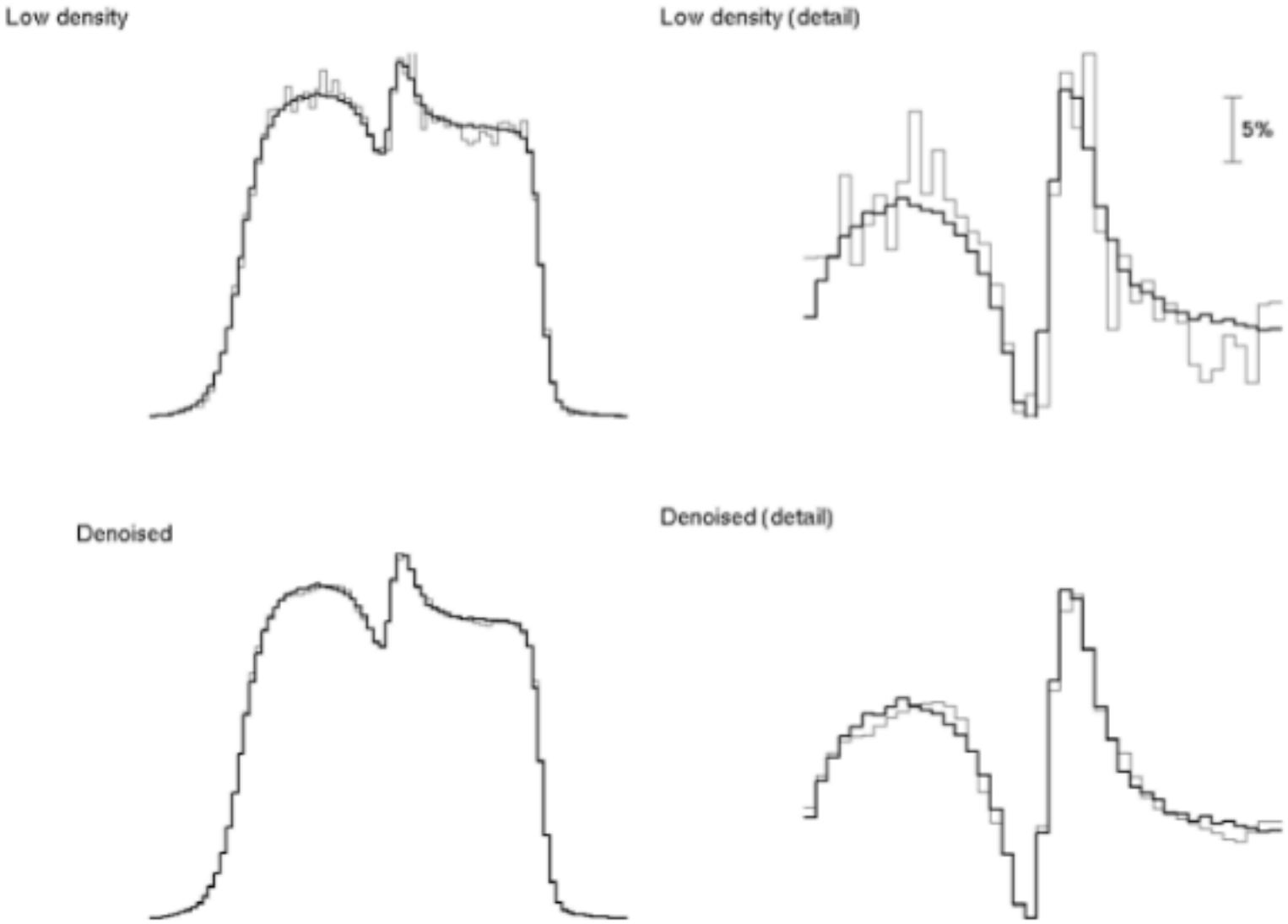
Denoised



Denoised (detail)



2Me- dose distribution

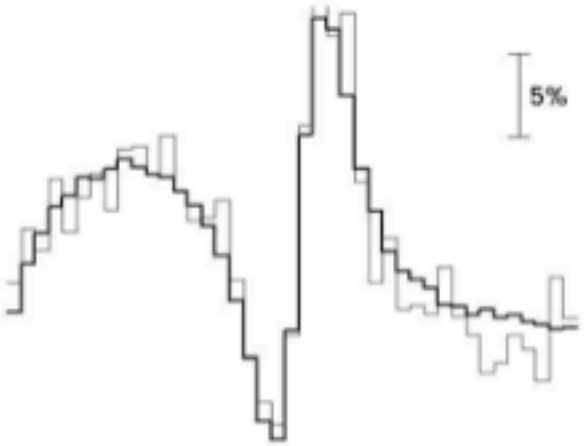


4Me- dose distribution

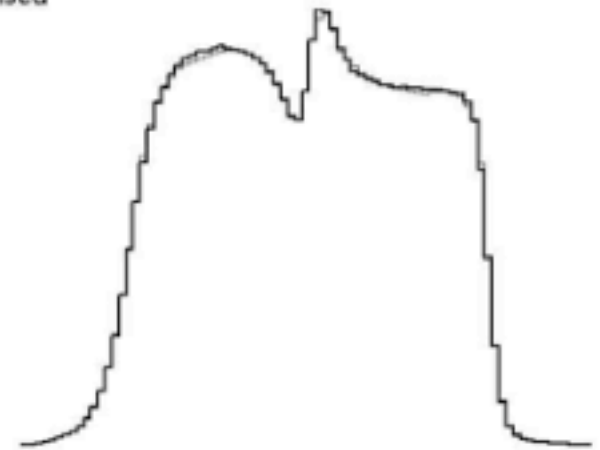
Low density



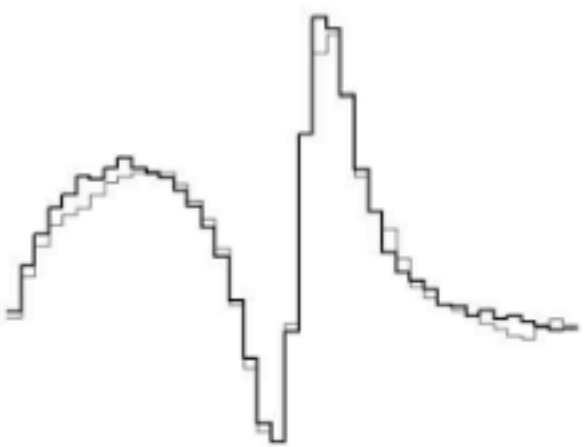
Low density (detail)



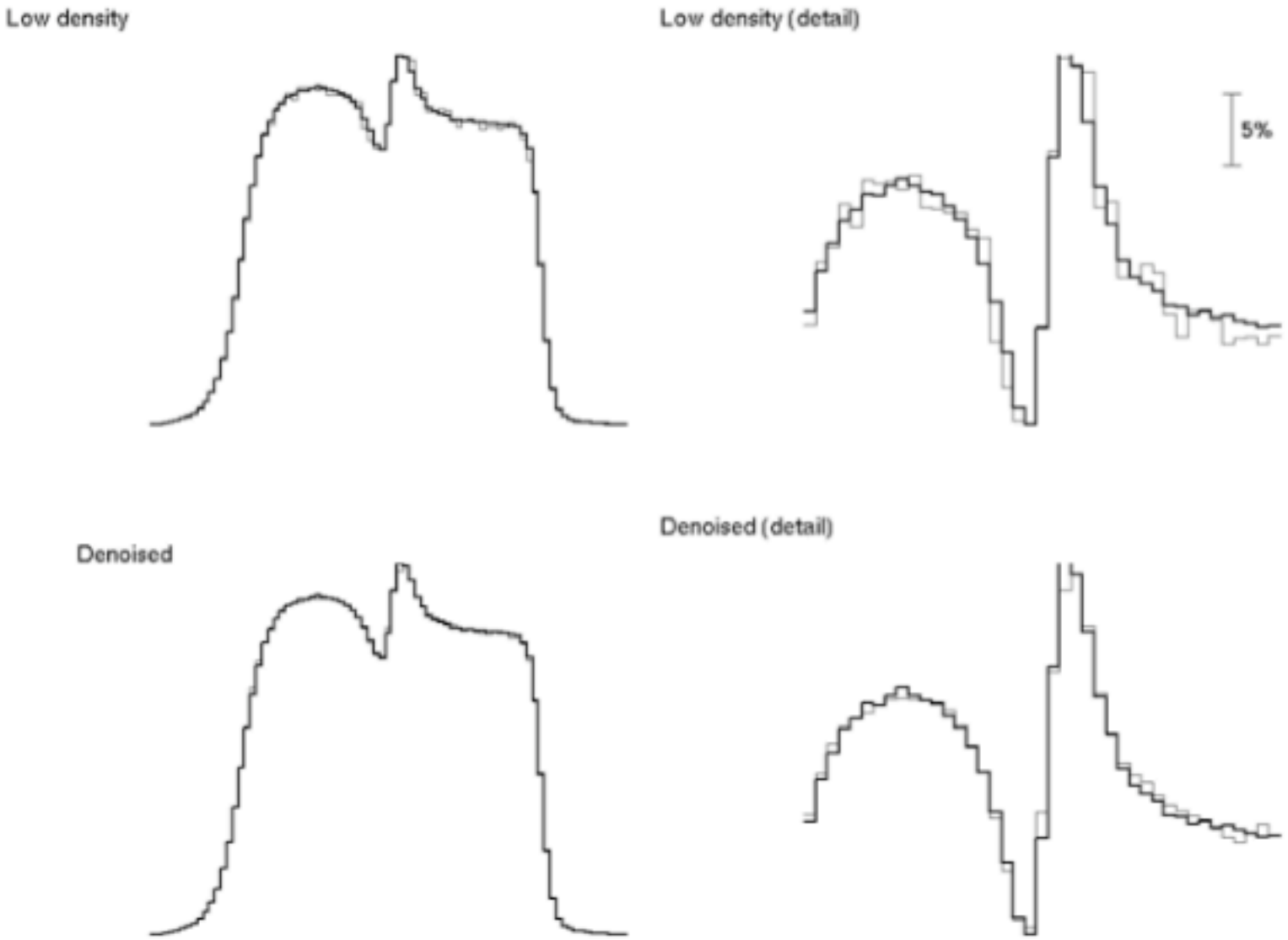
Denoised



Denoised (detail)



8Me- dose distribution



16Me- dose distribution

Denoising Method Actual Residuals

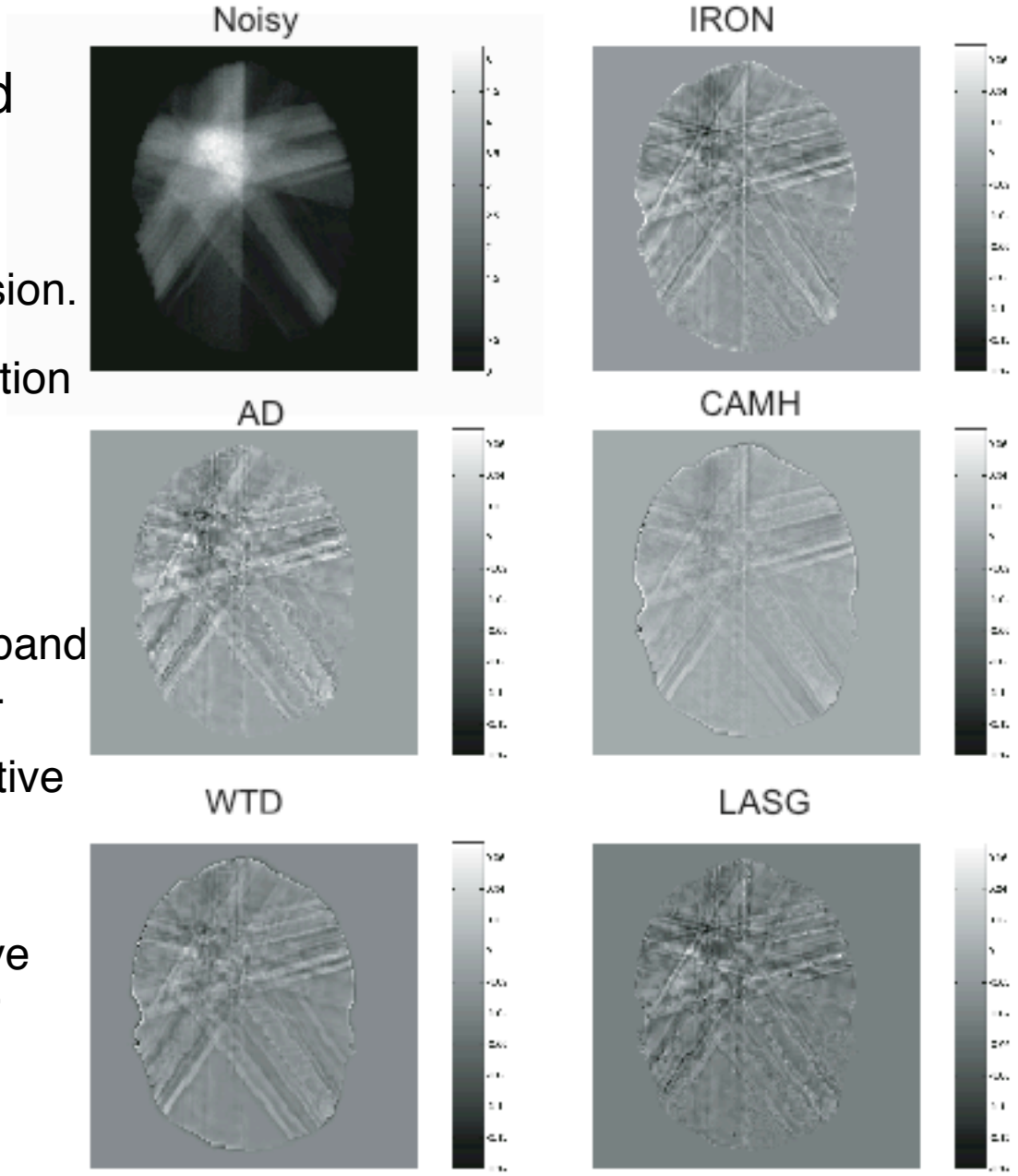
AD: anisotropic diffusion.

IRON: iterative reduction of noise method formulated as an optimization problem.

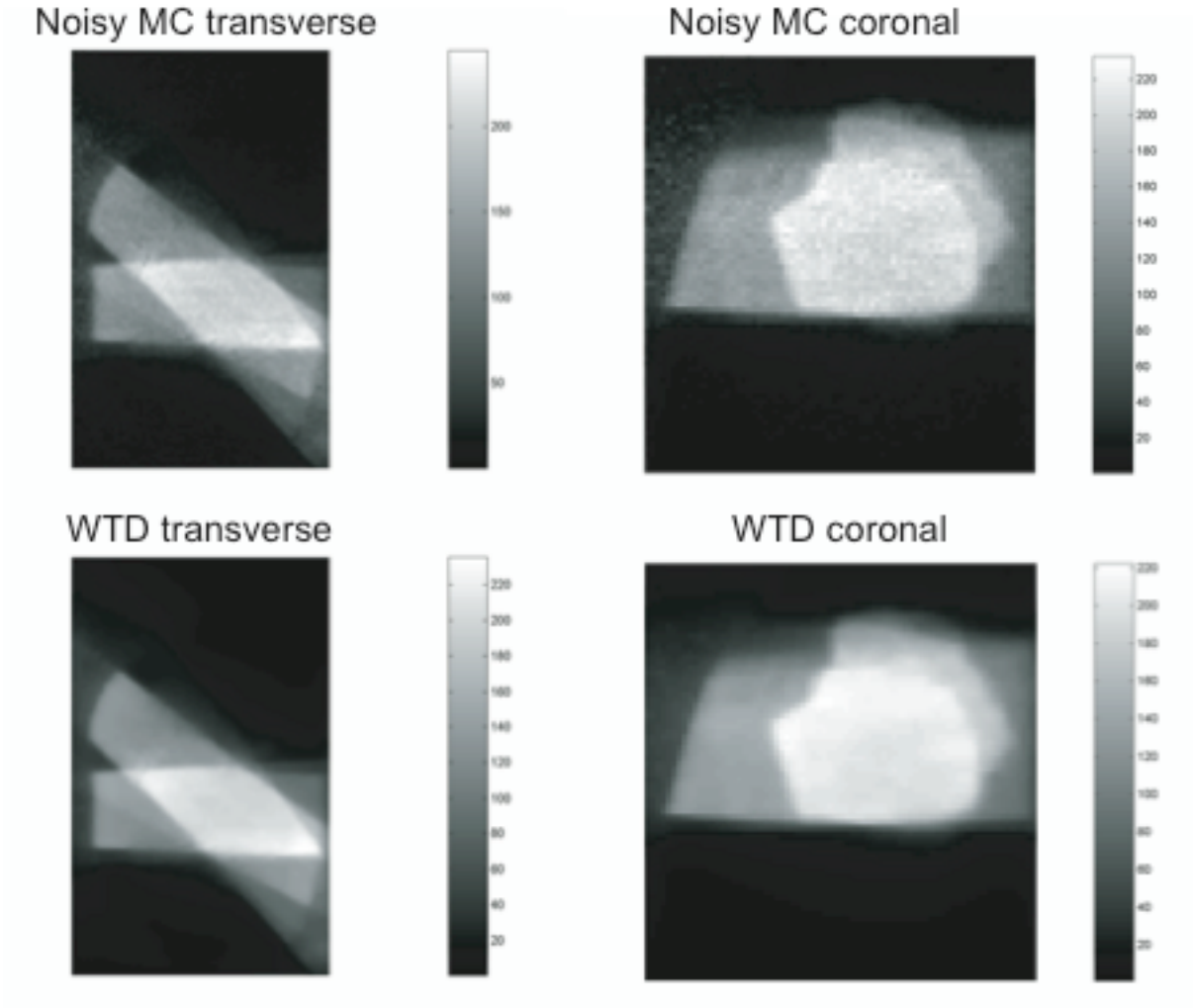
WTD: 3D wavelet denoising with subband adaptive thresholding.

CAMH: content adaptive mean-median-hybrid filtering.

LASG: locally-adaptive Savitzky-Golay curve-fitting.



Denoising Method on 3D Monte Carlo Simulation



Hypotheses for denoising applications

– limit is smoother than instances
    + use smooth wavelet approximation

– simple averaging works to increase SNR
    + a slow solution exists

– instances have independent additive or multiplicative noise
    + different combinations of denoised frames have different noise

– real data is not too variable
    + oracle threshold determination method works

References:

J.O.Deasy, M.V.W., M.Picard. *Accelerating Monte Carlo simulations of radiation therapy dose distributions using wavelet threshold de-noising*. **Medical Physics 29**:10(Oct.2002),2366–2373

I.El Naqa, I.Kawrakow, M.Fippel, J.V.Siebers, P.E.Lindsay, M.V.W.,M.Vicic, K.Zakarian, N.Kauffmann, J.O.Deasy. *A comparison of Monte Carlo dose calculation denoising techniques.* **Physics in Medicine and Biology 50**(2005),909–922

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