Tailored Excitation Pulse Design – Research Update

fMRI Group Meeting

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2024.11.26

Outline

- ISMRM Abstract: *Impact of Spatially Selective Signal Suppression on BOLD fMRI Reliability*
- ROI-Image-Quality Driven RF Pulse Design

Impact of Spatially Selective Signal Suppression on BOLD fMRI Reliability

Submission to ISMRM 2025 Abstract

ROI-Image-Quality Driven RF Pulse Design

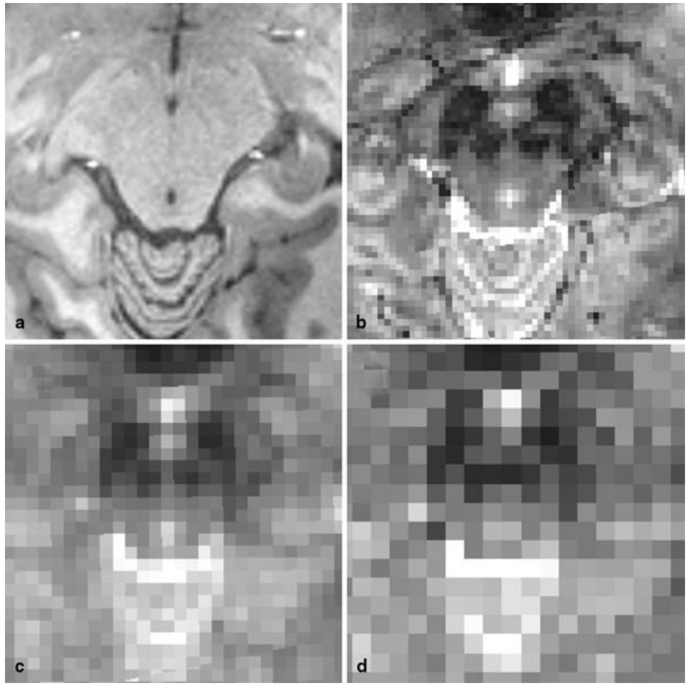
Impact of Spatially Selective Signal Suppression on BOLD fMRI Reliability

Submission to ISMRM 2025 Abstract

Motivation: rFOV Imaging

Potential Benefits:

1. Reduced scan time
2. Enhanced image resolution
3. Improved image quality in EPI due to shorten echo train length



Application:

Brainstem/ Spinal cord fMRI [1]

Table 1 Brainstem-specific problems in fMRI and some possible solutions for them

Problem	Possible solutions
Brainstem nuclei are very small compared to cortical structures	Choose image resolution of ~2 mm or higher
	Increase SNR by acquiring more volumes, using specialized coils or higher field strengths
	Use parallel imaging, multi-band imaging or partial FOV acquisitions to minimize spatial distortions and keep scanning time within limits
	Use spatial smoothing with caution (≤3 mm FWHM)

[1]Beissner, F., Clin Neuroradiol (2015) 25:251–257

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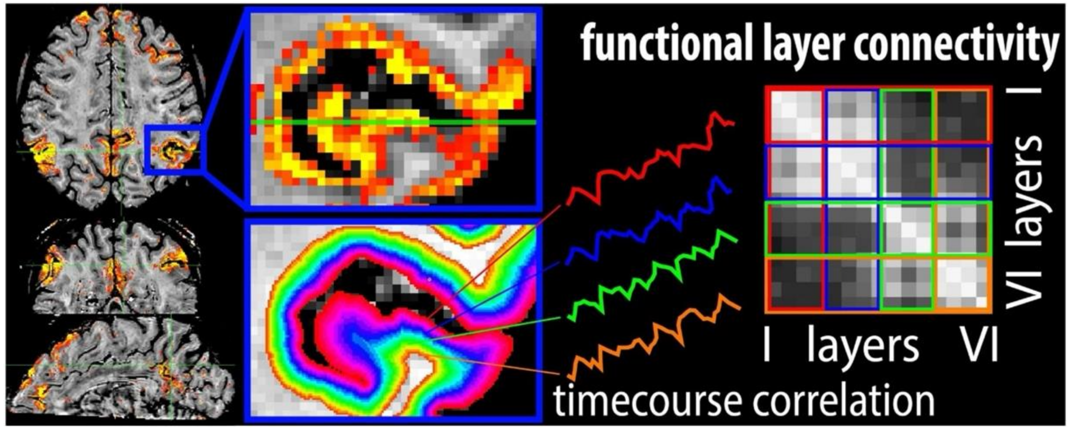


motor cortex), the approach of thicker MRI-slices can help improve sensitivity. However, to fully grasp the neural representation of laminar activation across the folded cortical ribbon in higher-order brain areas with variable folding patterns, isotropic submillimeter resolutions are vital.

Application:

Brainstem/ Spinal cord fMRI [1]

Layer-specific fMRI [2]

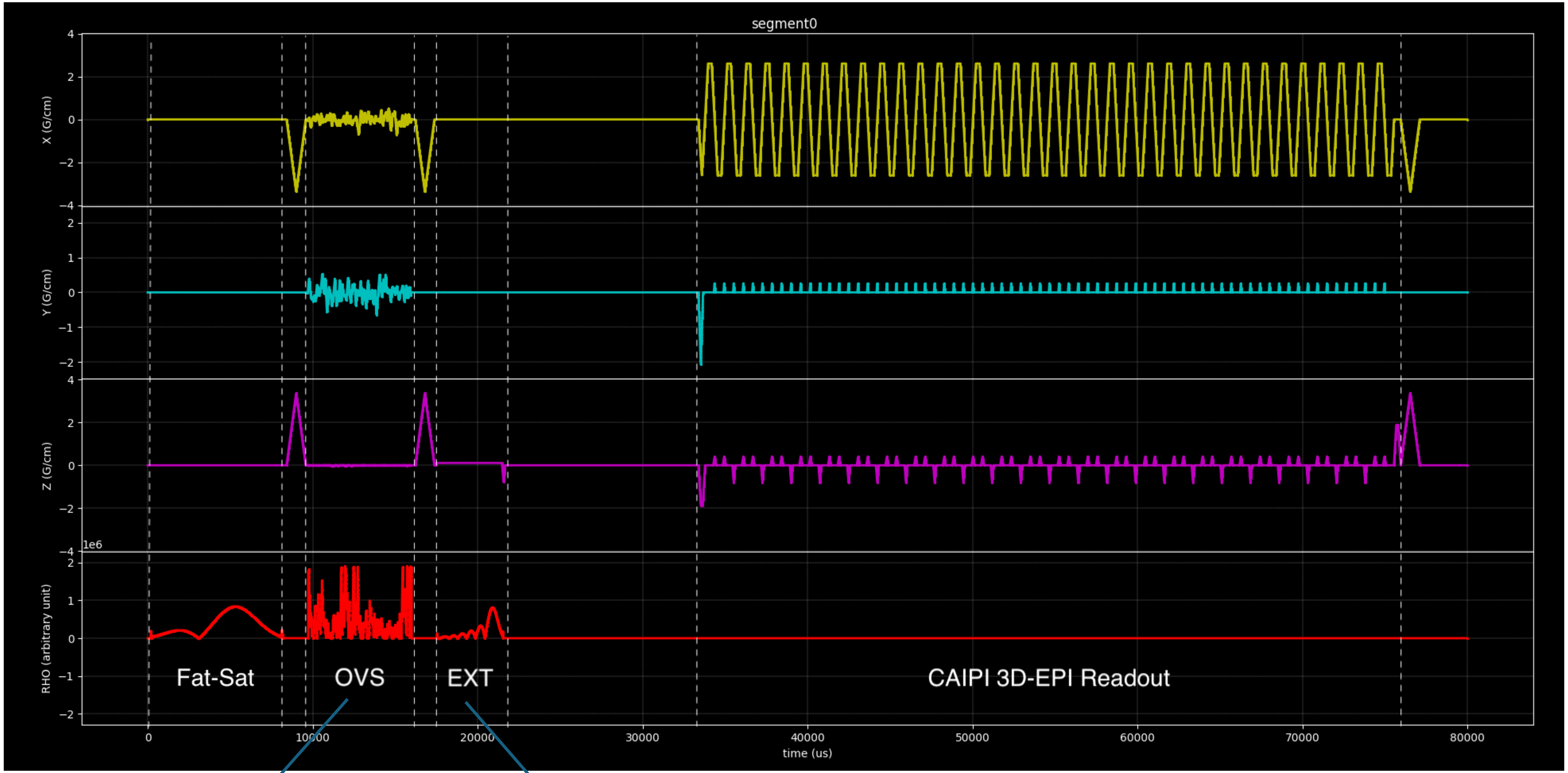
[1]Beissner, F., Clin Neuroradiol (2015) 25:251–257

[2]Huber, L., et al., Progress in Neurobiology 207 (2021) 101835

Synopsis

- We can restrict FOV by a short (6ms) outer-volume suppression (OVS)
- However, the impact of OVS on the sensitivity/specificity of fMRI detection is unclear
- We obtained 7.5-fold accelerated **CAIPI 3D-EPI** BOLD fMRI data during four repetitions of a block finger-tapping task in a healthy subject, both **w/ and w/o OVS**. We assessed test-retest reliability of the activation maps using **receiver-operating-characteristic** (ROC) analysis.

Sequence: SPGR with CAIPI 3D-EPI readout



2D in-plane selective;
6ms

1D slab-selective;
2ms

OVS: Outer-volume suppression

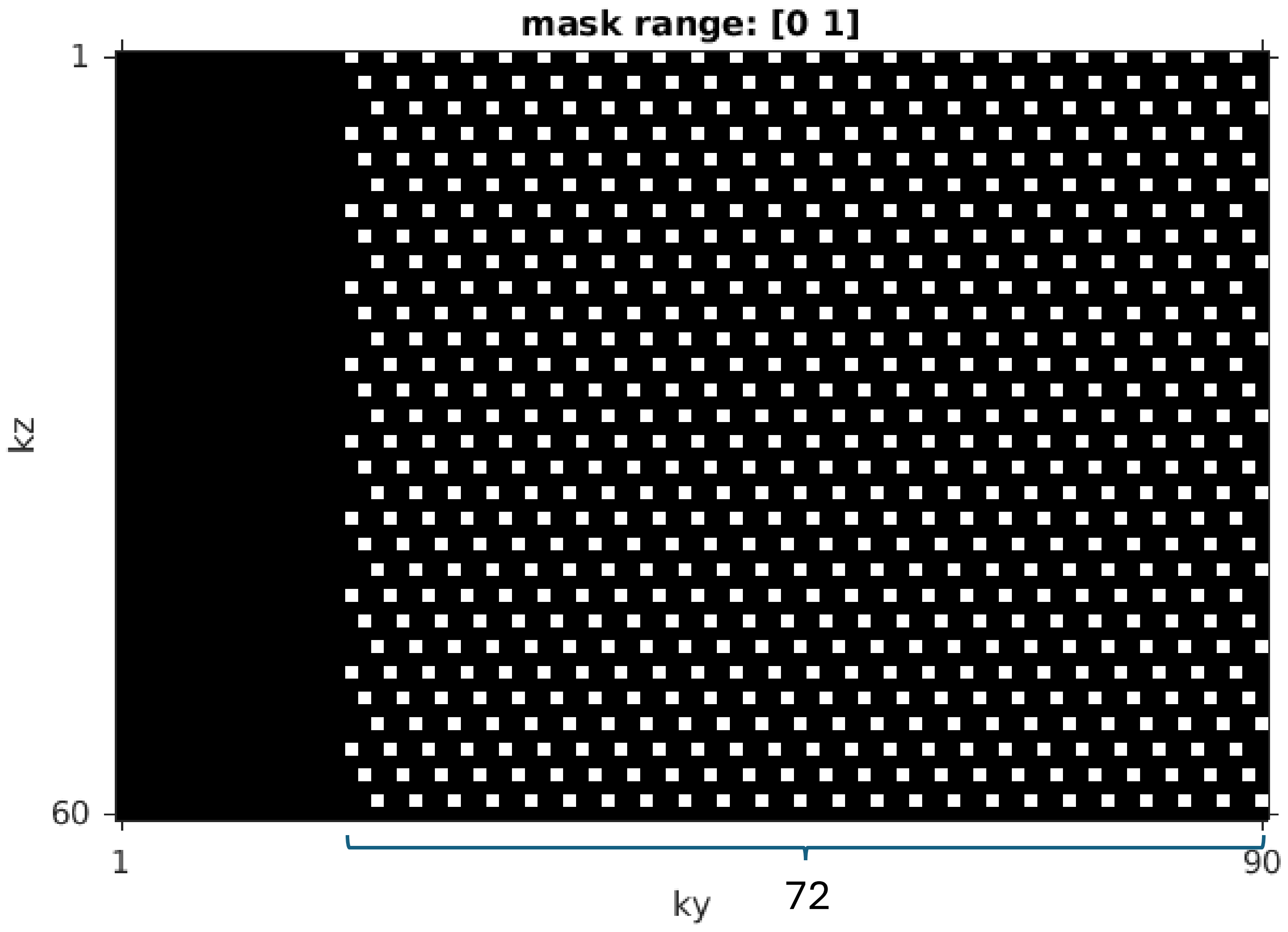
CAIPI Sampling Pattern

Ry= 3; Rz=2
Partial ky = 72/90

Matrix size:
90x90x60

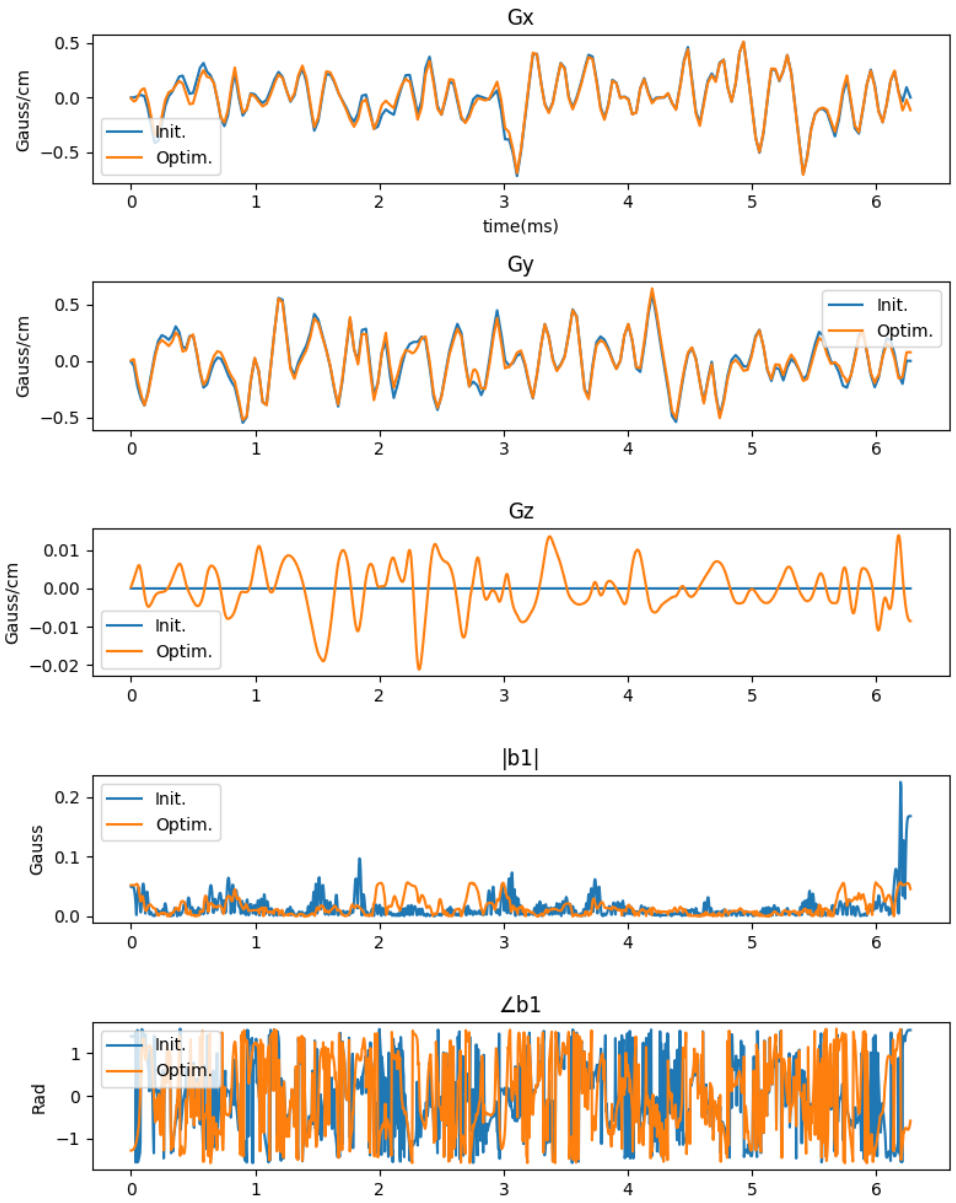
Resolution:
2.4mm^3

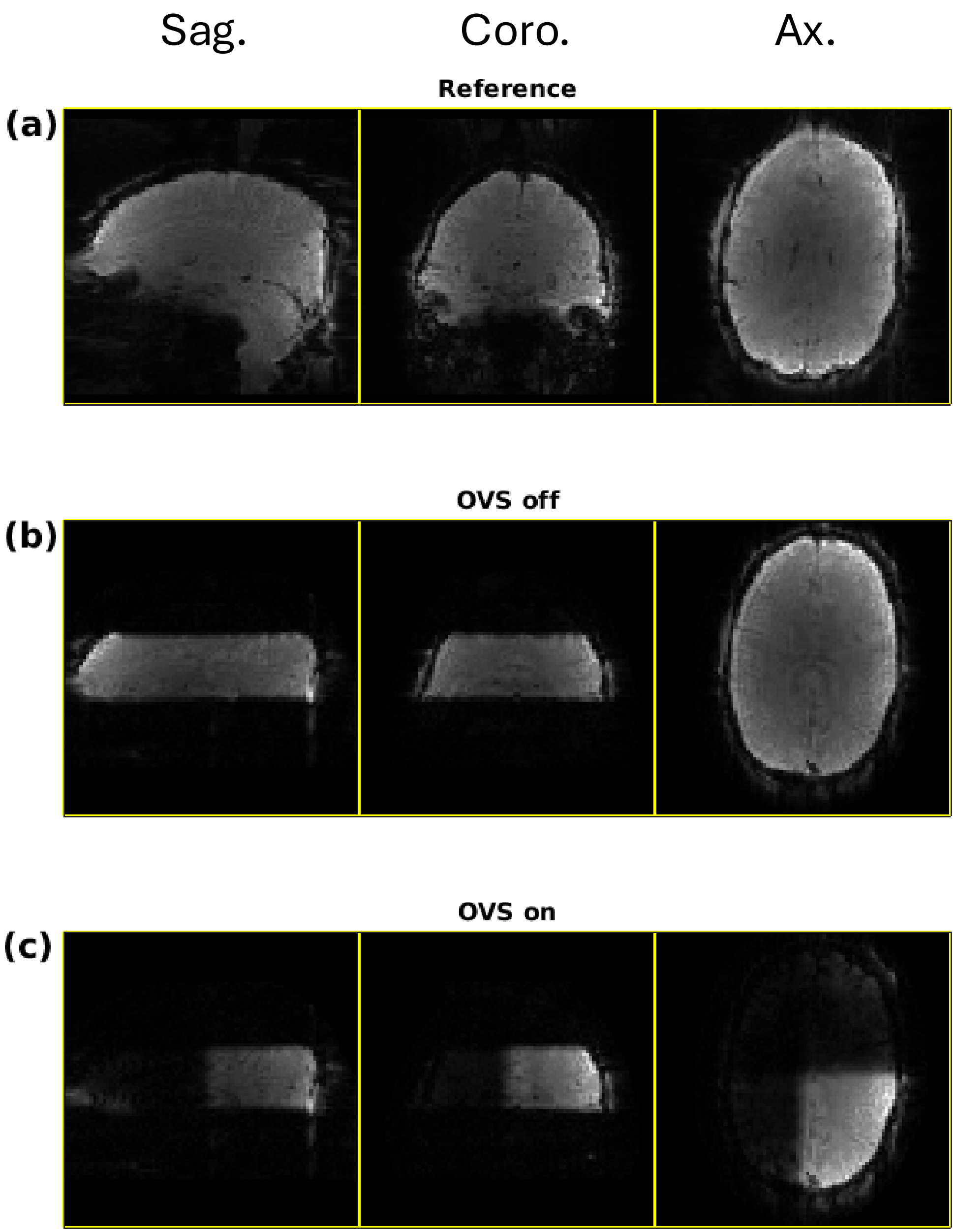
TR: 0.8s
TE=30ms



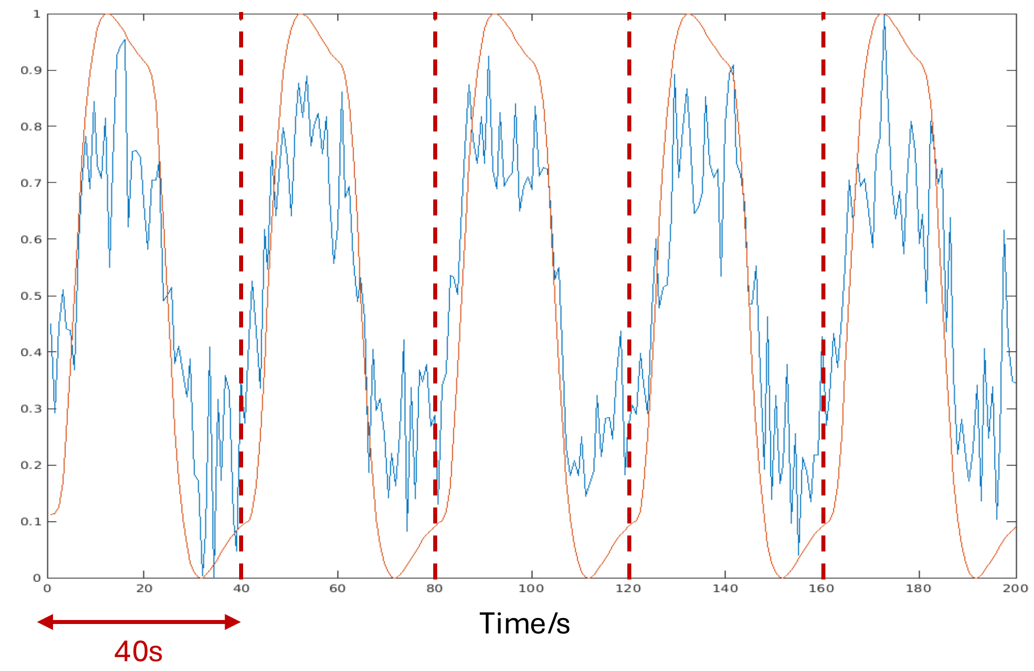
Felix A. Breuer, et al., Magnetic Resonance in Medicine, 53(3):684–691, 2005

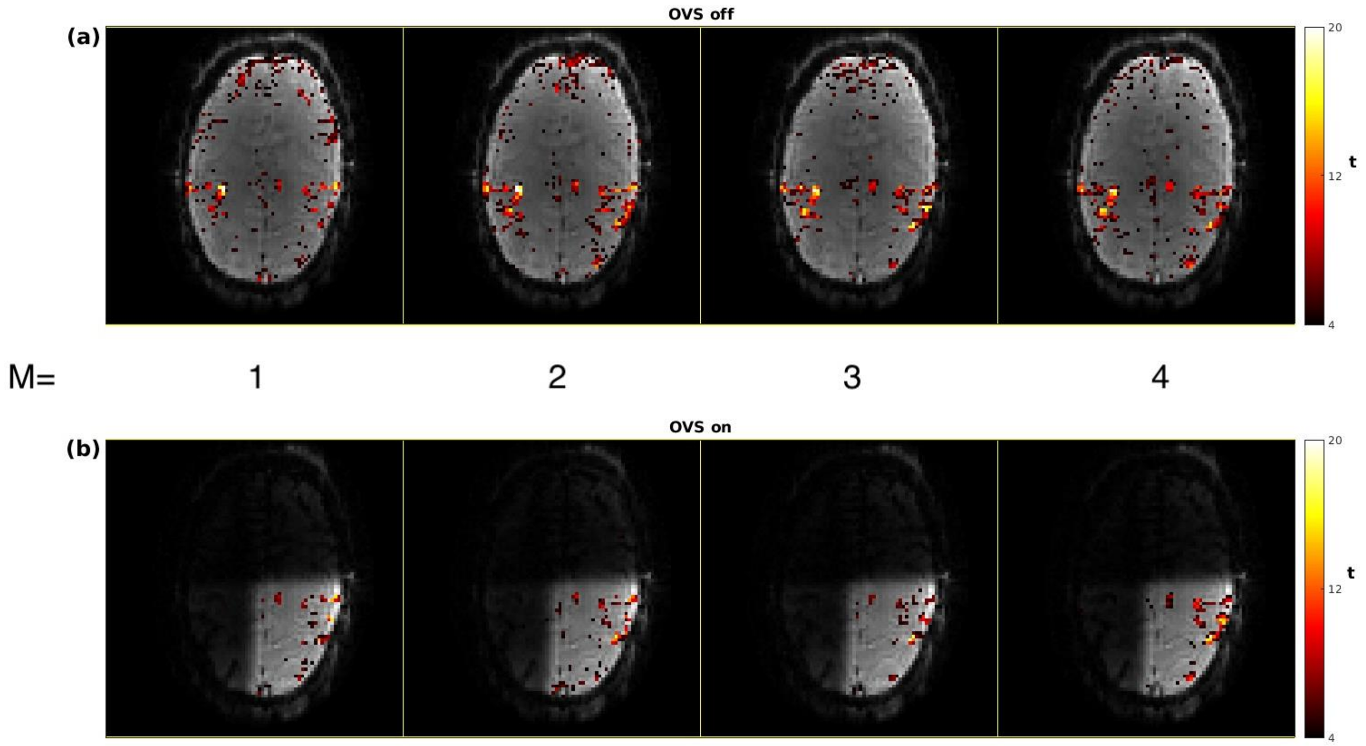
Structural Scan





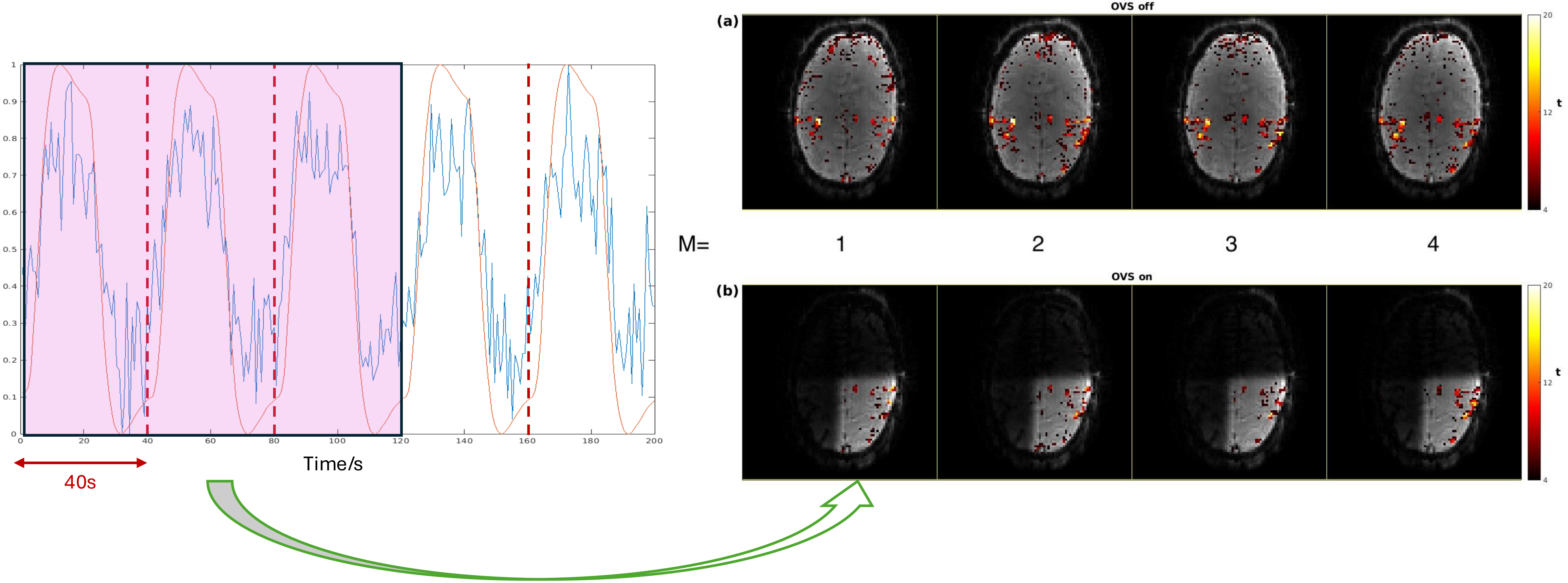
fMRI Finger-tapping test





20s rest + 20s tapping = 1 block
5 blocks = 1 repetition
4 repetitions for both OVS off and on, alternatively on-off-on-off-on-off-on-off

fMRI Finger-tapping test



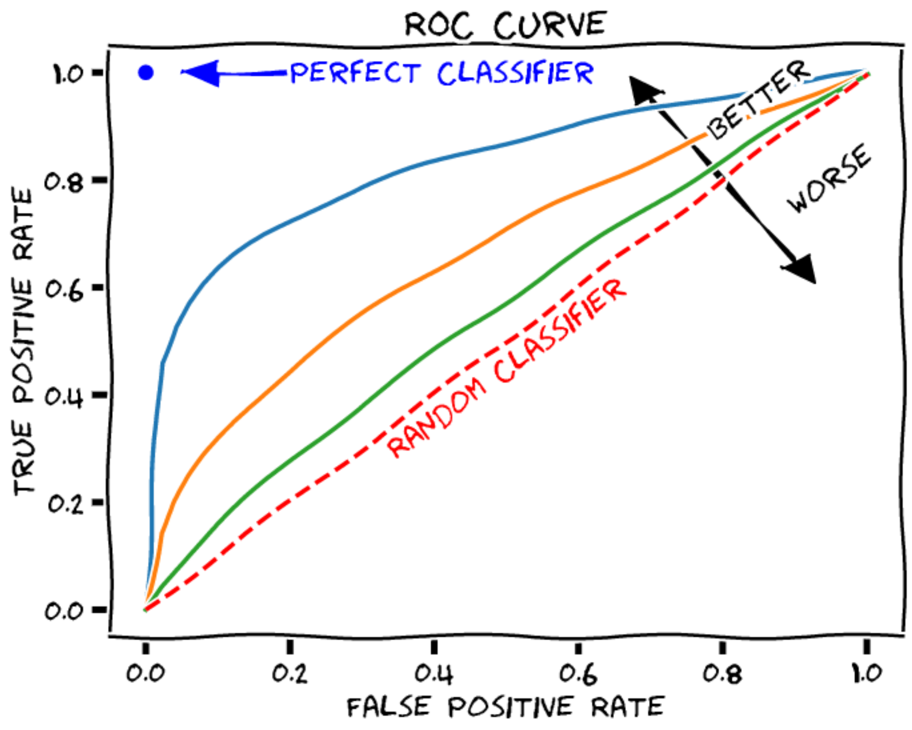
T-score maps; Threshold at 4

Test-Retest Reliability

Sweep the threshold value, for each threshold, calculate (FPR,TPR), get a dot in the ROC curve

$$\mathrm{FPR} = \frac{\mathrm{FalsePostive}}{\mathrm{FalsePositive} + \mathrm{TrueNegative}} \triangleq p_I$$ “False Alarm”

$$\mathrm{TPR} = \frac{\mathrm{TruePositive}}{\mathrm{FalseNegative} + \mathrm{TruePositive}} \triangleq p_A$$ “Hit”



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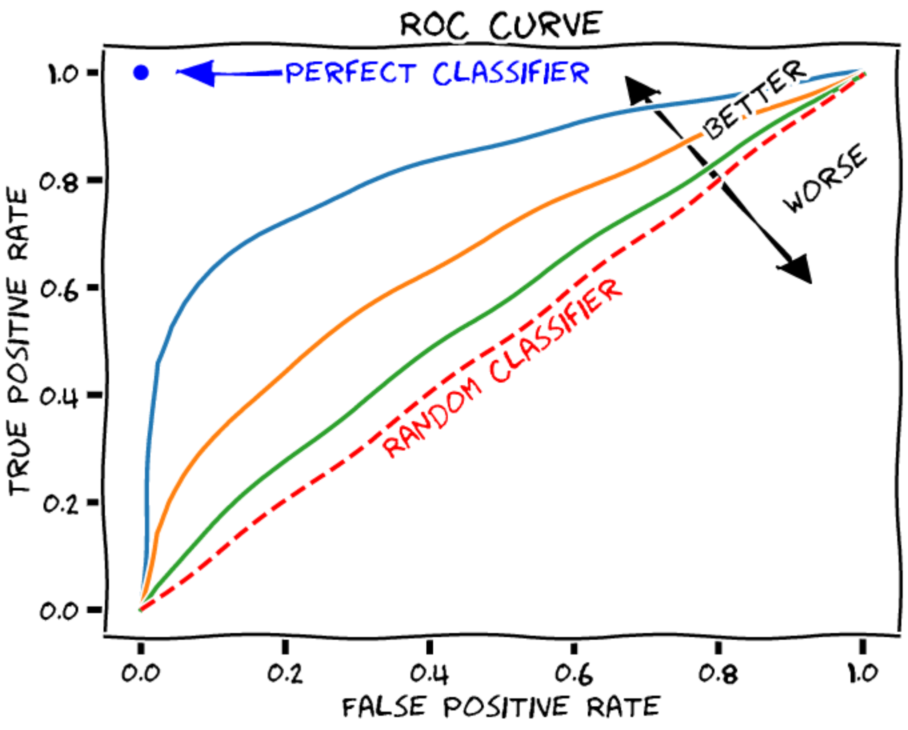

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Q: Which one is better: guess all positive, or guess all negative? (suppose in fMRI, proportion of truly activated voxels is far less than 1/2)

Test-Retest Reliability

Sweep the threshold value, for each threshold, calculate (FPR,TPR), get a dot in the ROC curve

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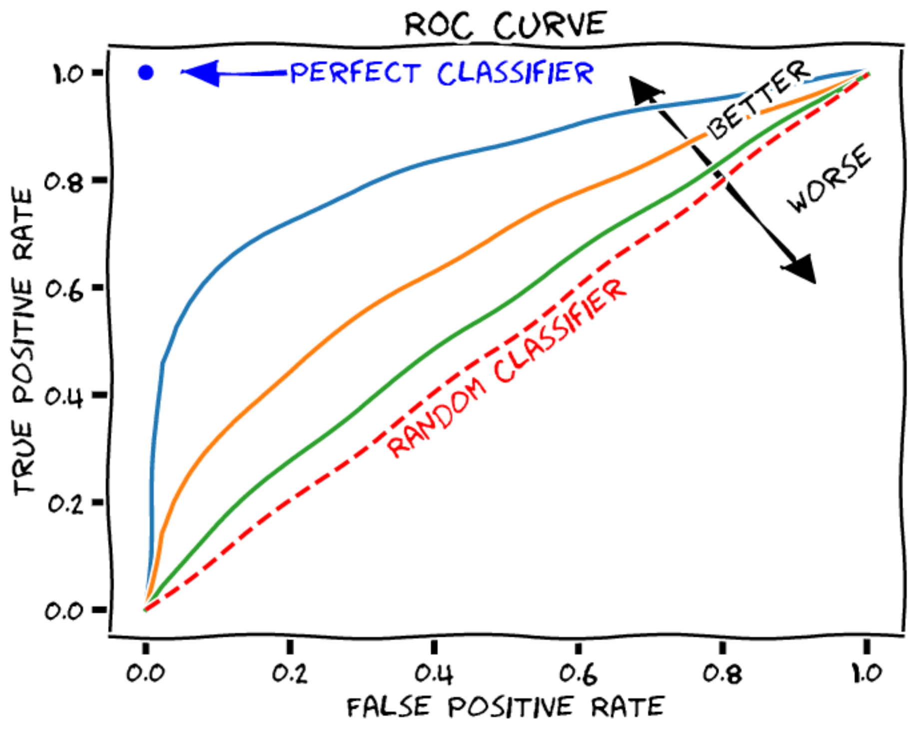
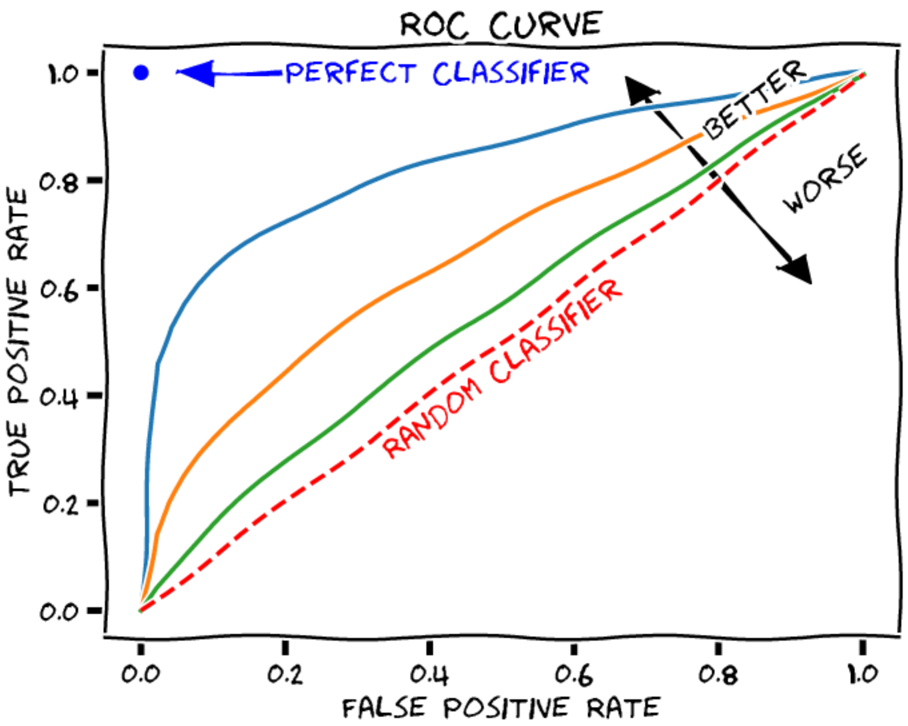


Q: How do we know the ground truth activation classification?

Test-Retest Reliability

Sweep the threshold value, for each threshold, calculate (FPR,TPR), get a dot in the ROC curve



$$\mathrm{FPR} = \frac{\mathrm{FalsePostive}}{\mathrm{FalsePositive} + \mathrm{TrueNegative}} \triangleq p_I$$ “False Alarm”

$$\mathrm{TPR} = \frac{\mathrm{TruePositive}}{\mathrm{FalseNegative} + \mathrm{TruePositive}} \triangleq p_A$$ “Hit”

Q: How do we know the ground truth activation classification?

- Long scan;
- Statistic Model

Entails multiple repetitions ($M \geq 4$) of experiment

Mixed-Binomial Model[1,2]

Assumptions:

- The behavior of voxels across different trials is i.i.d.
- The behavior of each voxel is independent of other voxels
- All voxels behave according to the same probability distribution

[1] Genovese, C.R, et al.,(1997). Magn. Reson. Med., 38: 497-507.
[2] Noll, D.C., et al., (1997). Magn. Reson. Med., 38: 508-517.

Mixed-Binomial Model

λ: proportion of truly active voxels
p_A: TPR
p_I: FPR

Raw reliability map:

$$R_v = \text{Number of times out of M repititions a voxel v is classified active}$$

Assume R_v is drawn from a mixture of two binomial distributions:

$$R_v \sim \lambda \cdot \text{Binomial}(M, p_A) + (1 - \lambda) \cdot \text{Binomial}(M, p_I)$$

Due to independence assumption, the likelihood function of parameters p_A, p_I, λ, only depends on the counts:

$$n_k = \sum_{v \in V} \mathbb{I}_{\{R_v = k\}} = \text{Number of voxels that are classified active k out of M repititions}$$

Mixed-Binomial Model

Let $\boldsymbol{n} = (n_0, n_1, \dots, n_M)$ be the **histogram-vector**.

(The log of the) Posterior likelihood function of parameters p_A, p_I, λ:

$$l(p_A, p_I, \lambda \mid \boldsymbol{n}) = ln\mathbb{P}((p_A, p_I, \lambda \mid \boldsymbol{n}) \cong \sum_{k=0}^{M} n_k \ln[\lambda p_A^k (1 - p_A)^{(M-k)} + (1-\lambda) p_I^k (1 - p_I)^{(M-k)}]$$

We estimate the parameters by the method of **Maximum Likelihood (ML)**.

Mixed-Binomial Model

Dependent likelihood model:

We use the same statistic maps (e.g., t-score) to generate a series of reliability maps by selecting K different thresholds $\tau_0 < \tau_1 < \cdots < \tau_{K-1}$.

These reliability maps should **share a common** $\boldsymbol{\lambda}$, while at each τ_k, the points $(p_I^{(k)}, p_A^{(k)})$ are different, $k = 0, \dots, K-1$.

Define: p_{Ak} is the probability that a truly active voxel is classified active at k of the threshold levels and similarly for p_{Ik}, $k = 0, \dots, K$.

Note that $p_{AK} = \sum_{j=0}^{K-1} p_{Aj}$, $p_{IK} = \sum_{j=0}^{K-1} p_{Ij}$.

Mixed-Binomial Model

Dependent likelihood model:

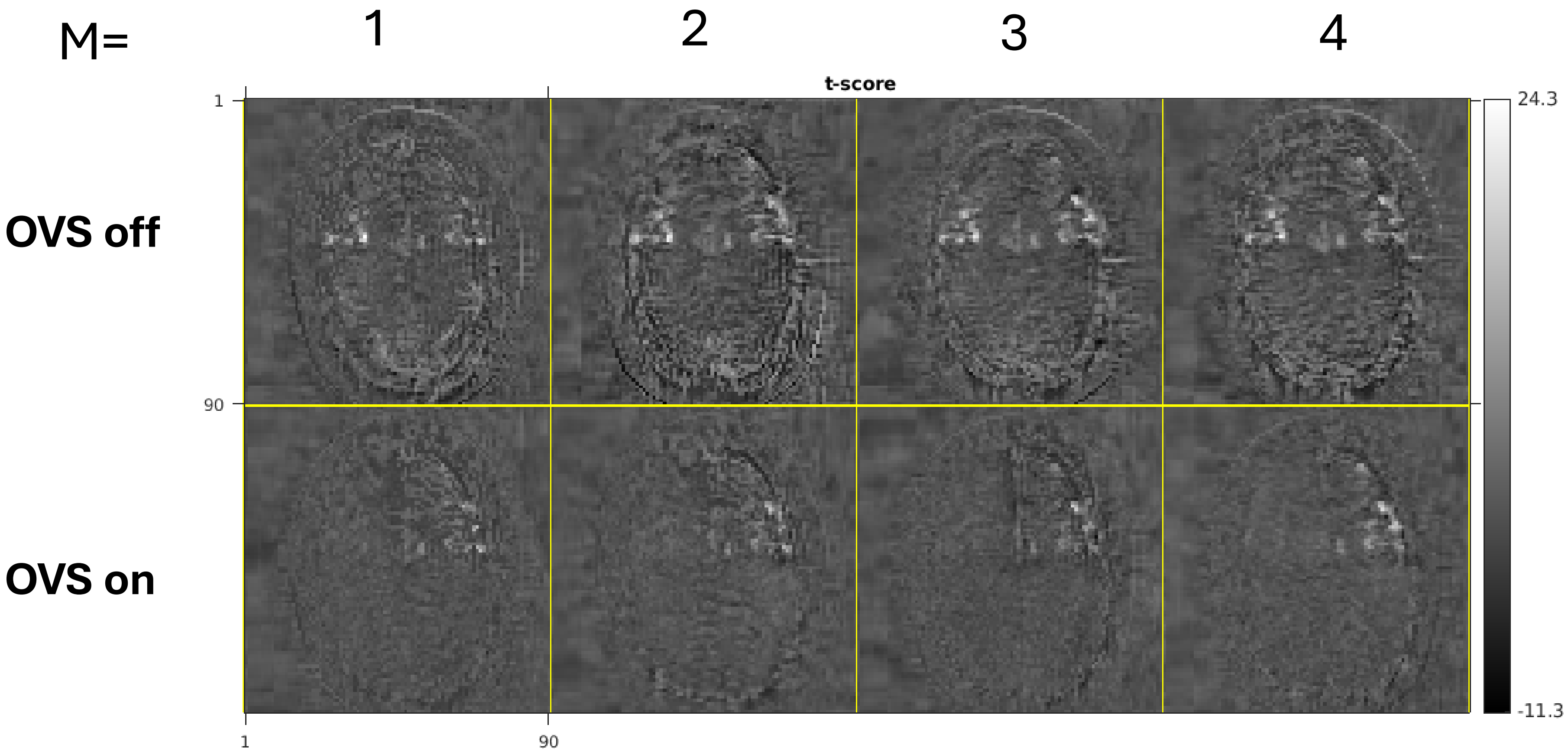
Define $n_{\boldsymbol{t}}$ for $\boldsymbol{t} = (t_0, \ldots, t_K)$, to be number of voxels classified active at k threshold levels t_k times (out of *M)* for each $k = 0, \ldots, K$.

The dependent likelihood function is:

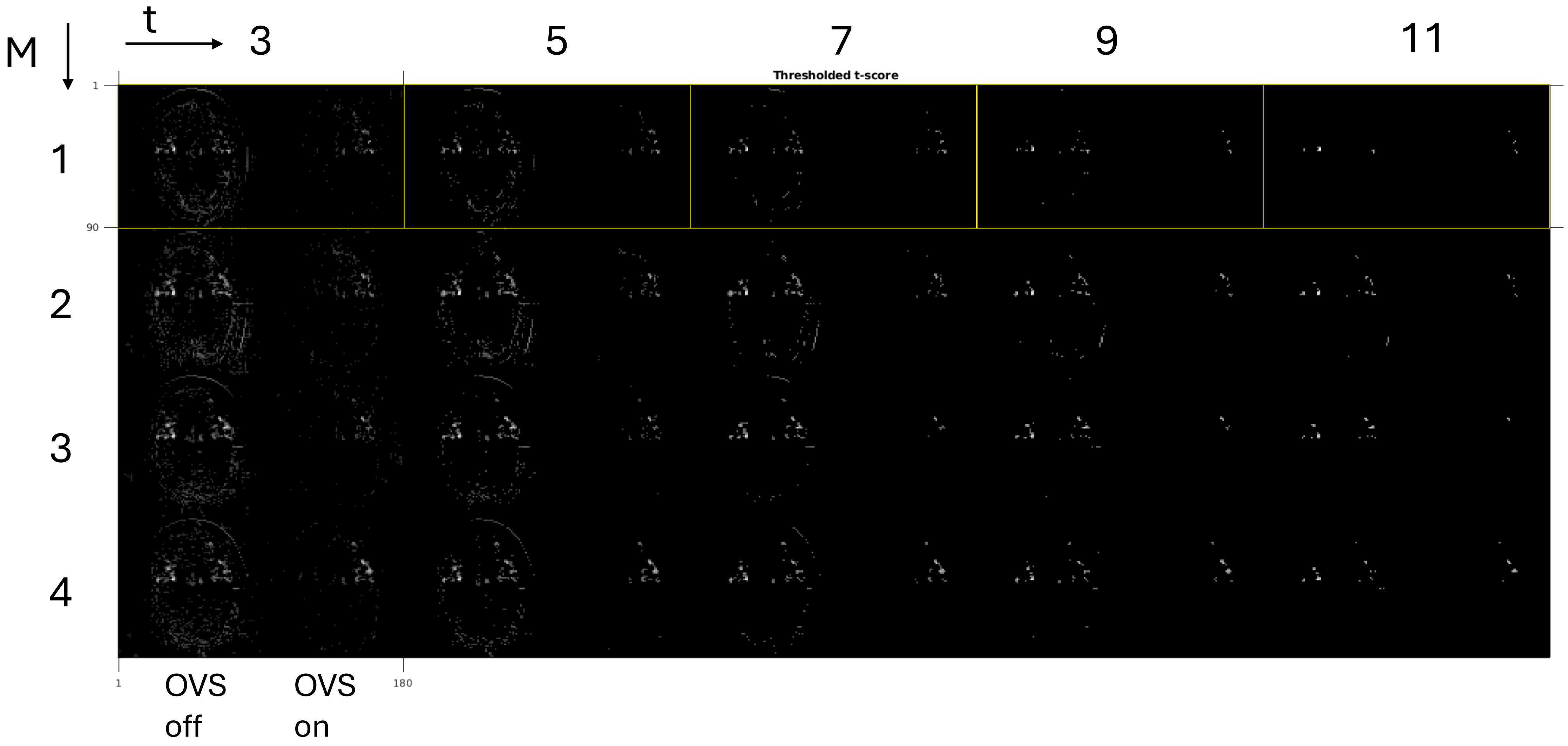
$$l_{dep}(\boldsymbol{p_A}, \boldsymbol{p_I}, \lambda \mid \boldsymbol{n}) = \sum_{\boldsymbol{t}} n_{\boldsymbol{t}} ln[\lambda \prod_{k=0}^{K} p_{Ak}^{t_k} + (1 - \lambda) \prod_{k=0}^{K} p_{Ik}^{t_k}]$$

The parameters of interest: $p_A^{(k)} = \sum_{j=k}^{K} p_{Aj}$, $p_I^{(k)} = \sum_{j=k}^{K} p_{Ij}$

Raw t-score maps

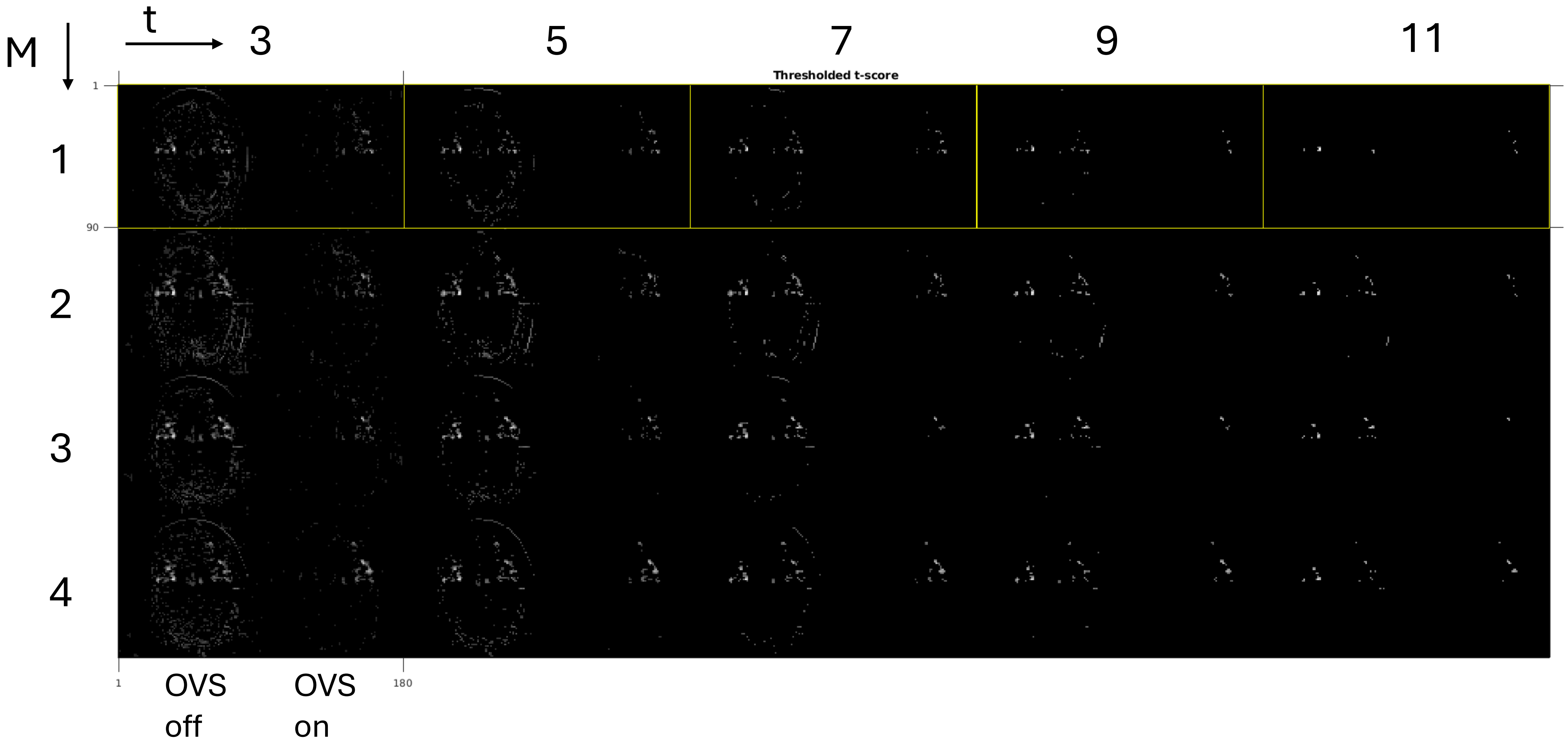


Thresholded t-score maps

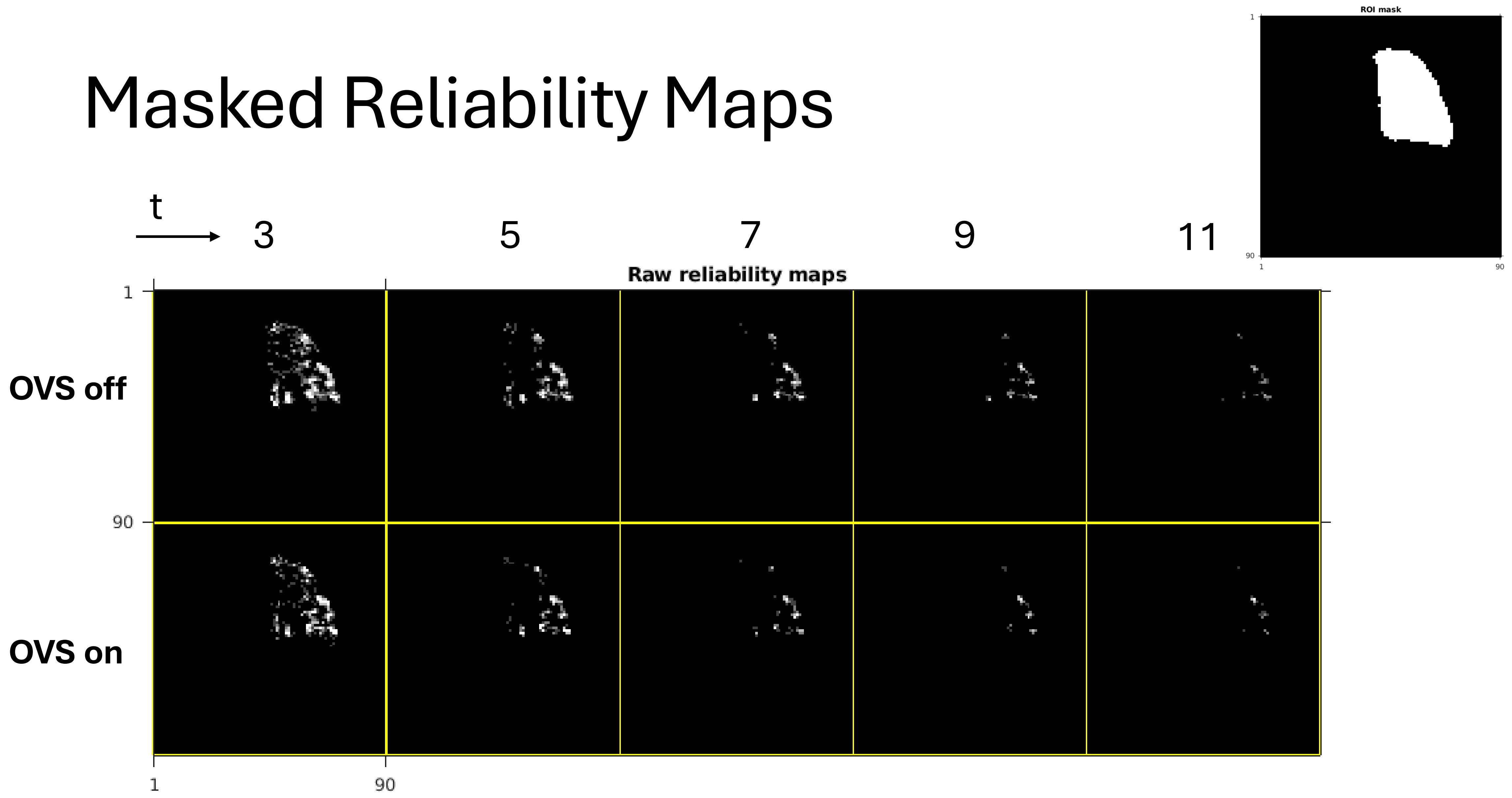


Thresholded t-score maps

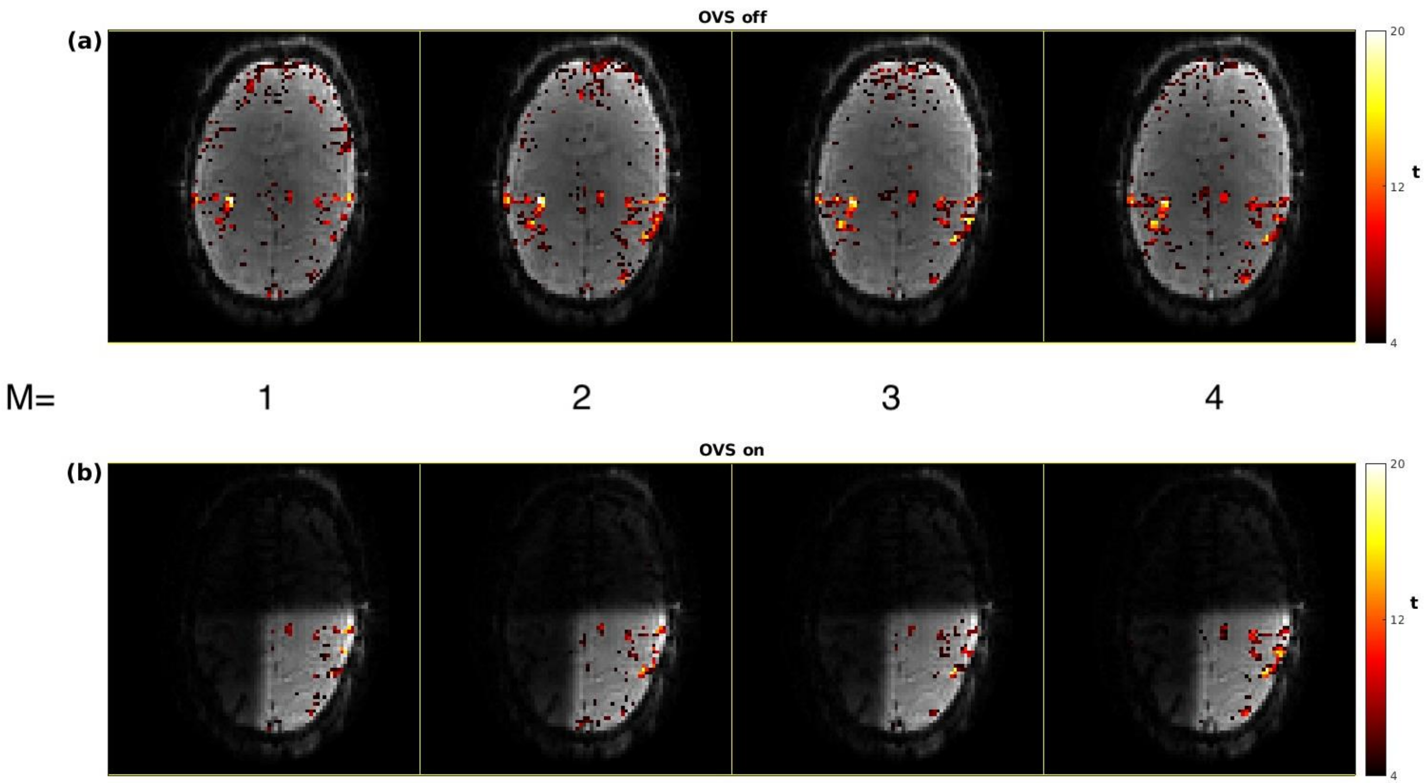
Q: Suppose a voxel is classified active at k=3 of the thresholds, which three would it be?



Masked Reliability Maps



Activation Maps

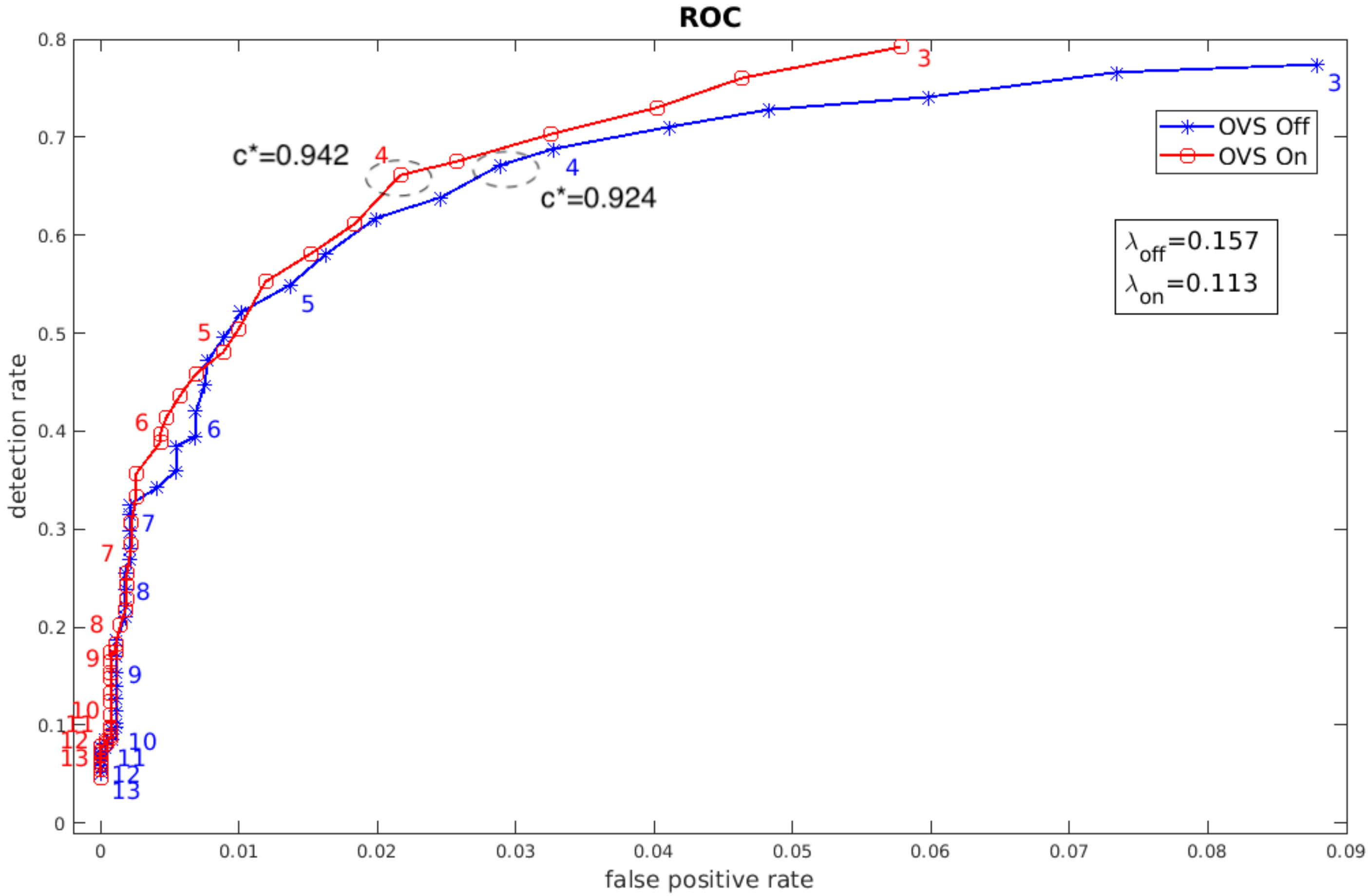


Receiver operating characteristic (ROC) curve

Optimal threshold:
$\tau^* = \arg\max c(\tau) = \lambda p_A + (1-\lambda)(1-p_I)$

Equivalently, at optimal threshold, the local slope of the curve is $(1-\lambda)/\lambda$.

At this point on the curve, the cost of removing one false positive voxel is the loss of one truly activating voxel.



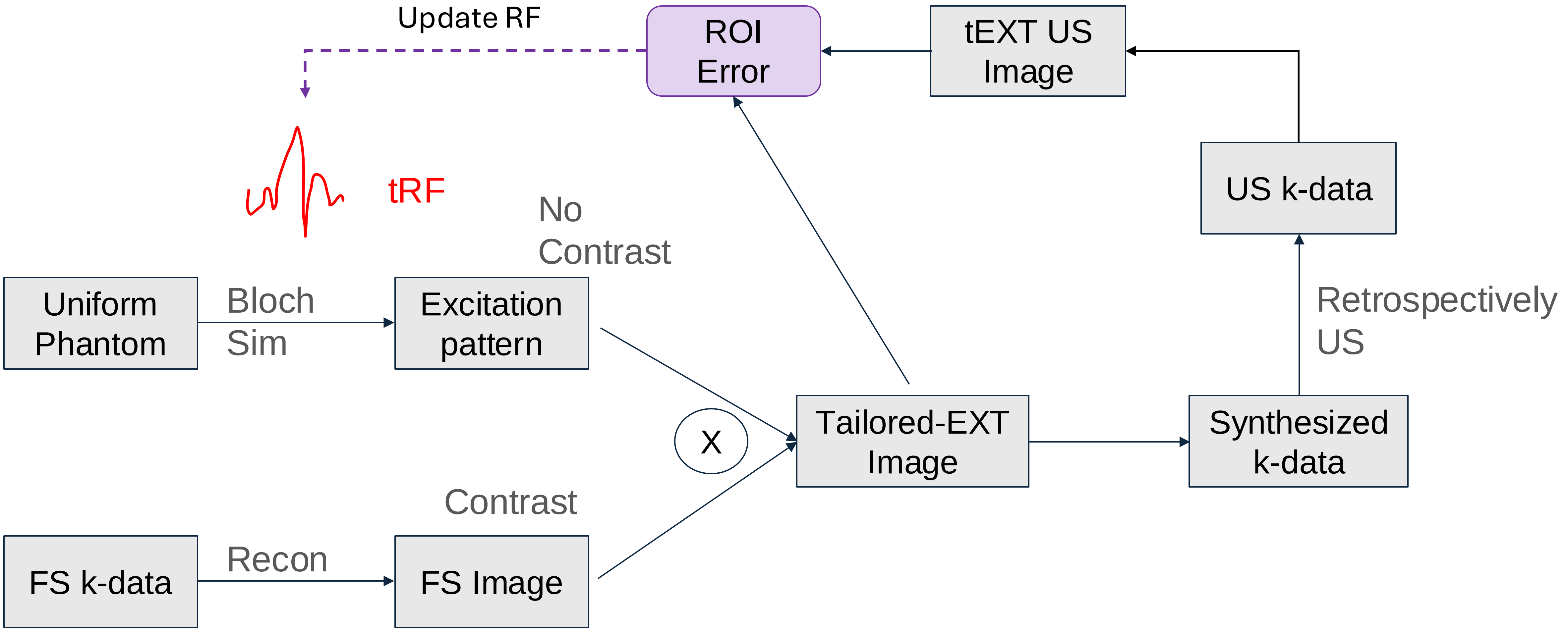
Conclusion

- We demonstrated in a motor task that our OVS pulse preserves sensitivity to BOLD fMRI activation.
- We also show that OVS pulse has somewhat improved test-retest reliability, though further investigation is needed for generalizability.
- We speculate the slight t-score decrease in OVS-on might be caused by the suppression of some in-flow spins from OV which may reduce the BOLD signal.

ROI-Image-Quality Driven RF Pulse Design

Framework

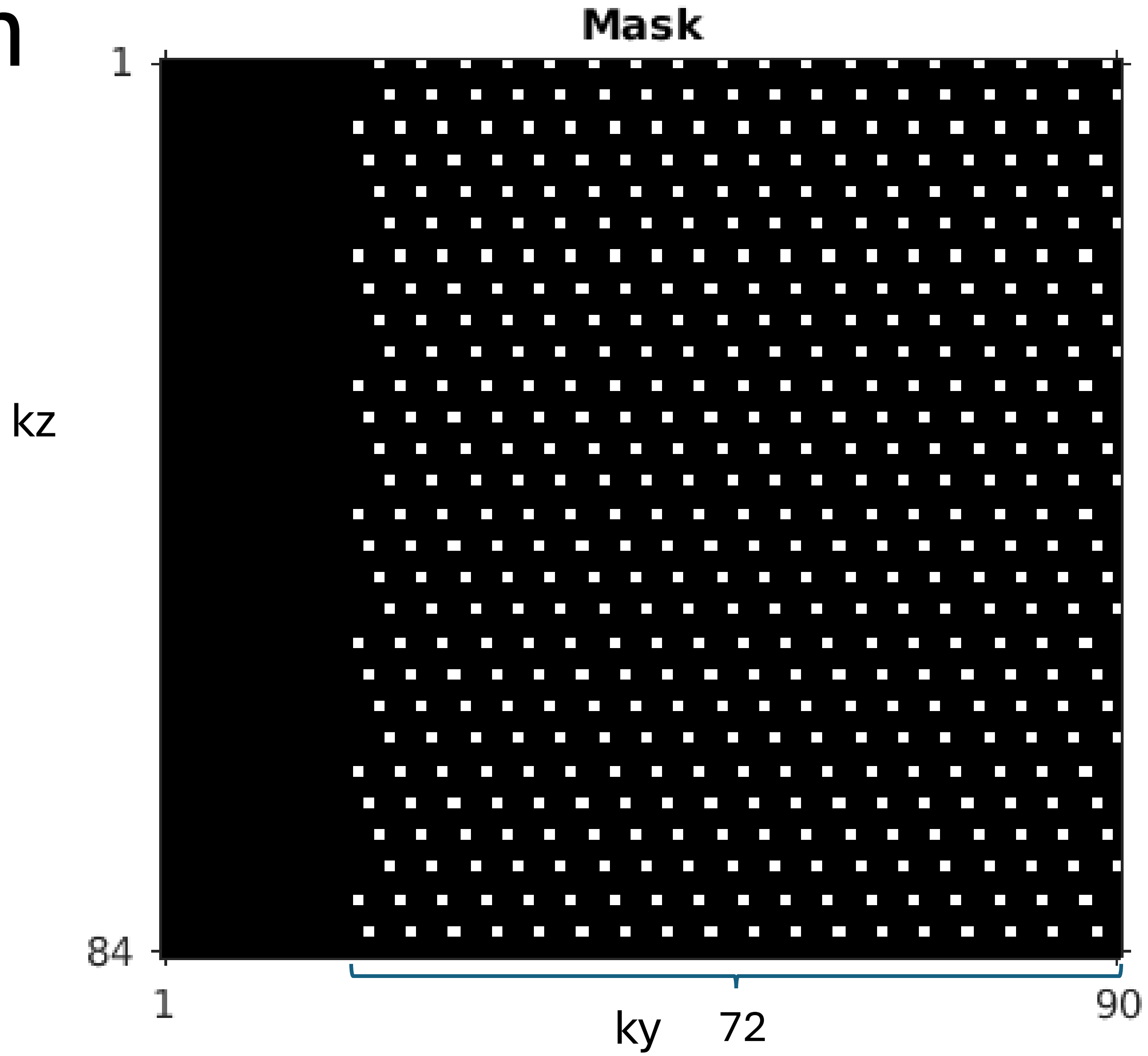
FS: Fully-sampled
US: Under-sampled
tRF: Tailored RF
tEXT: Tailored Excitation



CAIPI Sampling Pattern

Ry= 4; Rz=3
Partial ky = 72/90

Matrix Size:
90x90x84

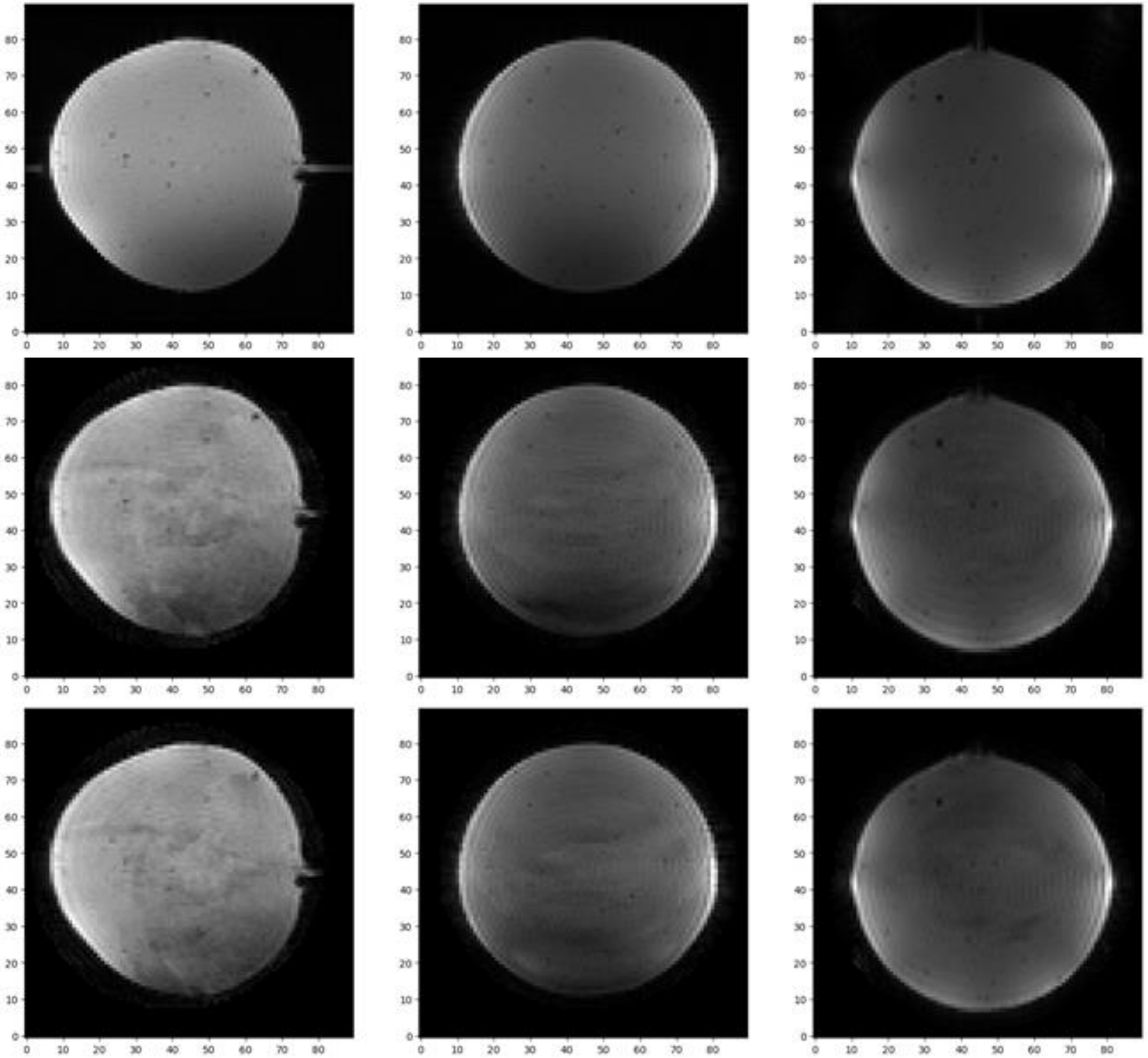


Sanity Check

Fully-sample

Retrospective

Prospective



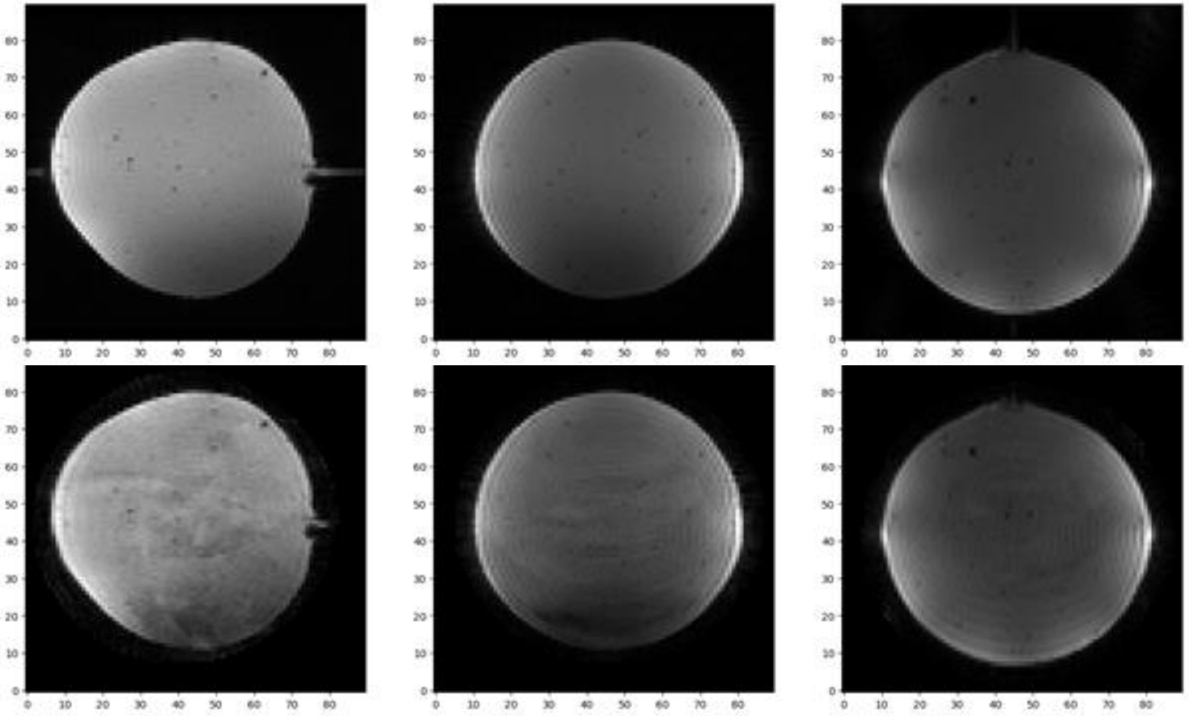
R=1

R=12; (pky=72/90)

R=12; (pky=72/90)

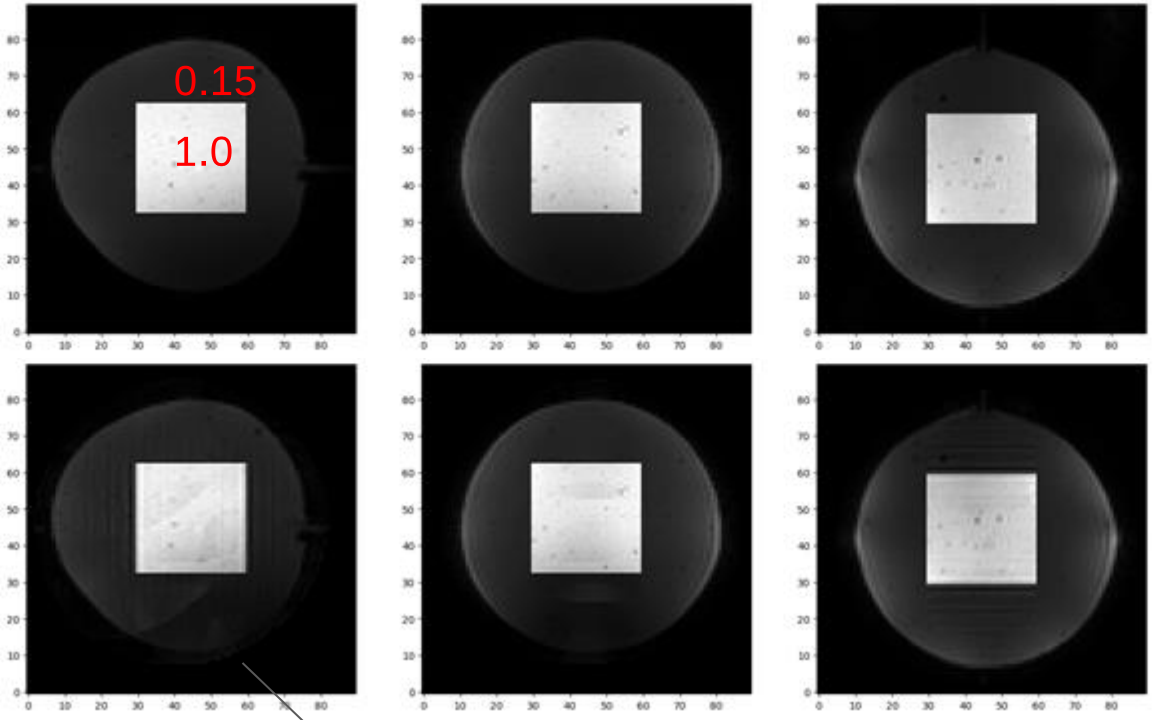
Artificial Weighting to Emulate tailored EXT

Fully-sampled



Retrospective
under-sampled
R=12

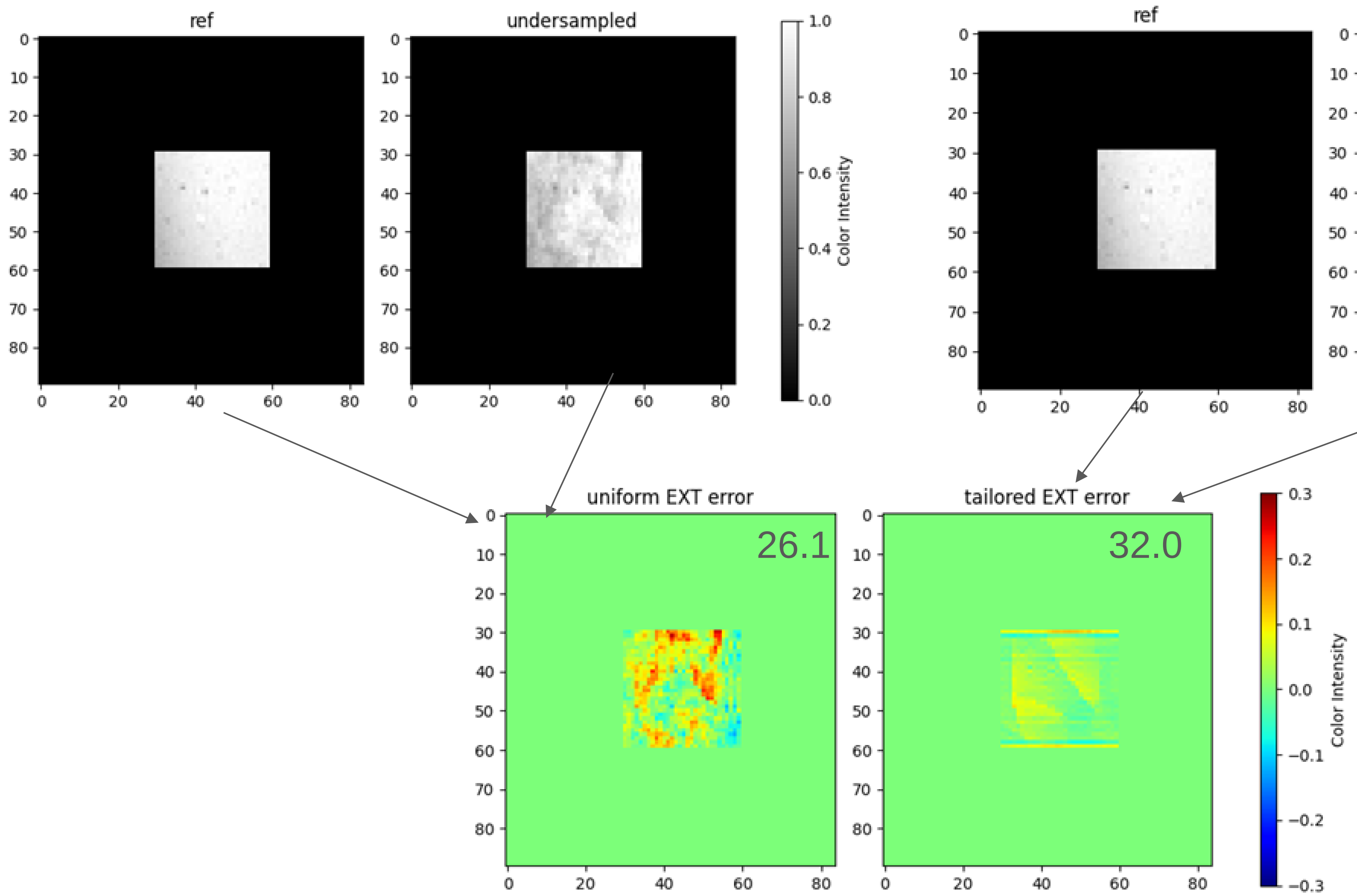
Fully-sampled w/ weighting



Retrospective
under-sampled
R=12

Masked → Abs → Normalize

Sagittal View

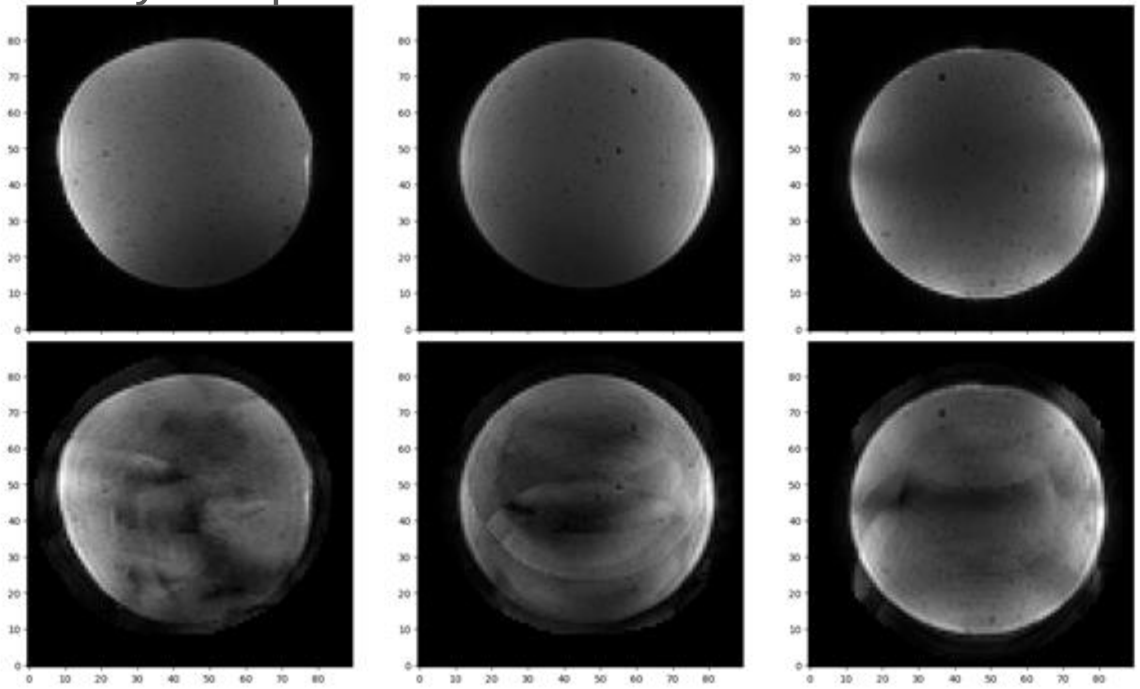


$$\lambda^* = \arg\min || \lambda \boldsymbol{v_1} - \boldsymbol{v_0} ||$$
$$= \frac{\boldsymbol{v_1^T v_0}}{||\boldsymbol{v_0}||_2^2}$$

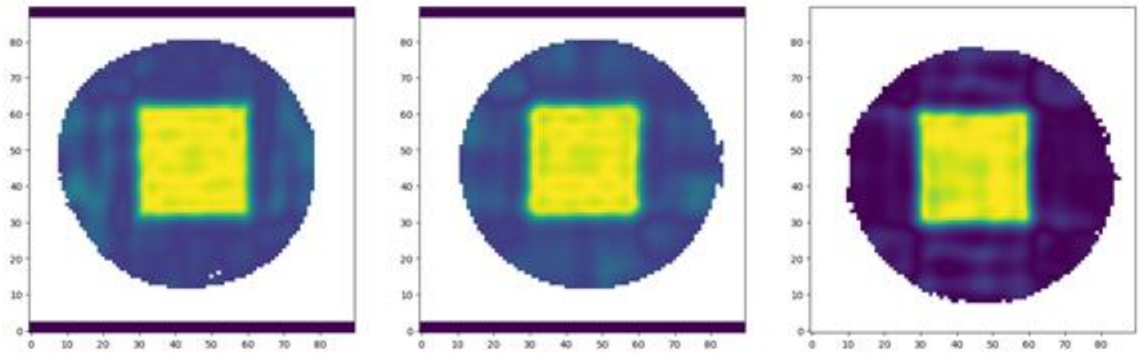
$$\boldsymbol{\hat{v}_1} = \boldsymbol{v_1} \cdot \lambda^*$$

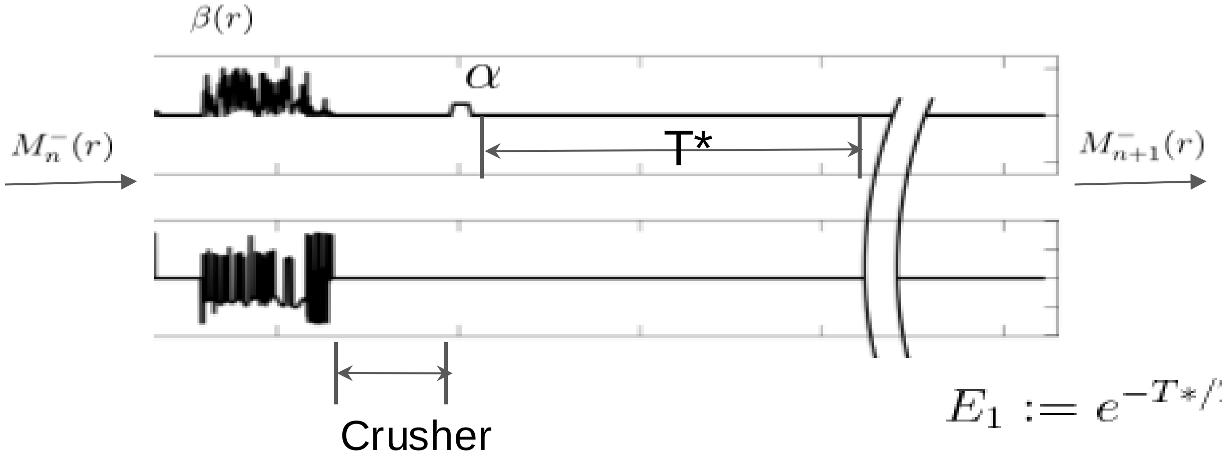
Data from another Scan

Fully-sampled



Prospective under-sampled R=12





$$E_1 := e^{-T*/T_1}$$

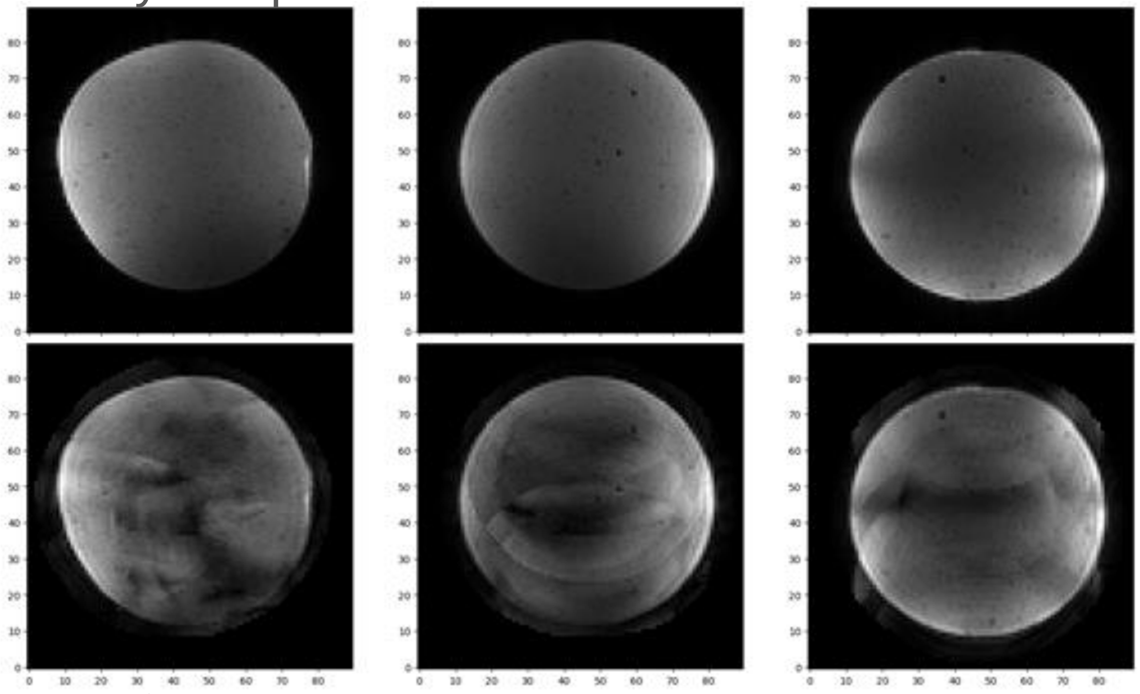
$$M_{SS} = \frac{M_0(1-E_1)}{1 - cos\beta(r) cos\alpha E_1} \cdot cos\beta(r)$$

$$M_{SS}^0 = \frac{M_0(1-E_1)}{1 - cos\alpha E_1}$$

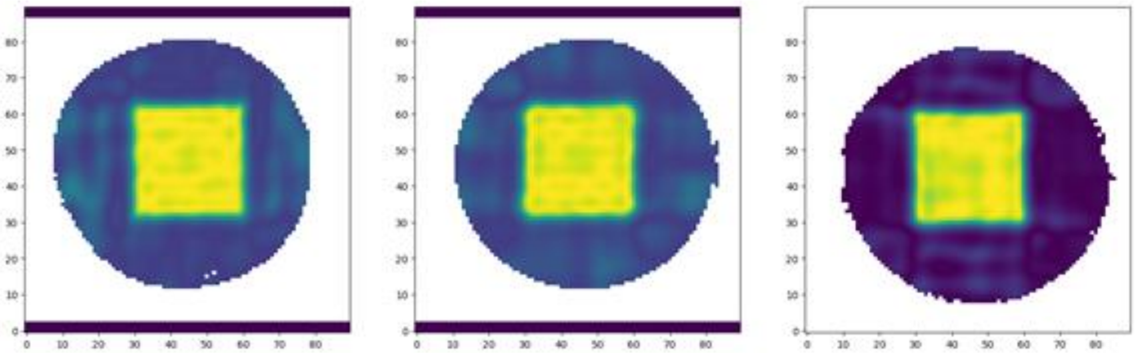
$$w := M_{SS}(r)/M_{SS}^0$$

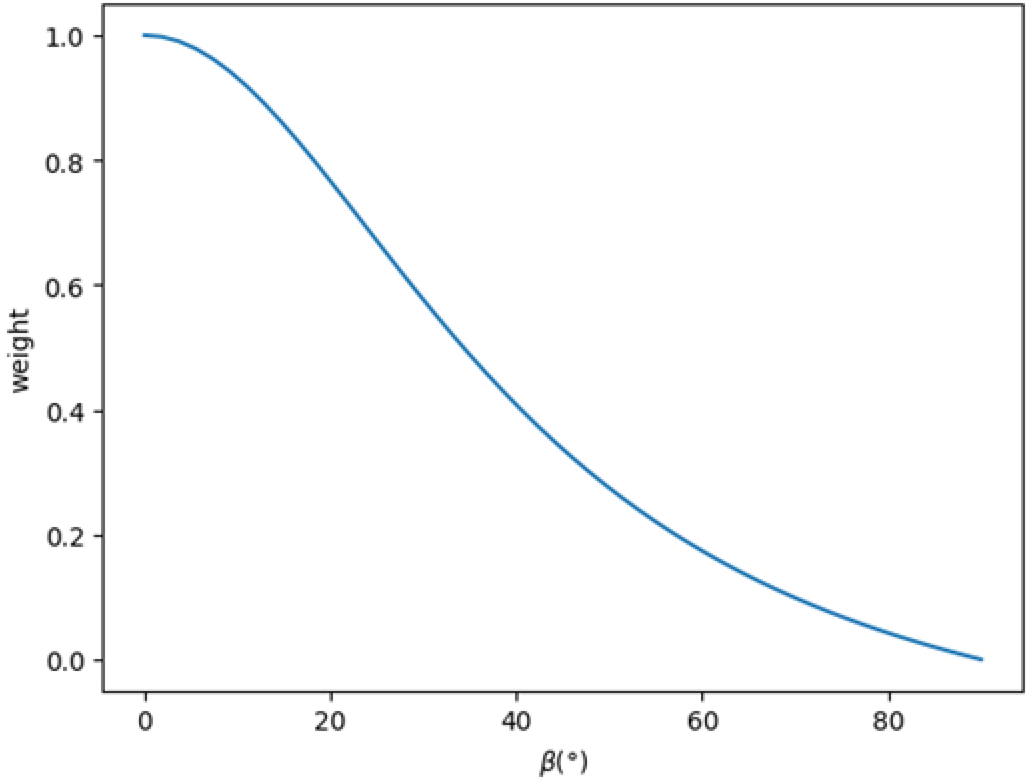
Simulated tailored EXT

Fully-sampled



Prospective under-sampled R=12





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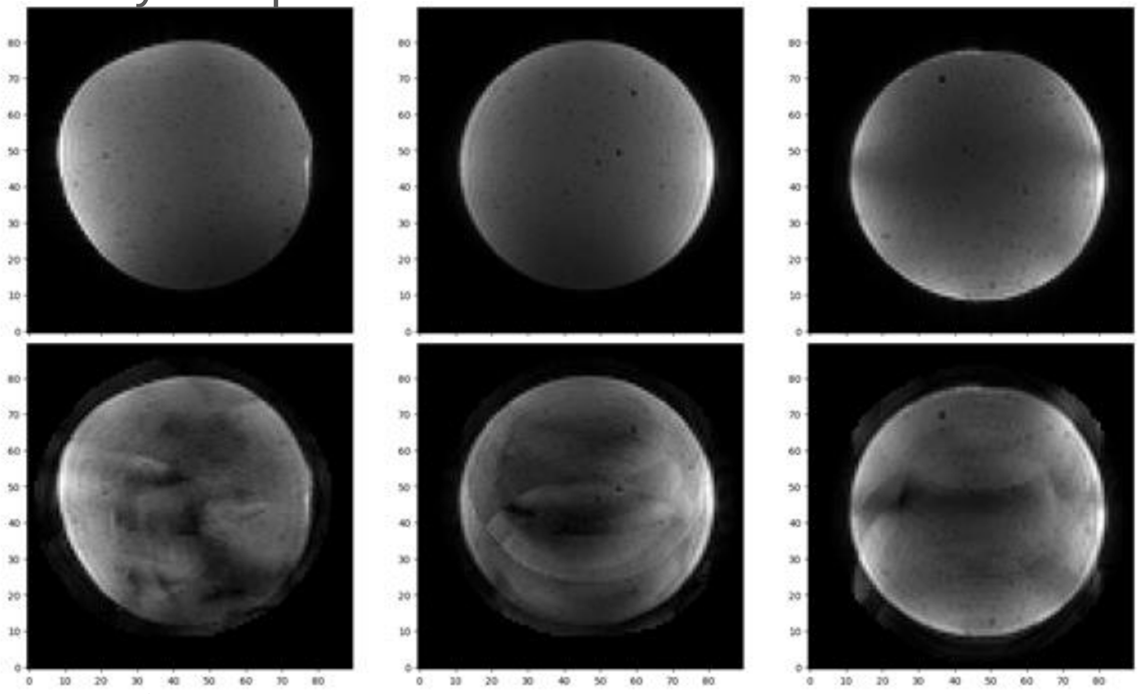
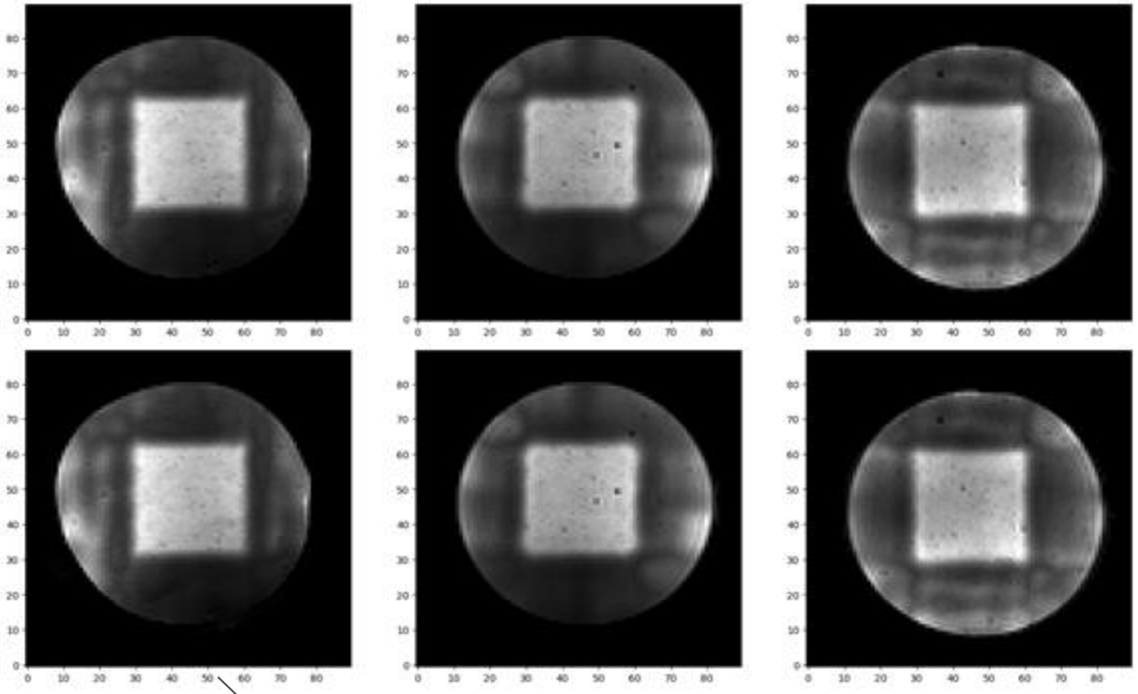
Fully-sampled



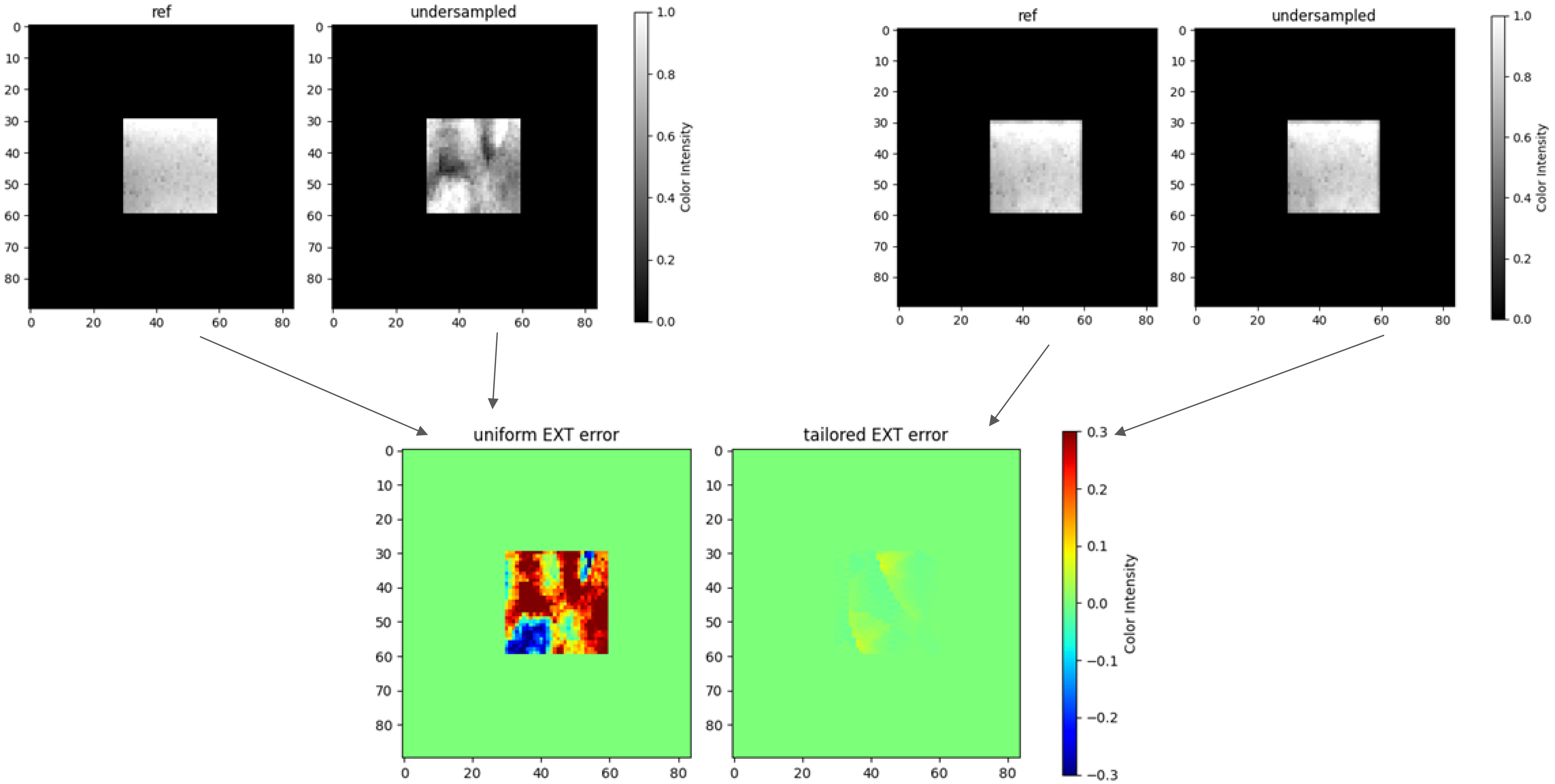
Prospective under-sampled R=12

Fully-sampled w/ simulated tEXT



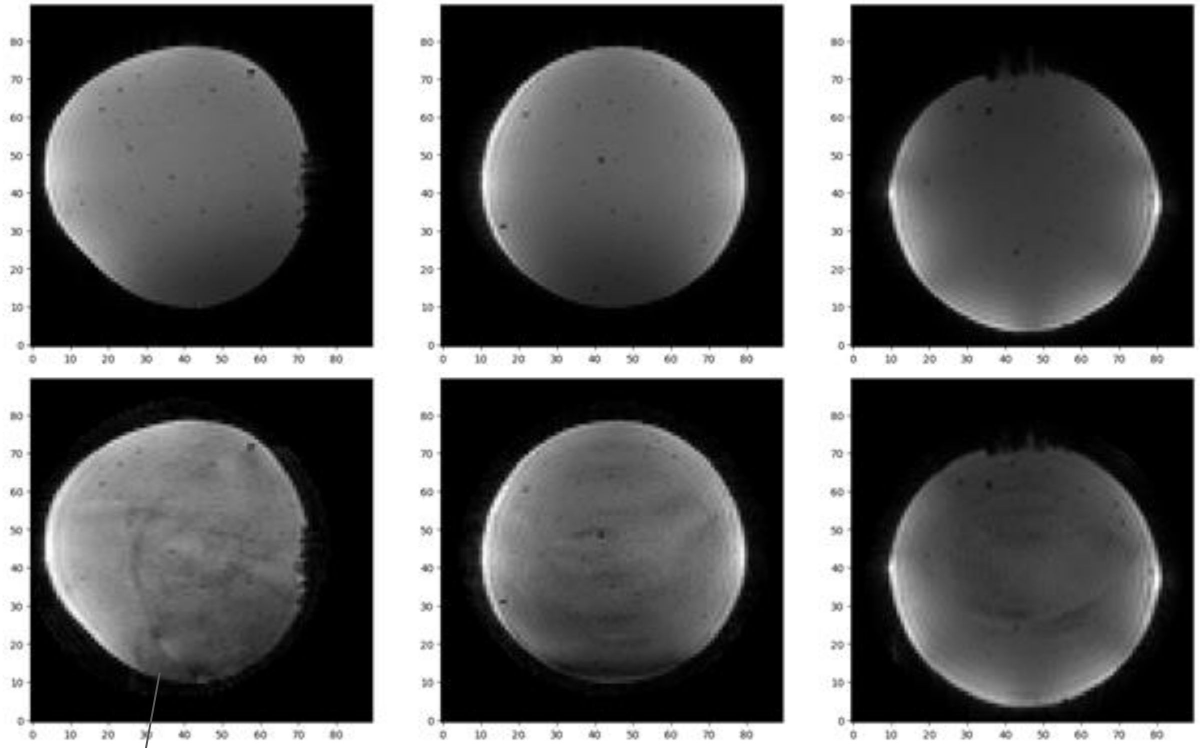
Retrospective under-sampled R=12

Simulated tailored excitation (tEXT)



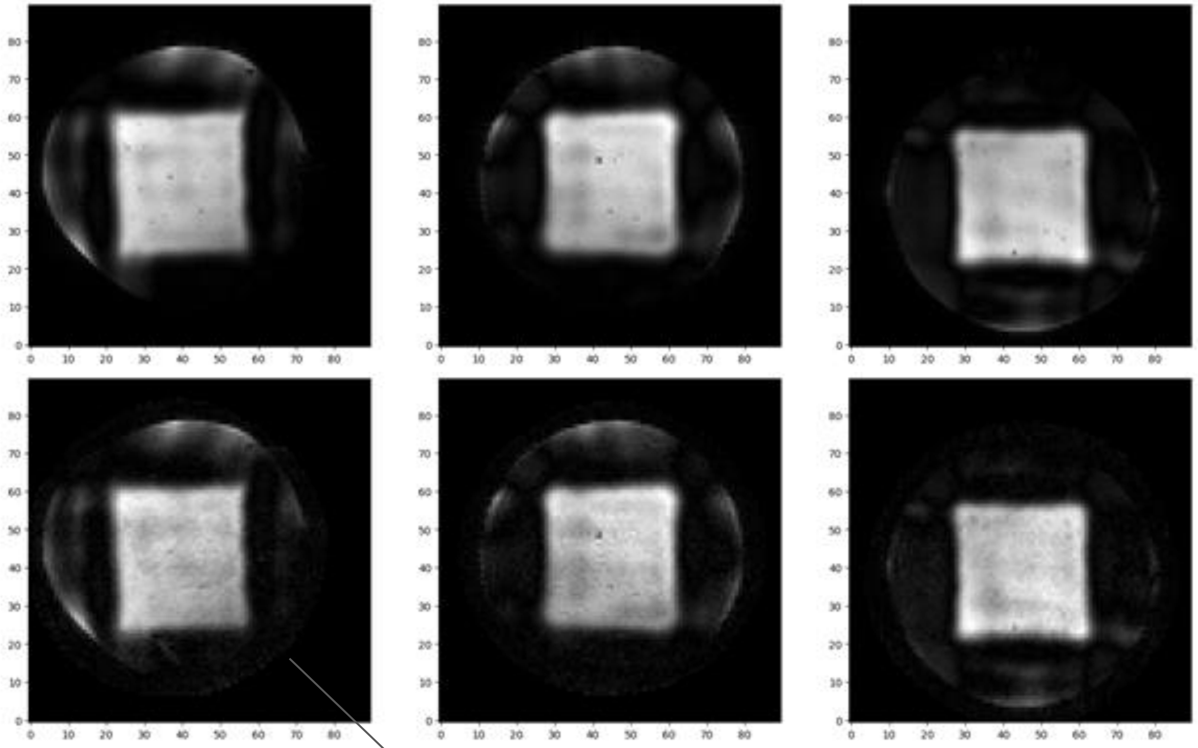
Real tailored excitation (tEXT)

Fully-sampled



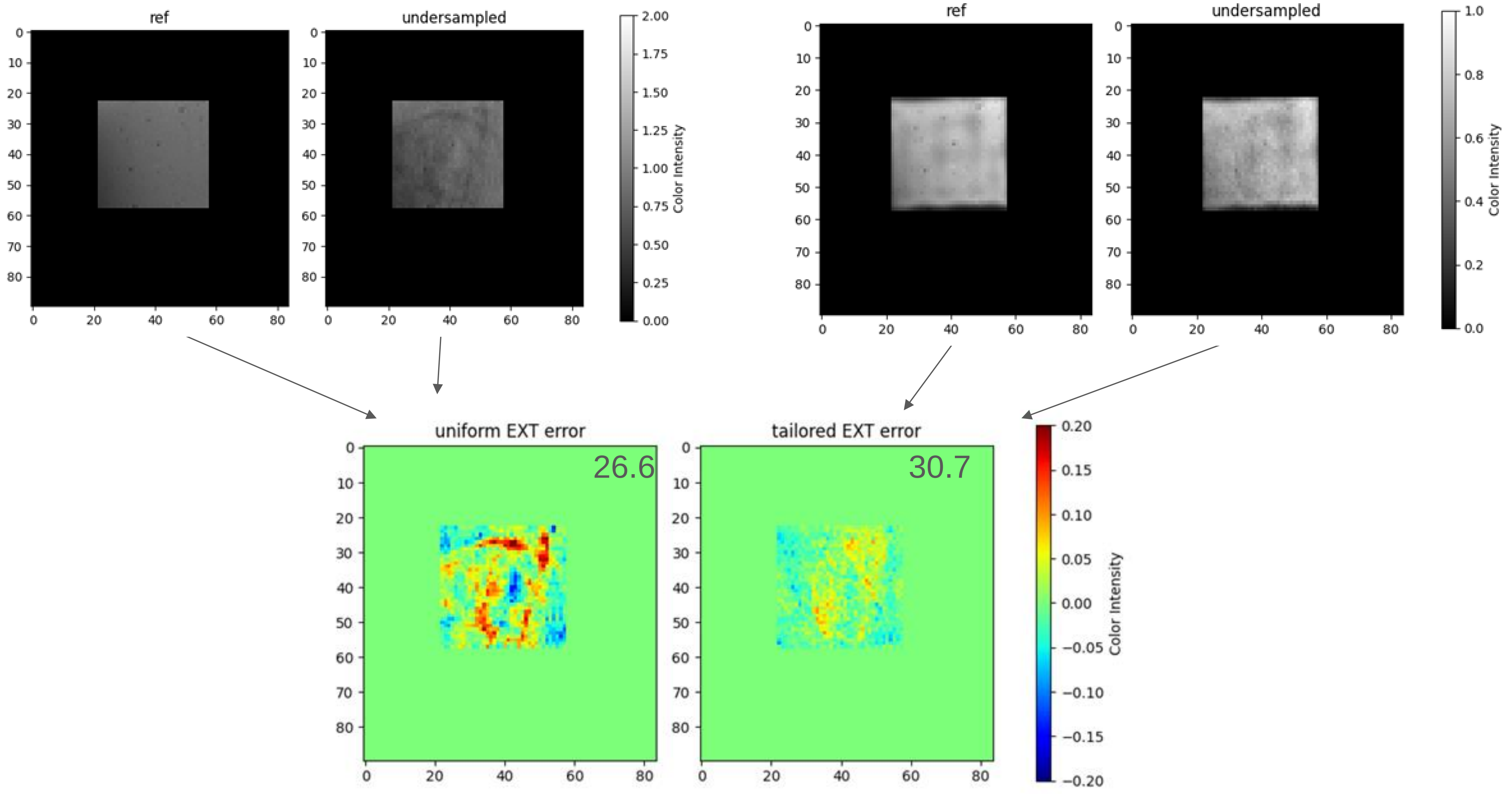
Prospective under-sampled R=12

Fully-sampled w/ (real) tEXT



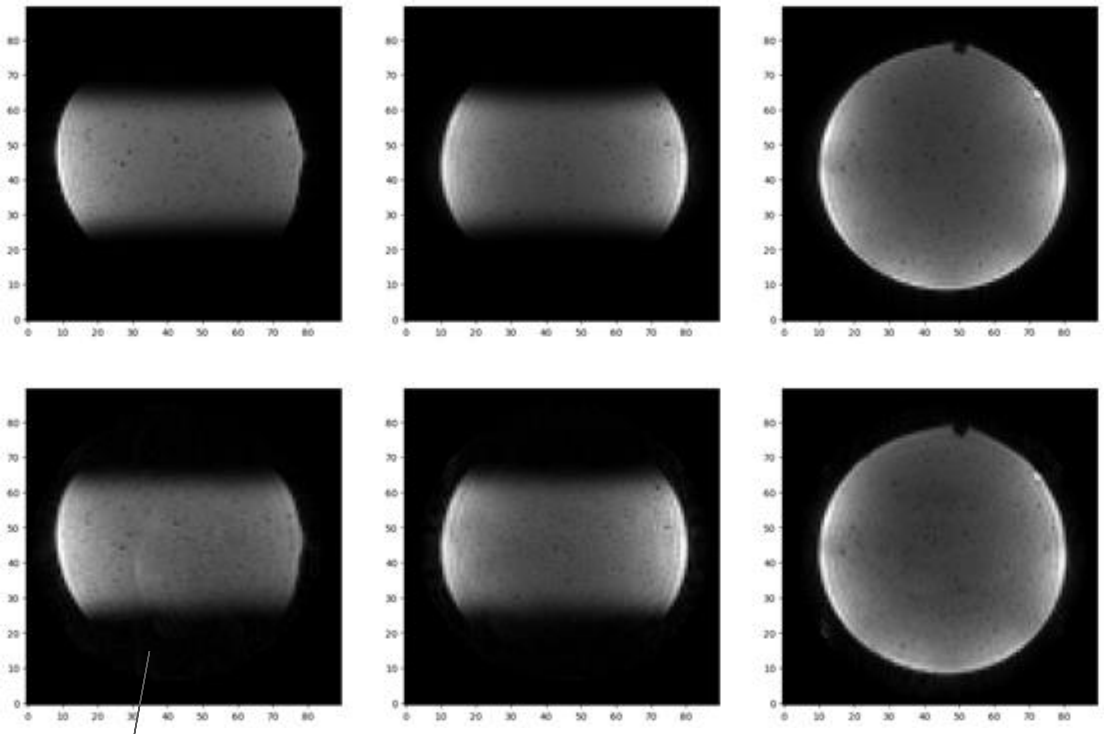
Prospective under-sampled R=12

Real tailored EXT



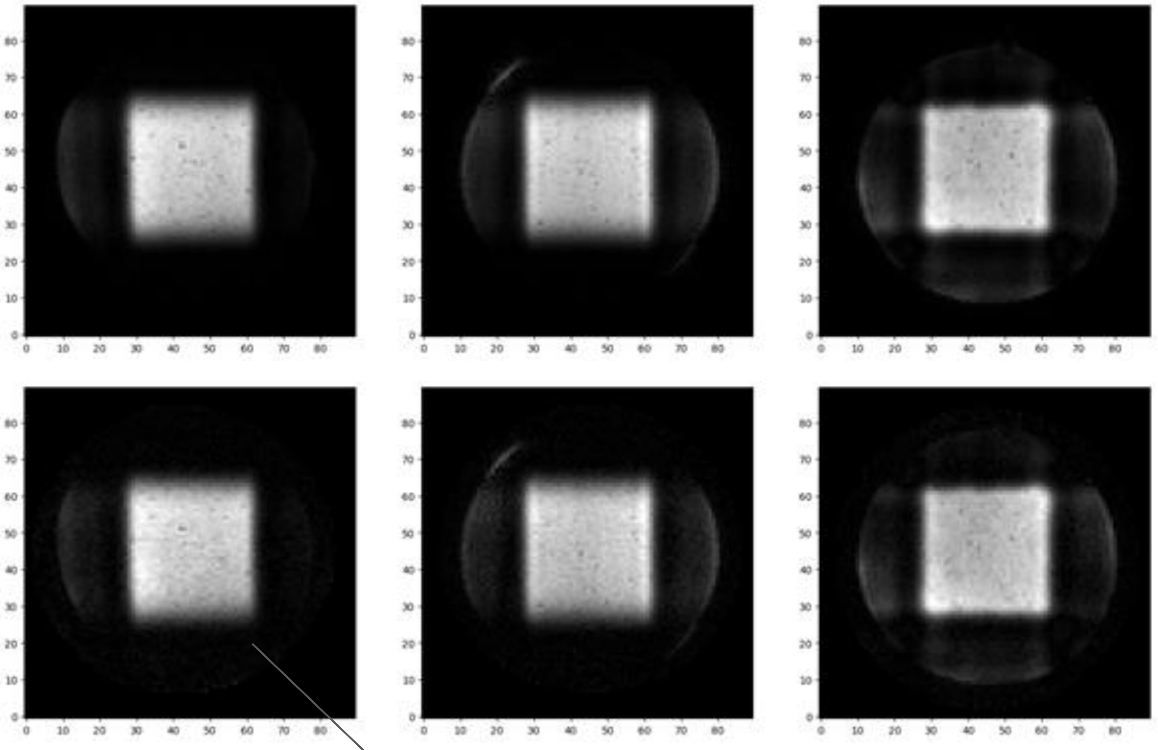
2D OVS + 1D EXT (20241122)

Fully-sampled



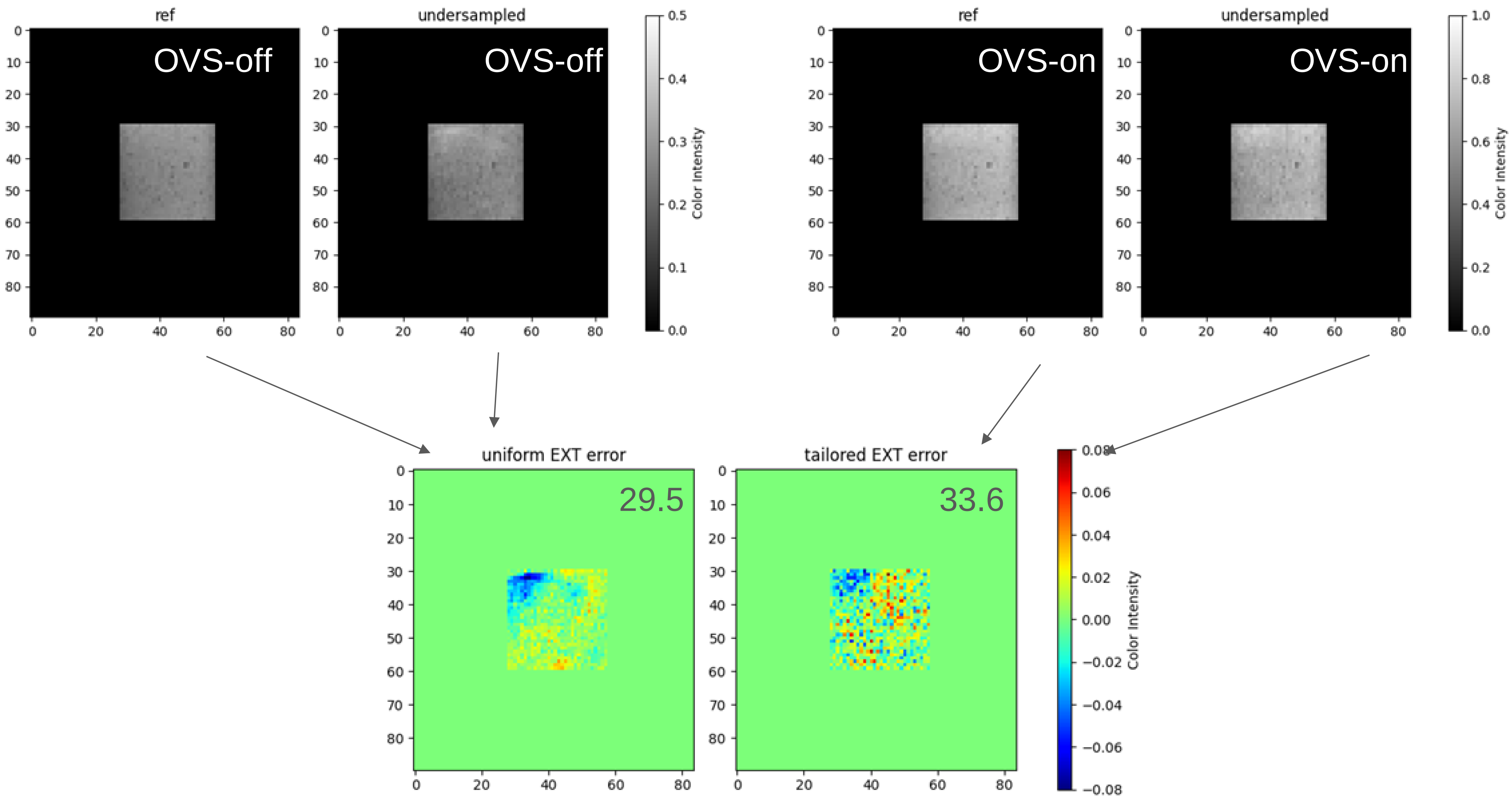
Prospective under-sampled R=12

Fully-sampled w/ (real) tEXT

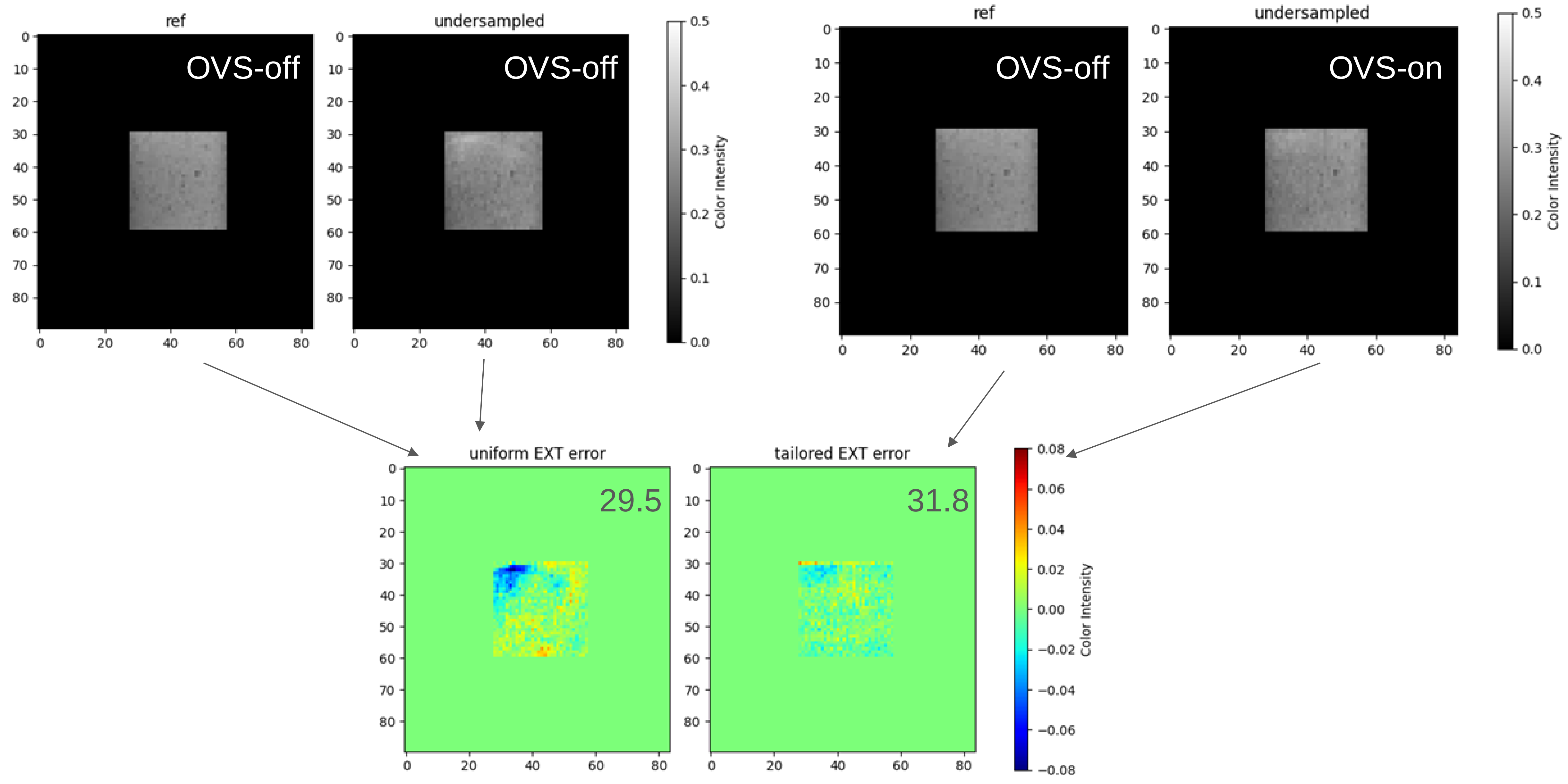


Prospective under-sampled R=12

2D OVS + 1D EXT (20241122)

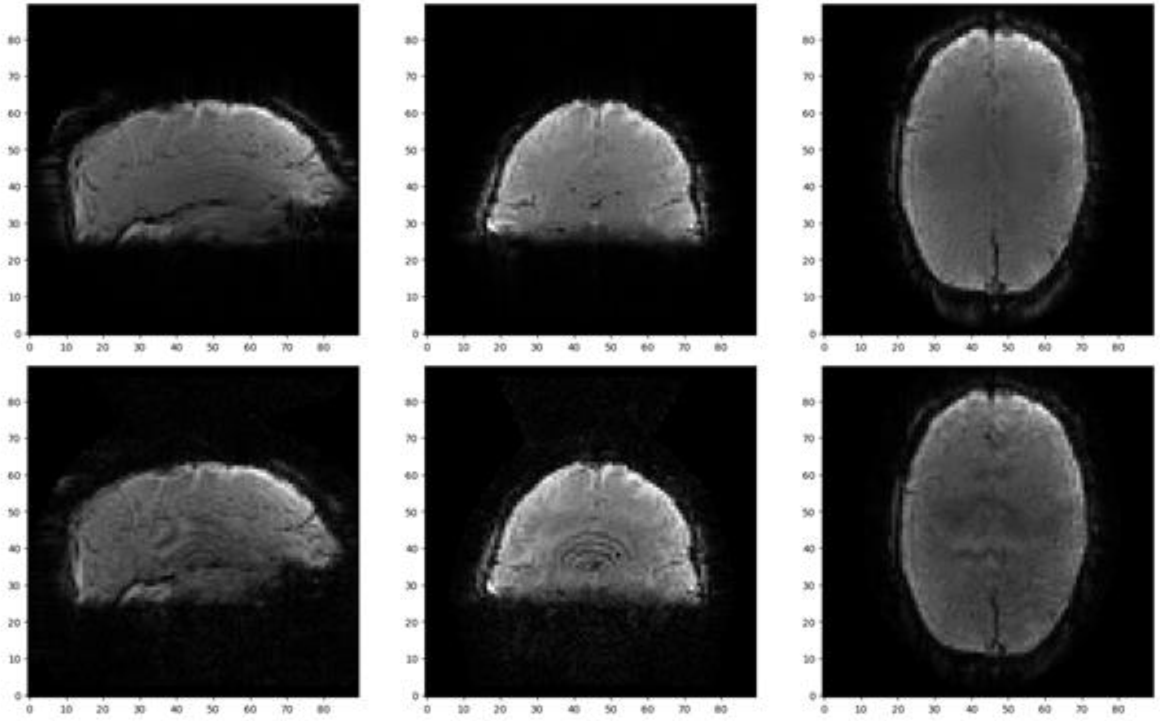


2D OVS + 1D EXT (20241122)



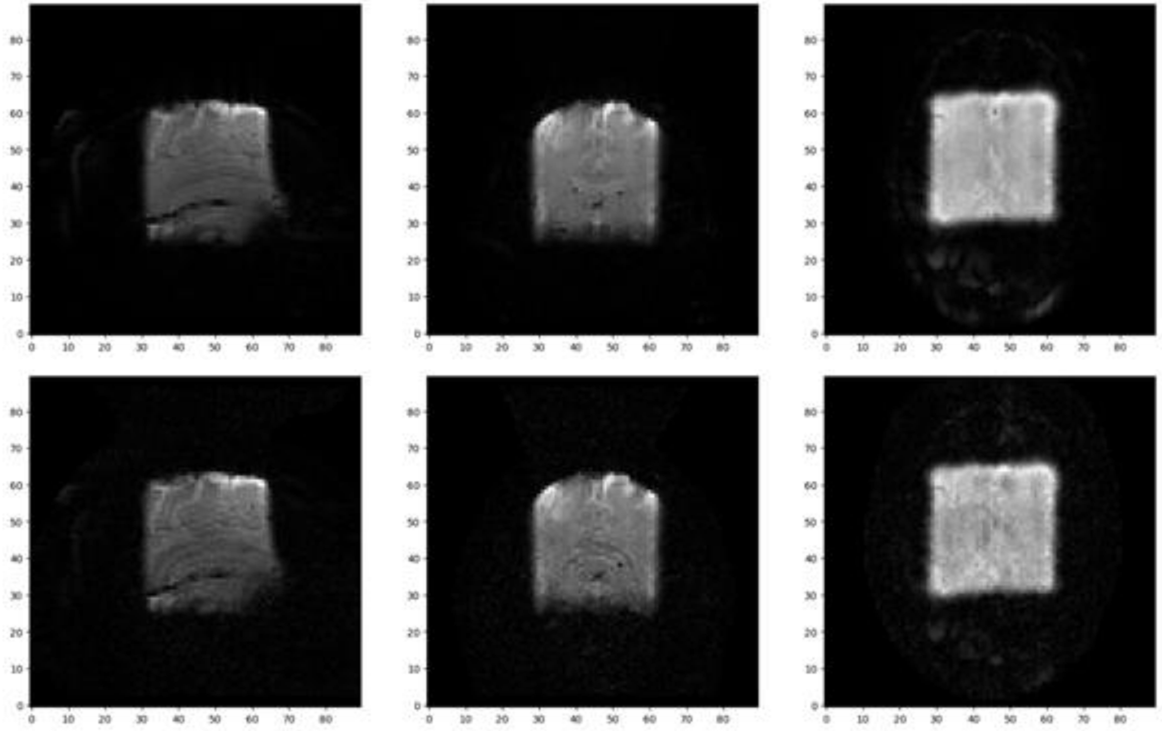
In Vivo (20241124)

Fully-sampled



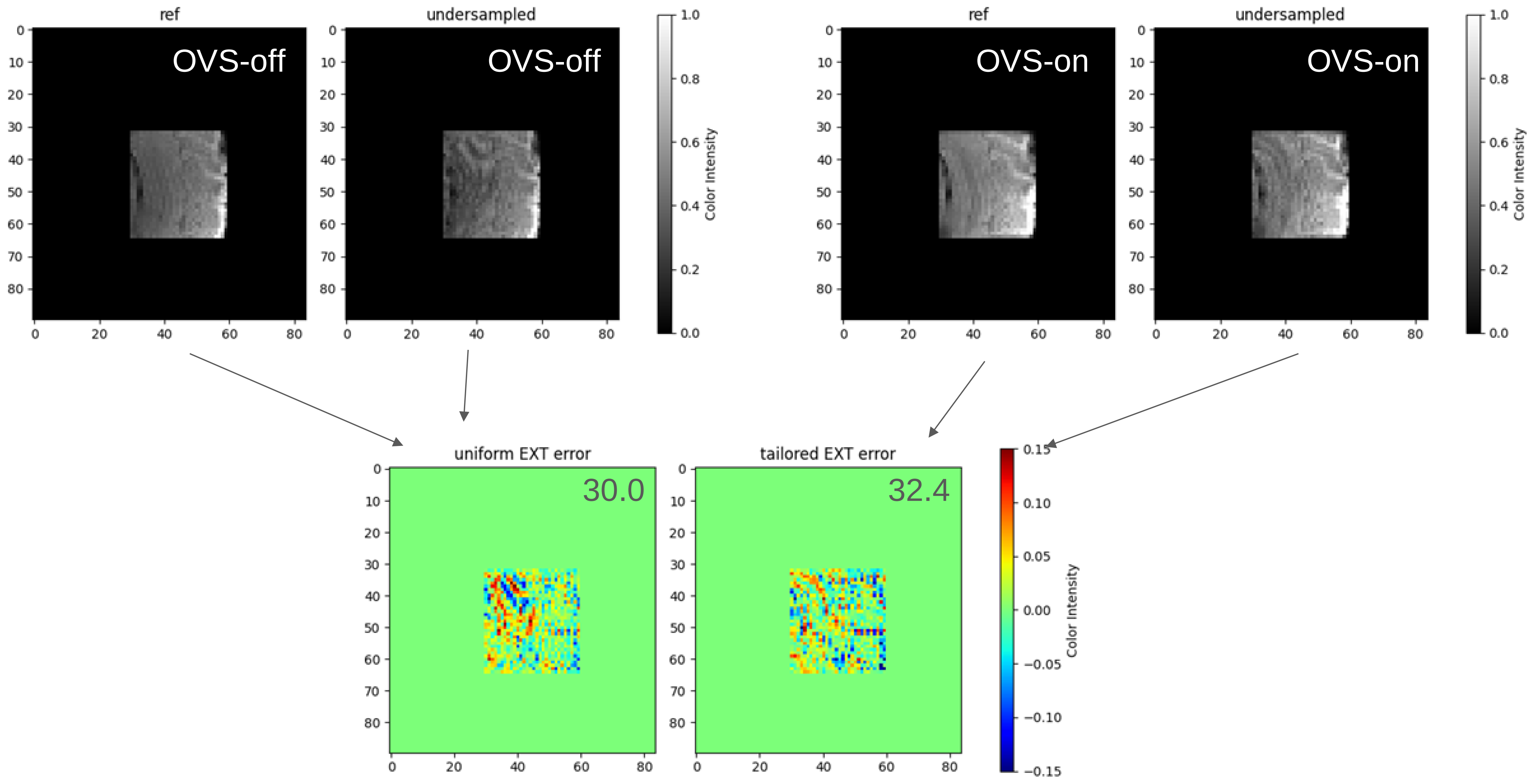
Prospective under-sampled R=12

Fully-sampled w/ (real) tEXT

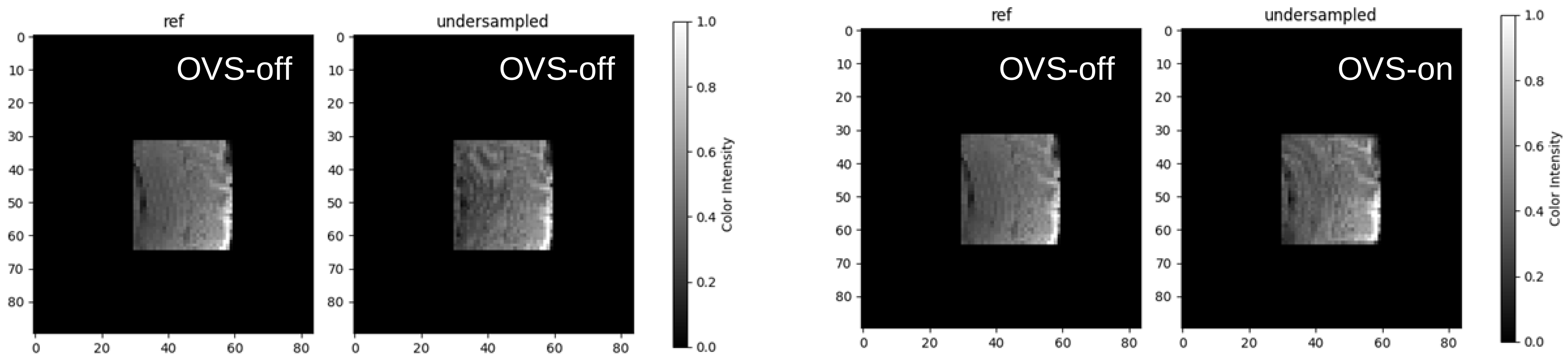


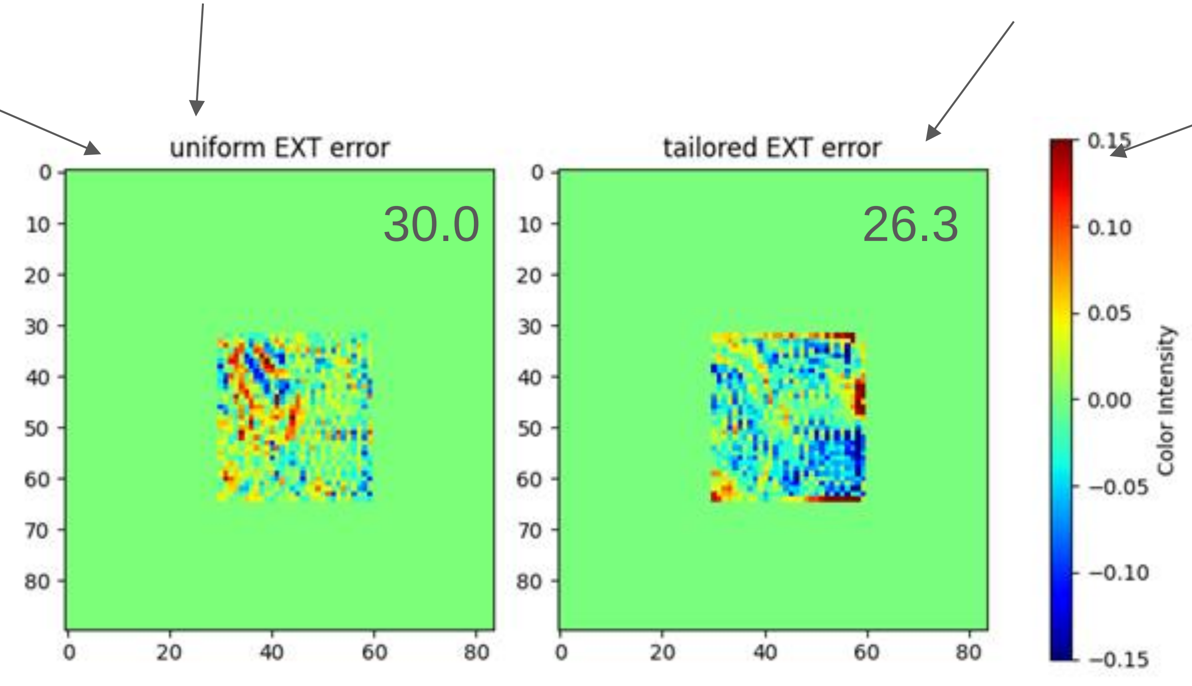
Prospective under-sampled R=12

In Vivo (20241124)



In Vivo (20241124)





IV excitation is not uniform for OVS-on

Next Step

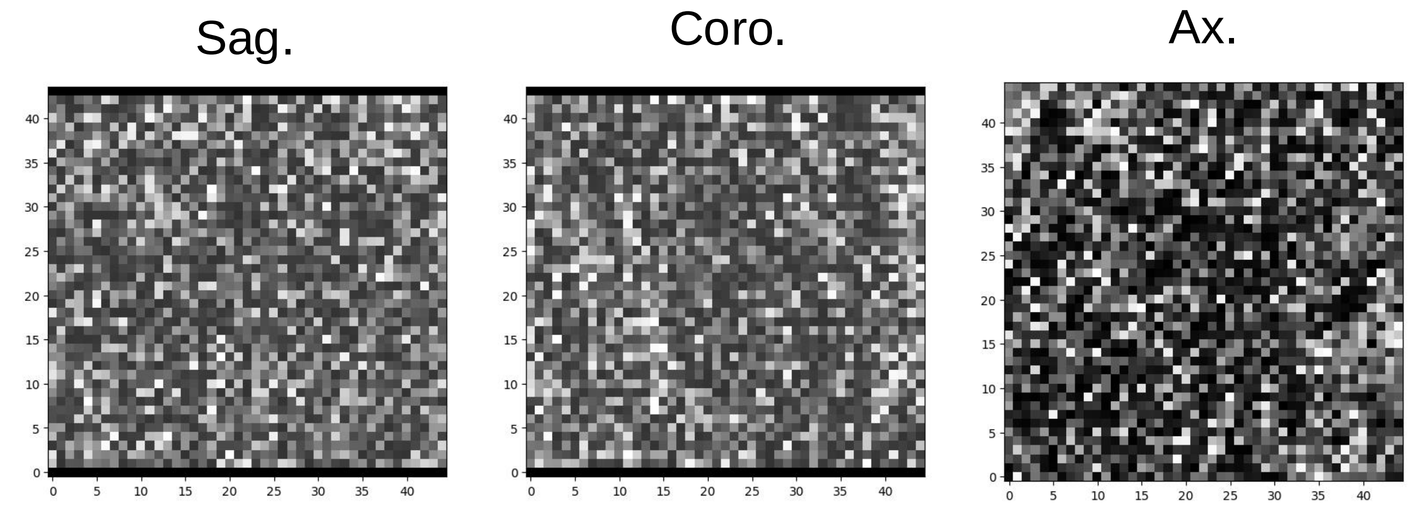
$$\mathcal{L} = \left|\left|I_{\mathrm{F}S}(\mathrm{OVSon}) - I_{\mathrm{US}}(\mathrm{OVSon})\right|\right|_2$$

- Design tRF based on ROI image quality (reduce aliasing as goal)

Next Step

$$\mathcal{L} = \left|\left|I_{\mathrm{F}S}(\mathrm{OVSon}) - I_{\mathrm{US}}(\mathrm{OVSon})\right|\right|_2$$

- Design tRF based on ROI image quality (reduce aliasing as goal)
- One Caveat: If only use ROI error between fully-sampled and under-sampled OVS-on images as loss, the optimized excitation pattern might be totally random!



Next Step

$$\mathcal{L} = \left|\left|I_{FS}(\text{OVSon}) - I_{\text{US}}(\text{OVSon})\right|\right|_2 + \lambda \cdot \mathcal{P}\left(\left|M_z^{tgt} - M_z^{tEXT}\right|_{\text{ROI}}\right)$$

- Design tRF based on ROI image quality (reduce aliasing as goal)
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- Enforce IV excitation uniformity as well, via, e.g., penalization

Next Step

$$\mathcal{L} = \left|\left|I_{\mathrm{F}S}(\mathrm{OVSon}) - I_{\mathrm{US}}(\mathrm{OVSon})\right|\right|_2 + \lambda \cdot \mathcal{P}\left(\left|M_z^{tgt} - M_z^{tEXT}\right|_{\mathrm{ROI}}\right)$$

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- One Caveat: If only use ROI error between fully-sampled and under-sampled OVS-on images as loss, the optimized excitation pattern might be totally random!
- Enforce IV excitation uniformity as well, via, e.g., penalization
- Optimize sampling scheme in synergy with the tRF