

# Where is Physiological Noise Lurking in $k$ -Space?

Toni Karvonen<sup>1,2</sup>, Arno Solin<sup>3</sup>, Ángel F. García-Fernández<sup>1</sup>, Filip Tronarp<sup>1</sup>, Simo Särkkä<sup>1</sup>, and Fa-Hsuan Lin<sup>4,5</sup>

<sup>1</sup>*Department of Electrical Engineering and Automation, Aalto University, Espoo, Finland*

<sup>2</sup>*Aalto NeuroImaging, Aalto University, Espoo, Finland*

<sup>3</sup>*IndoorAtlas Ltd., Helsinki, Finland*

<sup>4</sup>*Institute of Biomedical Engineering, National Taiwan University, Taipei, Taiwan*

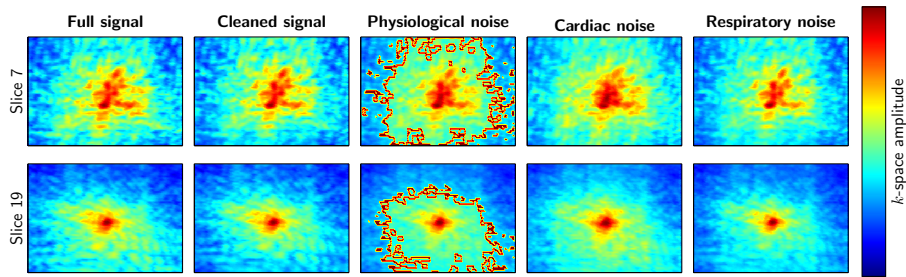
<sup>5</sup>*Department of Neuroscience and Biomedical Engineering, Aalto University, Espoo, Finland*

## Synopsis

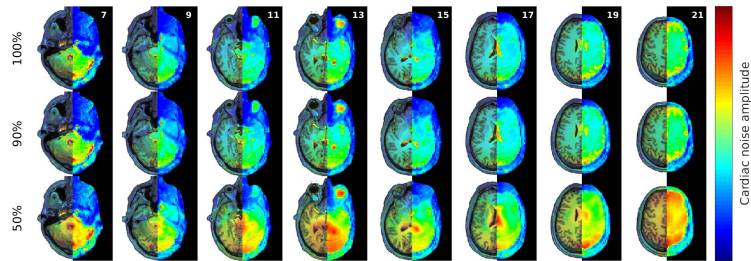
We analyze the structure of physiological noise in the  $k$ -space of BOLD fMRI. We use DRIFTER which is an algorithm based on optimal Bayesian smoothing techniques for separation of the fMRI signal to a BOLD signal component and physiological noises. DRIFTER is run independently for each spatial frequency and it is shown that the physiological noise lies in the  $k$ -space points with low spatial frequency and that its amplitude is proportional to the BOLD signal. This result suggests that we can lower the computational burden without losing estimation accuracy by running DRIFTER only on a subset of  $k$ -space points.

## 1 Purpose

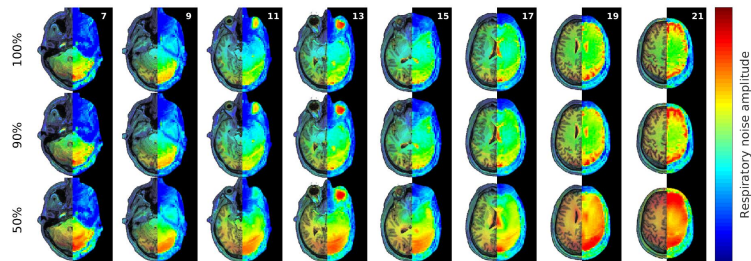
Structured non-white noise resulting from cardiac and respiratory activity can account for over a third of the total standard deviation in BOLD fMRI<sup>1</sup>, making proper treatment of these noise sources an essential part in enhancing the signal-to-noise ratio<sup>2</sup>. Removal of the structural noise is typically done retrospectively from the reconstructed images<sup>3,4</sup>, but it has been demonstrated<sup>5</sup> that working directly with the raw  $k$ -space data is possible and can result to more accurate noise estimates. In this work, we investigate the  $k$ -space structure of the physiological noise, as estimated by the DRIFTER algorithm<sup>3</sup>. Knowing this spatial distribution is important as such, but it can also be used for reducing the computational burden of the DRIFTER algorithm—as the DRIFTER processes each spatial frequency independently and most of the energy is concentrated to low frequencies, we can save computations by only processing a subset of the  $k$ -space.



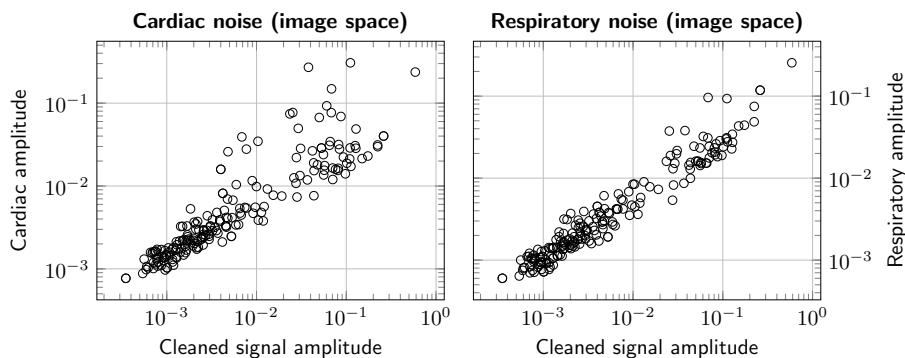
**Figure 1:** Logarithmic  $k$ -space amplitude maps averaged over time for slices 7 and 19. Columns from left to right: full signal; cleaned signal estimate by DRIFTER; total physiological noise with the contour enclosing those spatial frequencies that have largest amplitudes and constitute 90% of the total energy; cardiac noise estimate; respiratory noise estimate. Magnitudes in different maps are not comparable. Spatial frequency range, in units of  $1/\text{mm}$ , is from  $-0.29$  to  $0.29$  on the horizontal axis and from  $-0.14$  to  $0.14$  on the vertical one.



**Figure 2:** Cardiac noise amplitude maps, displayed with the corresponding anatomical images, reconstructed by DRIFTER using spatial frequencies constituting 100%, 90% and 50% of the physiological noise energy in  $k$ -space for selected slices. The magnitudes are logarithmic and not in scale between different slices or columns.



**Figure 3:** Respiratory noise amplitude maps, displayed with the corresponding anatomical images, reconstructed by DRIFTER using spatial frequencies constituting 100%, 90% and 50% of the physiological noise energy in  $k$ -space for selected slices. The magnitudes are logarithmic and not in scale between different slices or columns.

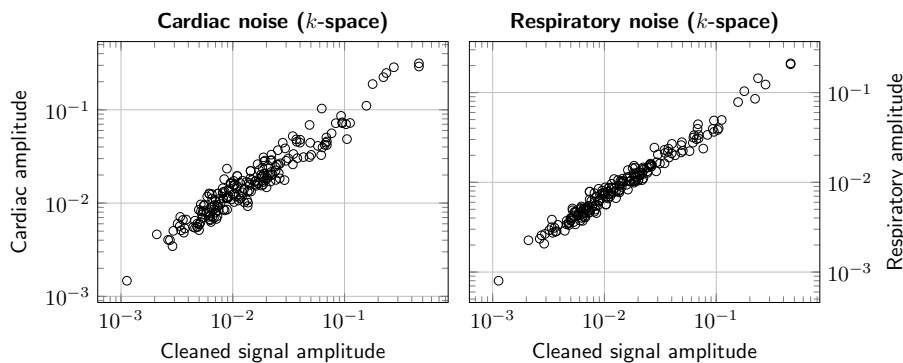


**Figure 4:** Logarithmic scatter plots of image space cardiac and respiratory noise versus cleaned signal amplitudes by DRIFTER for slice 7. The data points represent the cleaned signal amplitude (horizontal axis) and physiological noise amplitude (vertical axis) of individual image space voxels. The scales have been normalized.

## 2 Methods

The DRIFTER algorithm is a retrospective estimation scheme for identification and removal of physiological noise in fMRI data. It is based on Bayesian optimal filtering and smoothing methods from signal processing. The algorithm decomposes the data into different noise components and the “cleaned” BOLD signal. In this work we apply DRIFTER to raw  $k$ -space data. After this we select spatial frequencies that contain most of the energy and process only these. This kind of subset processing is only possible in  $k$ -space whereas processing only some of the image space voxels would make little sense. Specifically, we use DRIFTER to compute the overall physiological noise distribution in the  $k$ -space and then investigate how the reconstructed images are affected if only the those spatial frequencies containing 90% or 50% of the total physiological noise energy are processed further. The actual image reconstruction is done with Kaiser–Bessel regridding<sup>6</sup> and by weighting by the complete coil images when summing over the coil channels.

The test data consists of a 27-run set of raw resting state fMRI data and accompanying anatomical images of one volunteer. The data was obtained at Aalto AMI Centre of Aalto Neuroimaging, part of Aalto University School of Science, with a 3 T Siemens Skyra scanner using a 32-channel receive-only head-coil array. Parameters of the EPI sequence were TR: 77 ms; TE: 21 ms; FA: 60 degrees; FOV: 224 mm; matrix size: 64×64; voxel size: 3.5×3.5×6 mm, and those of the EPI trajectory were ramp times: 140  $\mu$ s; flat-top: 220  $\mu$ s; ADC readout time: 409.6  $\mu$ s. Each run had a length of approximately 30 seconds and consisted of a fixed reference slice and a second slice with the gap size between them advancing on each run. The reference cardiac and respiration signals were time-locked to the fMRI data with a peripheral (BIOPAC) pulse measure and a respiratory belt, respectively. The physiological signals were sampled with a frequency of 1 kHz. For the DRIFTER algorithm, two harmonic resonators were used with their frequencies for each run estimated from external cardiac and respiration signals.



**Figure 5:** Logarithmic scatter plots of  $k$ -space cardiac and respiratory noise versus cleaned signal amplitudes by DRIFTER for slice 7. The data points represent the cleaned signal amplitude (horizontal axis) and physiological noise amplitude (vertical axis) of individual spatial frequencies in the  $k$ -space. The scales have been normalized.

### 3 Results

The results are summarized in Figures 1–5. Figure 1 is instrumental and shows amplitude maps of the physiological noises in  $k$ -space for one slice. Figures 2 and 3 display how processing fewer spatial frequencies affects the reconstructed image space noise estimates. With 90% coverage there is little degradation but if half of the energy is discarded the estimates become markedly more blurred. Figures 4 and 5 demonstrate that there is, as has been suggested<sup>1</sup>, a linear relationship between cleaned signal and physiological noise magnitudes.

### 4 Discussion

The results reveal that the physiological noise is heavily concentrated to low spatial frequencies and its distributions roughly coincides with that of the total signal. The number of spatial frequencies required to contain most of physiological noise energy decreases fast: in the case of covering 90% of energy the numbers of spatial frequencies required were (the total number is 8192) 5212, 5115, 3839, 3610, 3896, 3700, 3813 and 3086 for the slices in Figures 2 and 3. That is, around half of the frequencies can be discarded with little degradation of image space noise estimates. These findings support the goal of reducing the computational cost by only considering a subset of the frequencies.

### 5 Conclusions

We have presented how physiological noise in fMRI is structured in the  $k$ -space and shown that DRIFTER algorithm (available for download<sup>7</sup>) can be applied to only a subset of spatial frequencies with little degradation of the noise estimates and that this approach can considerably improve the practical computational efficiency of physiological noise removal in fMRI.

## Acknowledgements

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