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# Improving Deconvolution of fMRI Signal with Sparse Paradigm Free Mapping Using Stability Selection

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## Motivation

- Estimate neuronal-related activity with no prior information on the timings of the blood oxygenation level-dependent (BOLD) events.
- Deconvolution algorithms estimate the neuronal-related activity via regularized least-squares estimators with L1 and L2-norms.
- Dilemma: how to select the regularization parameters that yield accurate results.
- Introduce two improvements over the previous Sparse Paradigm Free Mapping (SPFM) algorithm [1]:
  - Stability selection to avoid the selection of the regularization parameter [3].
  - Extension to estimate innovation signals in addition to activity-inducing signals [2].

## Data acquisition

- Finger tapping with the right index and thumb fingers every 45 seconds:
  - Trials of single tap during the first 6 minutes.
  - Trials of 10 taps quickly in the last 4 minutes.
- Two fMRI datasets in a 7T Siemens MR scanner:
  - High SNR: TR = 500 ms, voxel size = 3 x 3 x 3 mm<sup>3</sup>
  - Low SNR: TR = 2800 ms, voxel size = 1.2 x 1.2 x 1.2 mm<sup>3</sup>

## Equations

- In fMRI data analysis, the signal of a voxel is commonly modelled as the convolution of an underlying neuronal-related signal with the hemodynamic response function.
- We adopt this model of the neuronal-related component of the fMRI signal and deconvolve the voxel time series with a L1-norm regularized least-squares estimator (SPFM algorithm [1]).

$$y = H \cdot s + n \rightarrow \hat{s} = \operatorname{argmin}_s \frac{1}{2} \|y - Hs\|_2^2 + \lambda \|s\|_1$$

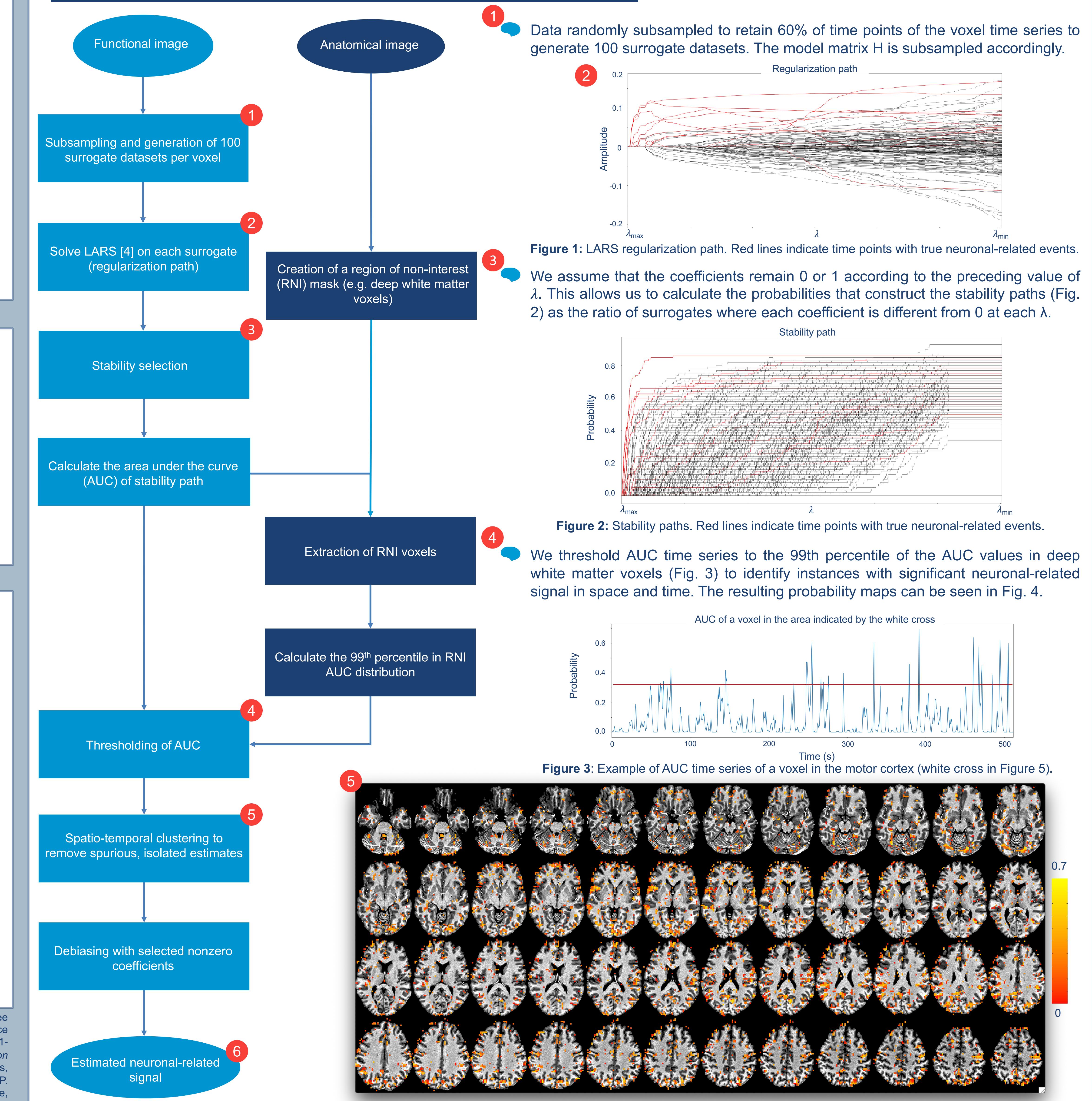
- We also represent the neuronal-related signal as a piecewise constant signal in terms of its innovation signal, which is a sparser representation of changes in amplitude of the neuronal-related signal and is more adequate for L1-norm regularization:

$$y = H \cdot L \cdot u + n; \quad u = D \cdot s$$

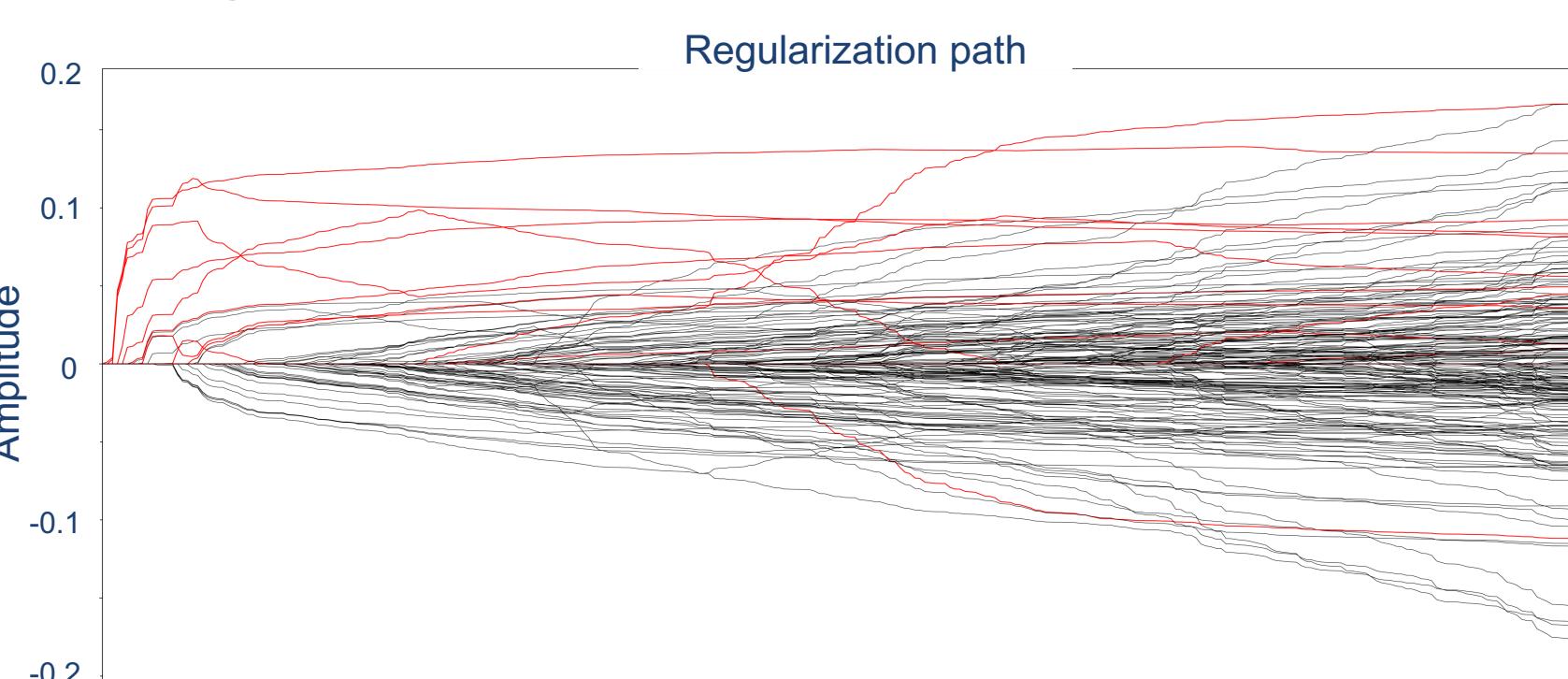
$$\hat{u} = \operatorname{argmin}_u \frac{1}{2} \|y - Hu\|_2^2 + \lambda \|u\|_1$$

- An appropriate choice of the regularization parameter  $\lambda$  is crucial. So far, no algorithm provides a robust, data-driven approach for this selection. We propose stability-based SPFM.

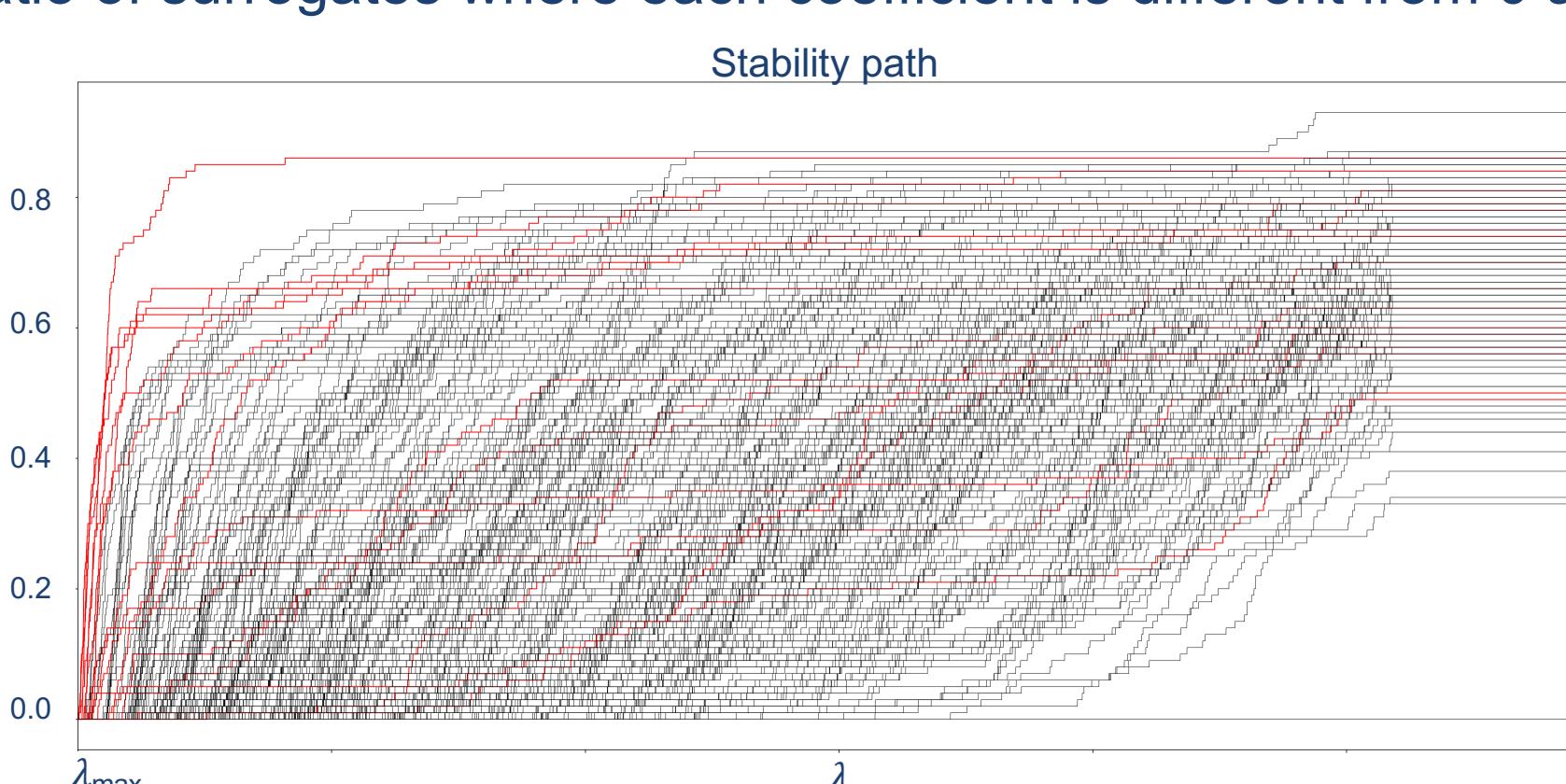
## Stability-based Sparse Paradigm Free Mapping



1 Data randomly subsampled to retain 60% of time points of the voxel time series to generate 100 surrogate datasets. The model matrix  $H$  is subsampled accordingly.



2 Figure 1: LARS regularization path. Red lines indicate time points with true neuronal-related events.  
We assume that the coefficients remain 0 or 1 according to the preceding value of  $\lambda$ . This allows us to calculate the probabilities that construct the stability paths (Fig. 2) as the ratio of surrogates where each coefficient is different from 0 at each  $\lambda$ .



3 Figure 2: Stability paths. Red lines indicate time points with true neuronal-related events.  
We threshold AUC time series to the 99th percentile of the AUC values in deep white matter voxels (Fig. 3) to identify instances with significant neuronal-related signal in space and time. The resulting probability maps can be seen in Fig. 4.

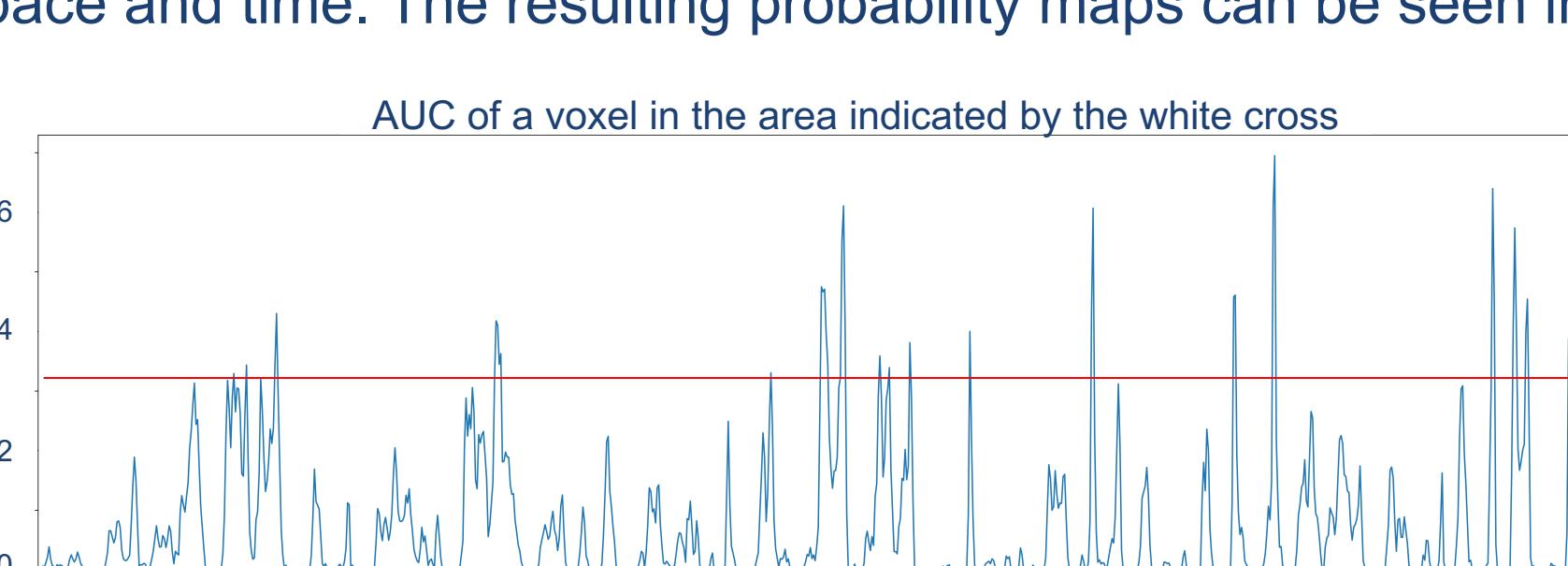


Figure 3: Example of AUC time series of a voxel in the motor cortex (white cross in Figure 5).

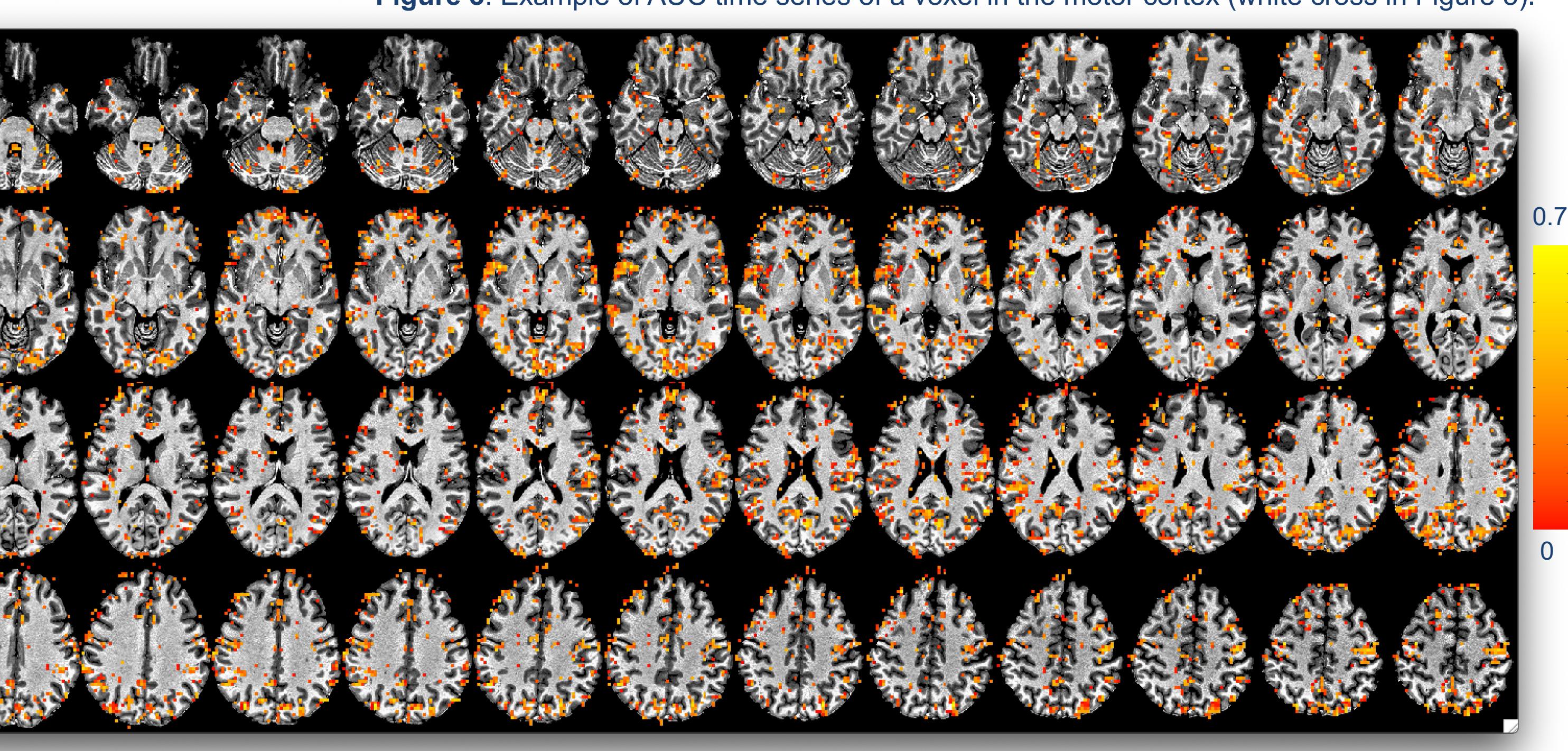
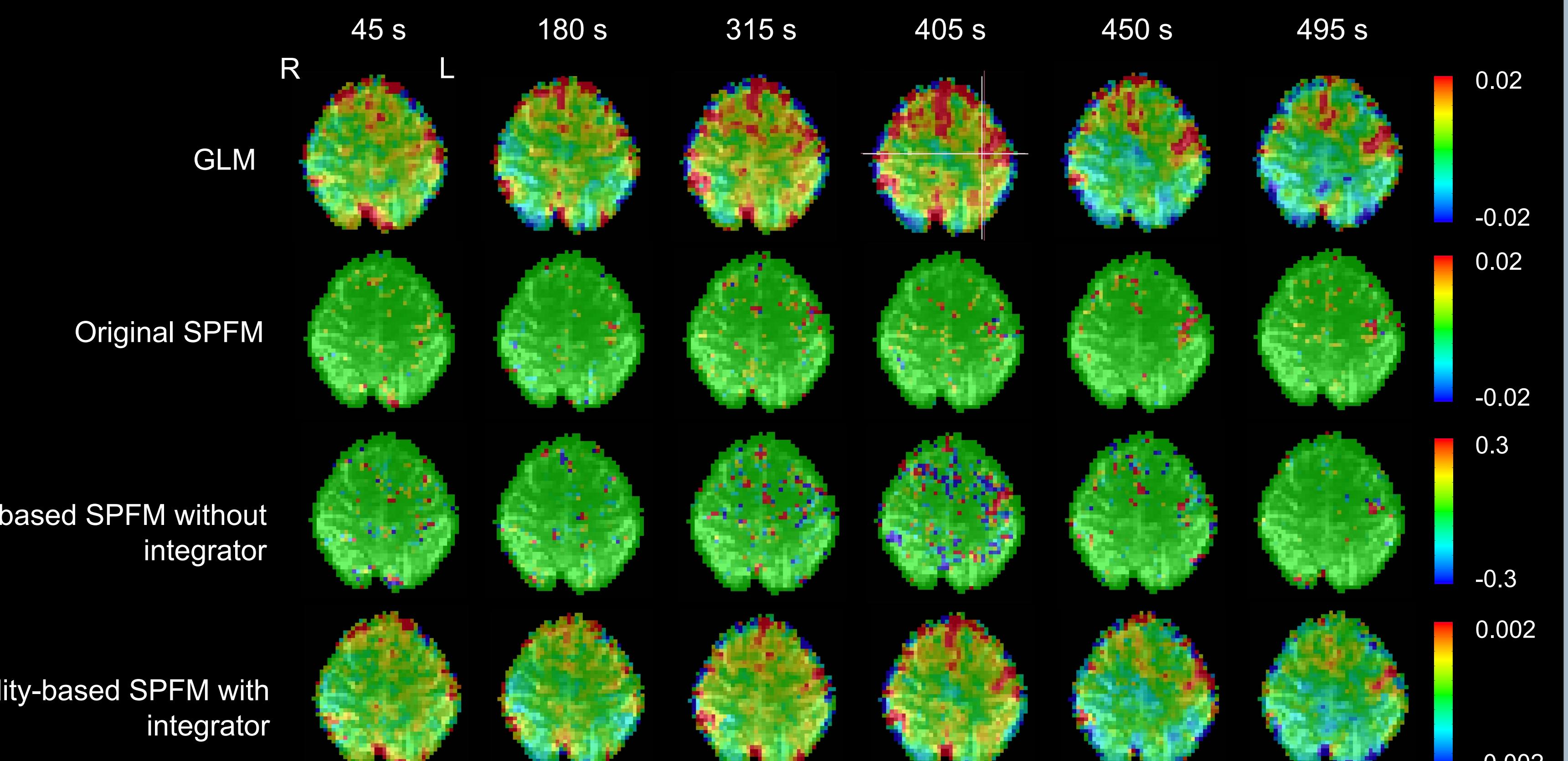


Figure 4: AUC probability maps at time 405 s after thresholding and spatio-temporal clustering.

6

## High SNR dataset (TR = 500 ms, voxel size = 3 x 3 x 3 mm<sup>3</sup>)



## Low SNR dataset (TR = 2800 ms, voxel size = 1.2 x 1.2 x 1.2 mm<sup>3</sup>)

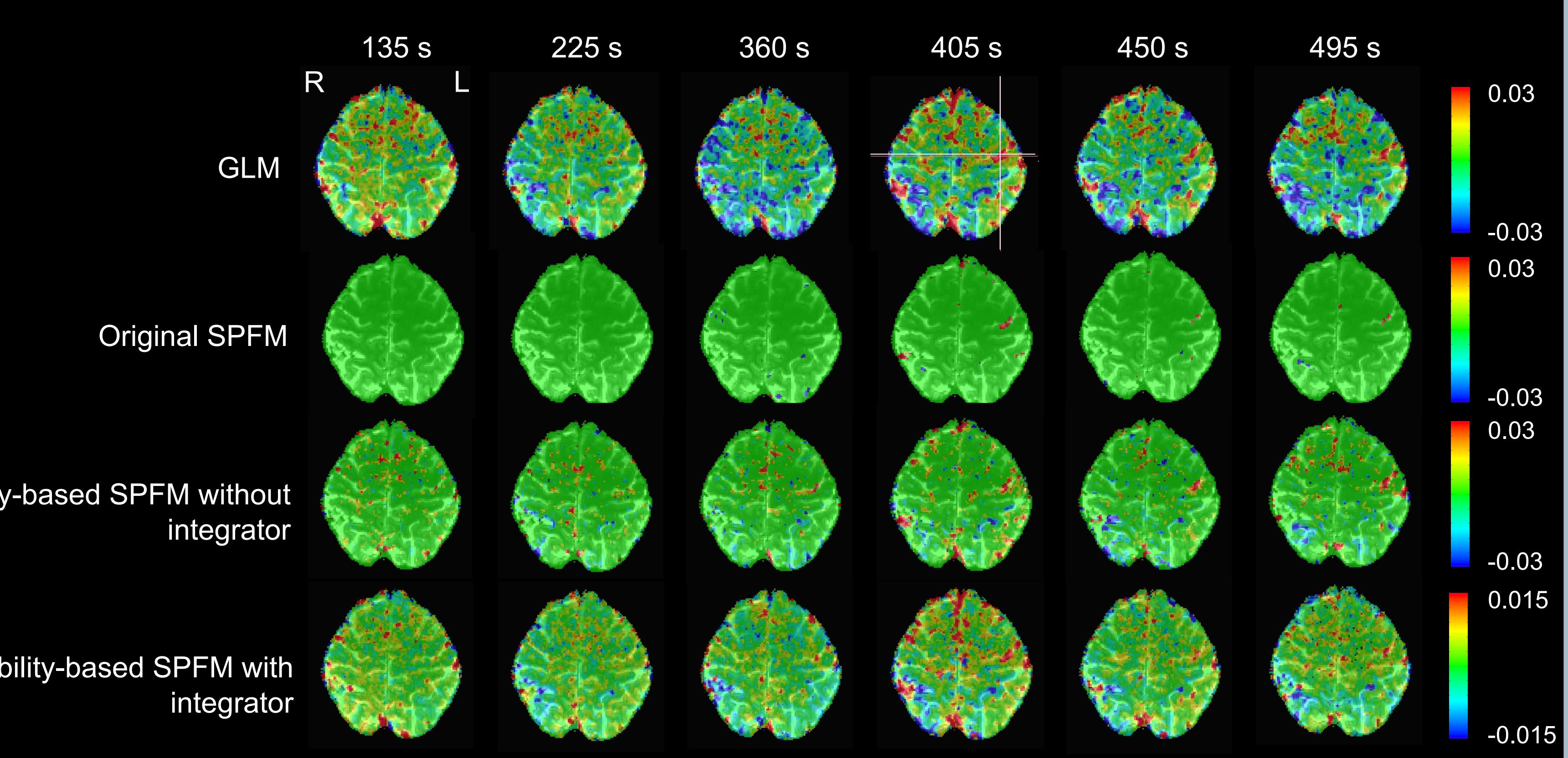


Figure 5: Comparison of the novel stability-based SPFM approach with the SPFM (3dSPFM) and trial-level GLM (3dDeconvolve) methods. Maps show the estimated neuronal-related signal of different finger-tapping events corresponding to different moments in time as shown above.

## Take-home messages

- Combination of SPFM with stability selection offers more robust estimates of neuronal-related activity, especially at low SNR.
- The addition of an integration operator allows to estimate innovation signals, yielding activity maps that are closer to the gold standard obtained with GLM trial-level analysis. Yet, the amplitude of the events might be underestimated, whereas their duration is overestimated.
- Improvements due to the integration operator highly depend on the paradigm; e.g. tasks with block events would benefit more than short event-related trials.

[1] C. Caballero-Gaude, N. Petridou, S.T. Francis, I.L. Dryden, and P.A. Gowland, "Paradigm Free Mapping with Sparse Regression Automatically Detects Single-Trial Functional Magnetic Resonance Imaging Blood Oxygenation Level Dependent Responses", Human Brain Mapping, vol. 34, pp. 501-518, 2013. [2] H. Cherkaoüi, T. Moreau, A. Halimi, and P. Ciuciu, "Sparsity-Based Blind Deconvolution of Neural Activation Signal in fMRI", Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 1323-1327, 2019. [3] N. Meinshausen and P. Bühlmann, "Stability Selection", J. R. Statist. Soc. B, vol. 72, pp. 417-73, 2010. [4] B. Efron, T. Hastie, I. Johnstone, and R. Tibshirani, "Least Angle Regression", The Annals of Statistics, vol. 32, pp. 407-499, 2004.