Denoise fMRI gradient interference on electrophysiological signals: using IS-NMF

IS: Itakura-Saito (IS) divergence
NMF: Nonnegative Matrix Factorization

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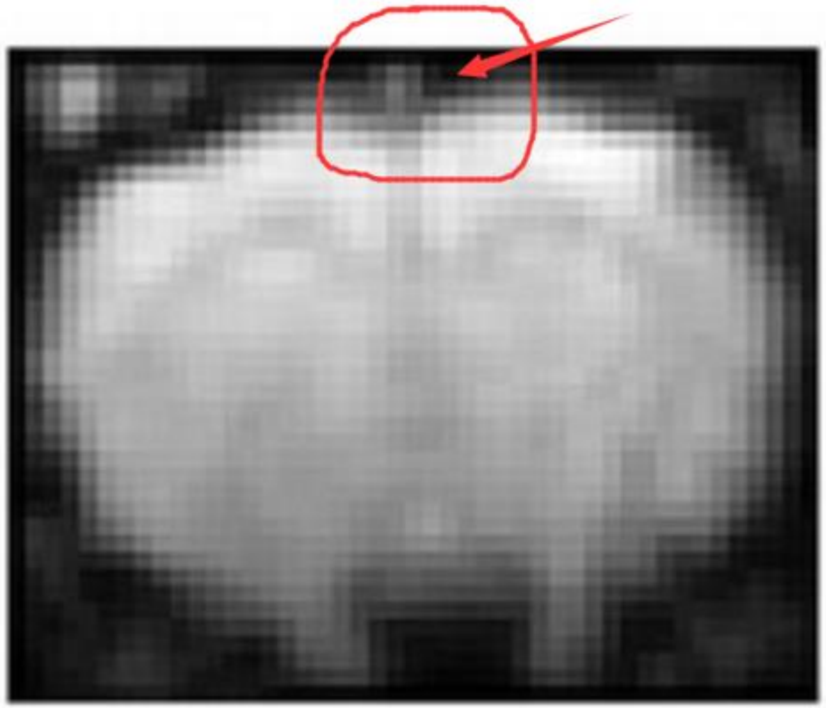
Acknowledgement: Dr. Yusuke Murayama

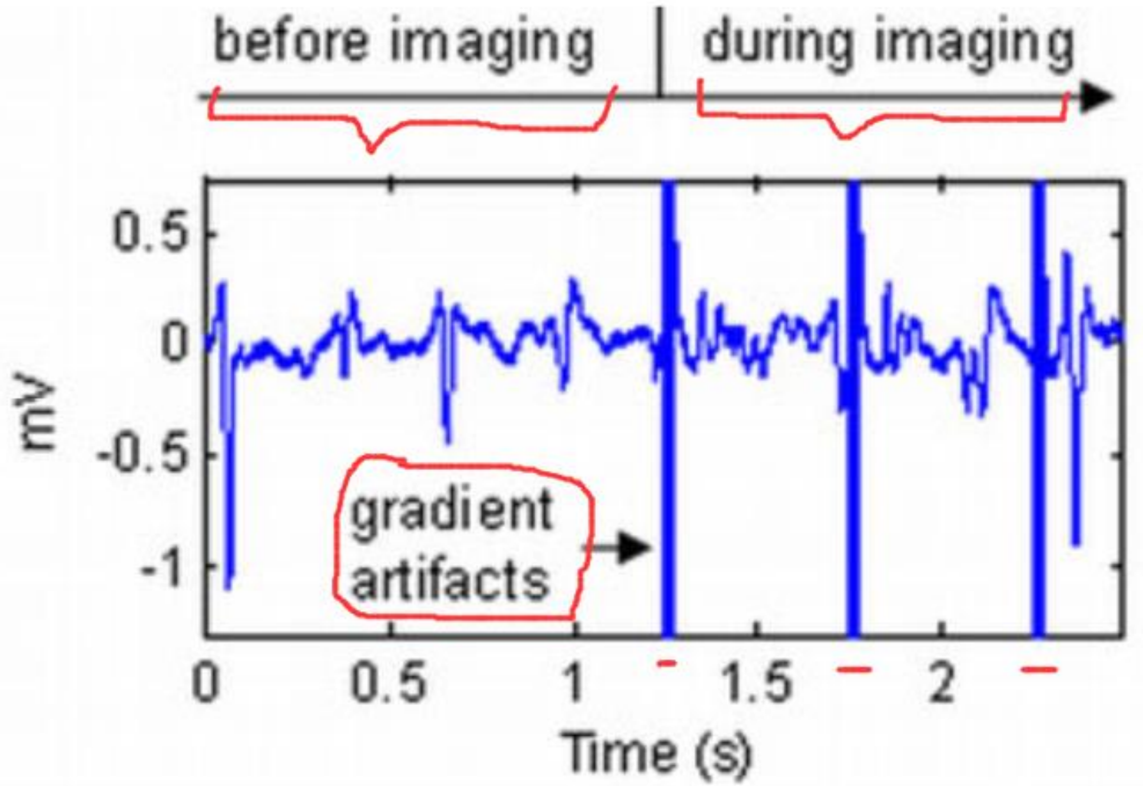
Overview

Simultaneous functional magnetic resonance imaging (**fMRI**) and electrophysiological (**Ephy**) recording induces fMRI gradient interference in Ephy signals. After **hardware compensation**, **IS-NMF denoise** can effectively remove residual artifacts and generate high quality Ephy data.

- **Problem:** fMRI gradient artifacts in Ephy signals
- **Method:**
  - **Hardware:** interference-compensation circuits;
  - **Software:** AAS (average artifact subtraction), PCA, NMF.
- **Results:** IS-NMF denoising workflow
- **Summary and Future** Improvement

Problem: fMRI gradient artifacts in Ephy

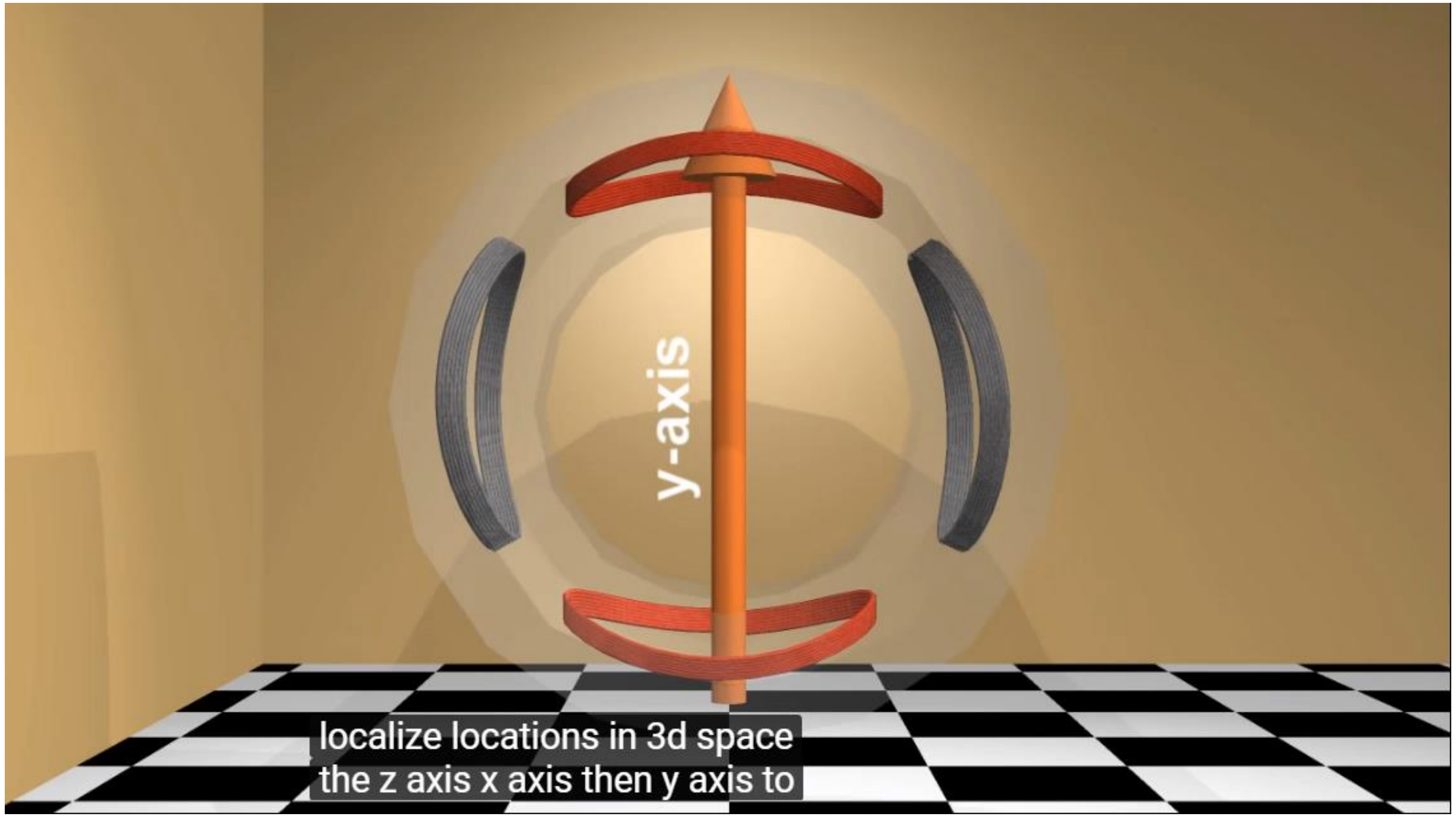


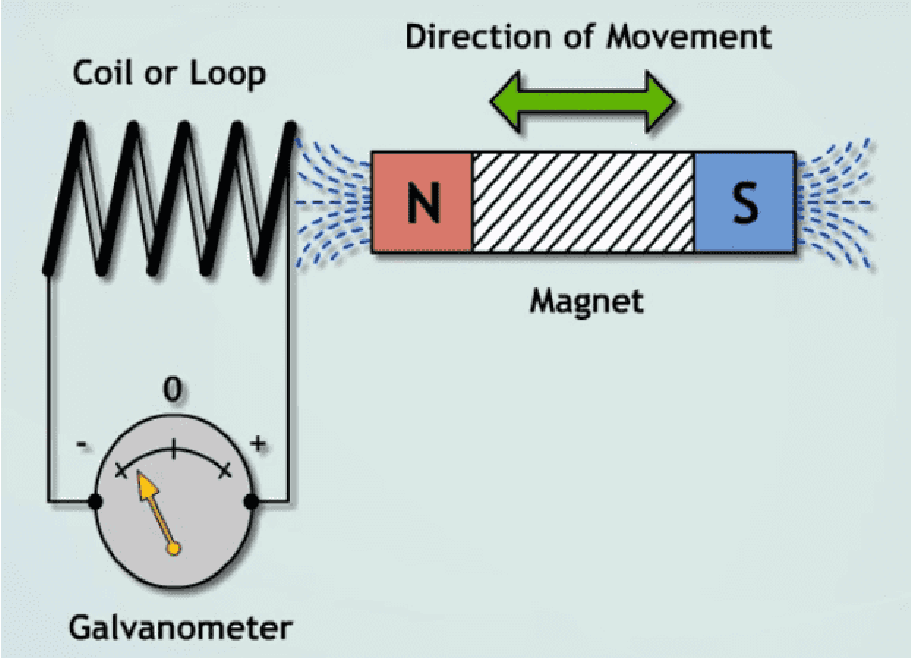


Raw electrophysiological signals contain **gradient artifacts** during **MRI imaging**

Problem: fMRI gradient artifacts in Ephy

(Dr. Klioze, 2013) [2]
Faraday's law picture electrical4u.com





fMRI performs rapidly **switching magnetic field** gradients,
which results in **gradient interference** on Ephy signals based on **Faraday's law**.

Methods to denoise gradient artifacts

Revised from (Rodolfo et al., 2018) [3]

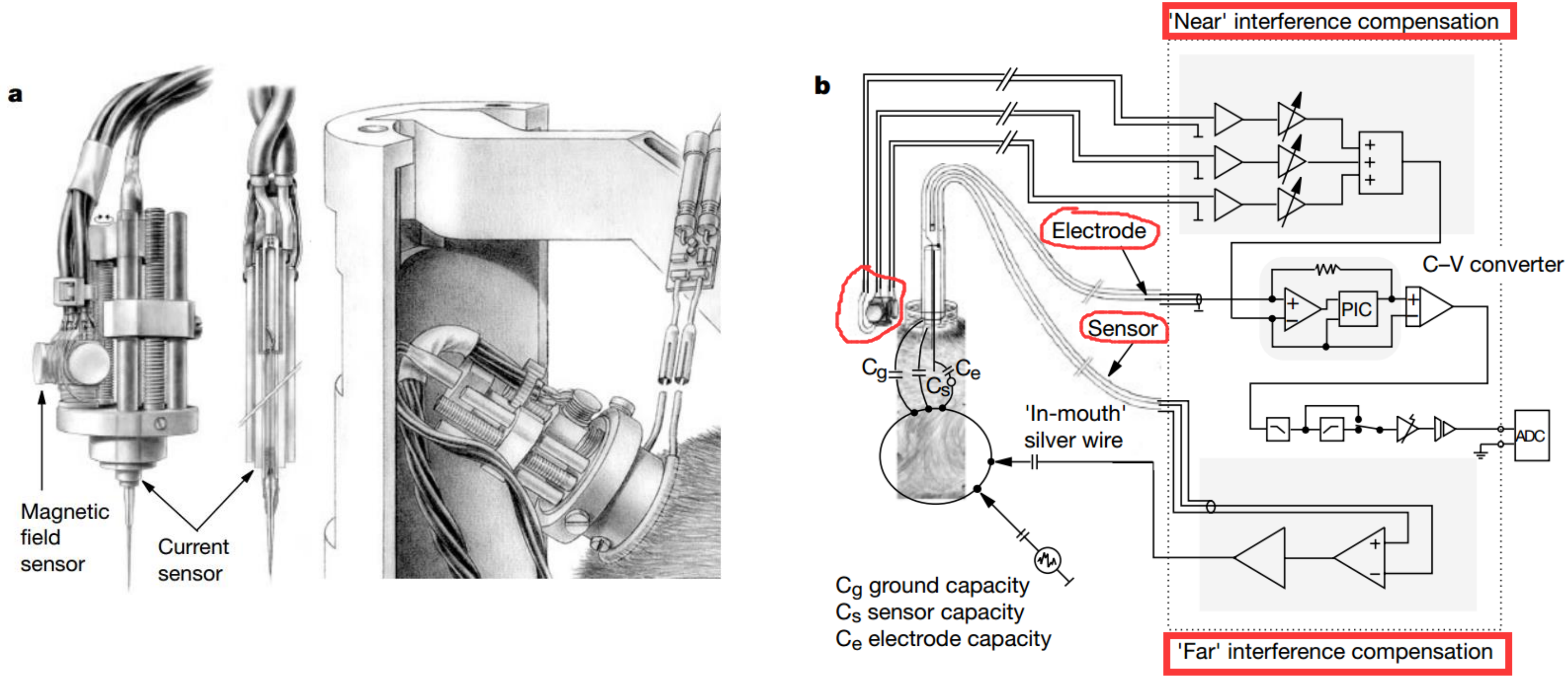
Methods	Description
Hardware-based	**Temporal filtering** (remove gradient artifacts frequency band)
	Reference gradient signals (near and far interference compensation circuits)
Software-based	Average artifact template subtraction (**AAS**) (average time-aligned signals for each noise pattern)
	Extract hidden noise components - Principal component analysis (**PCA**) - Independent component analysis (**ICA**) - Nonnegative matrix factorization (**NMF**)

"**Noisy Ephy signal** (recorded) = Original Ephy signal (hidden) + **Noise pattern signal** (hidden)"

Hardware Solution: compensation circuits

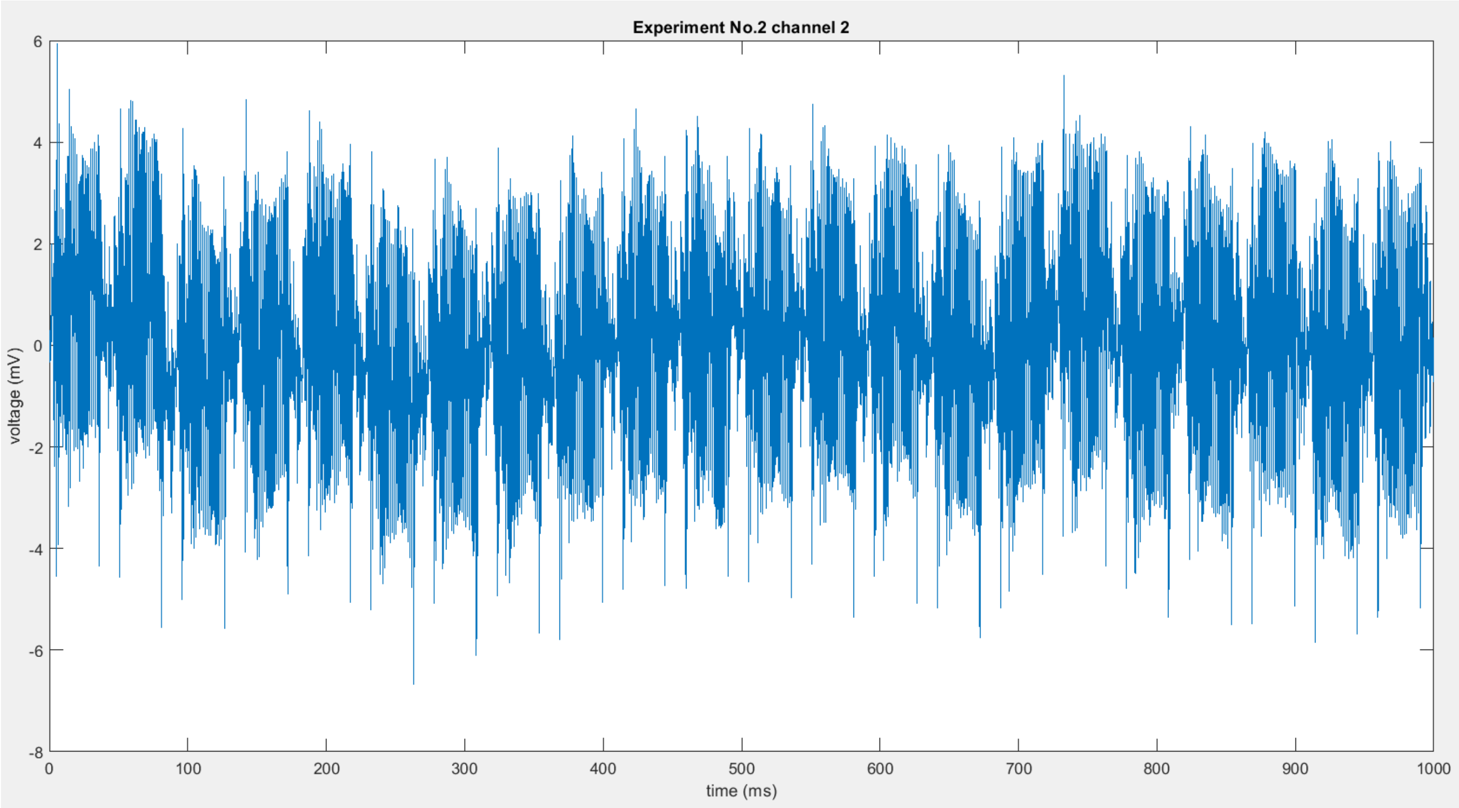
(Logothetis et al., 2001) [4]
(Oeltermann et al., 2007) [5]

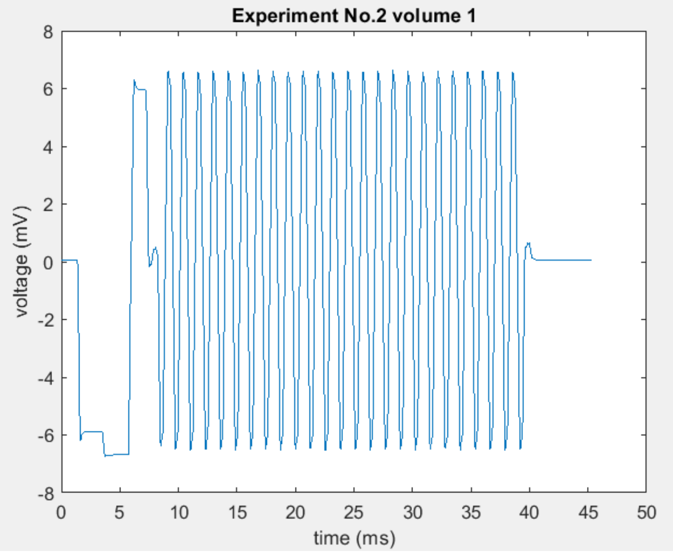
Two separate **interference-compensation circuits**:
- **Near interference** (induction within electrodes)
- **Far interference** (induction between electrodes and the ground)

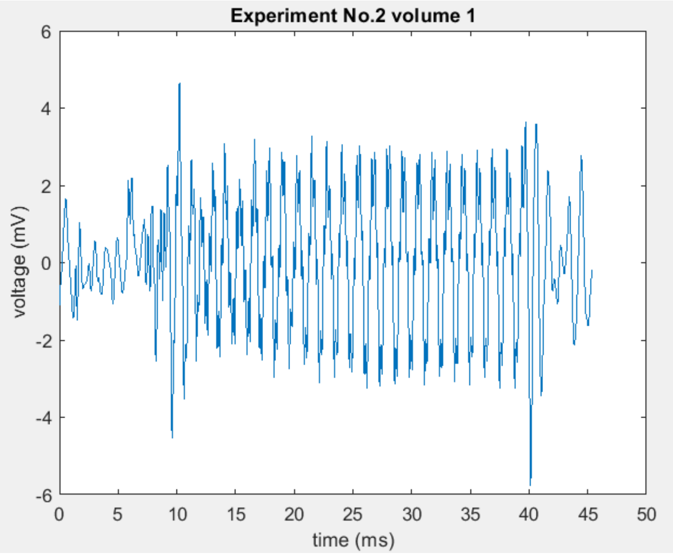


Software Solution: AAS

“Original Ephy signal = **Noisy Ephy signal** (recorded) - **Noise pattern signal** (hidden)”



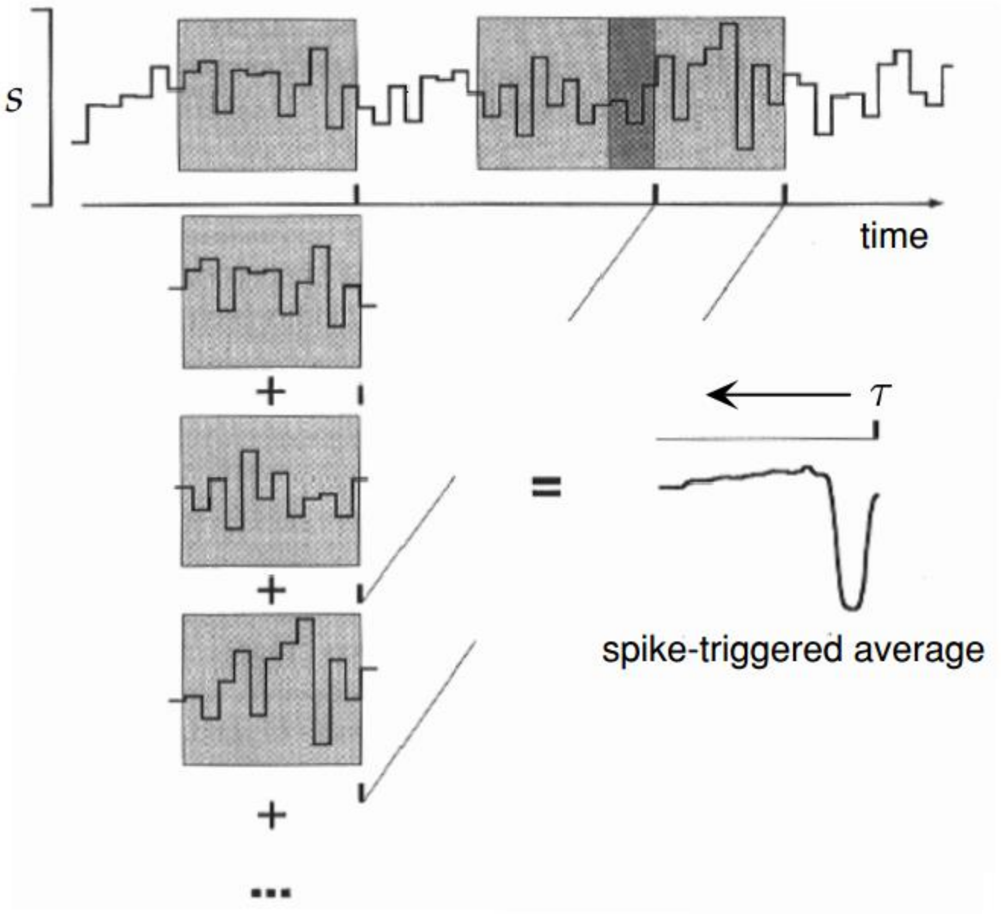




STA picture adapted from Rieke et al. 1997

Software Solution: AAS

AAS, average artifact template subtraction, is a conventional way to find the hidden noise structure like using **spike-triggered average** (**STA**) stimulus to estimate the receptive field.

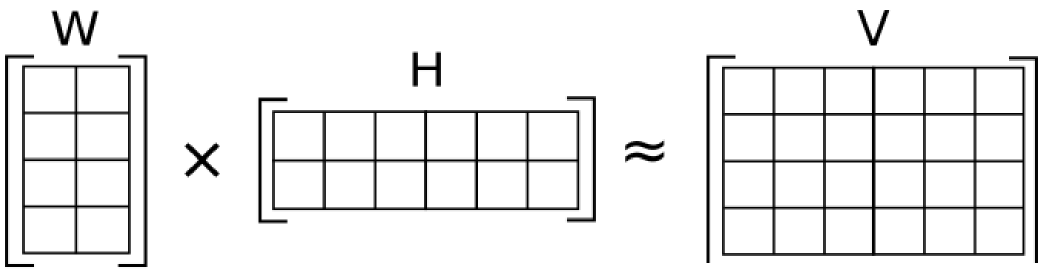


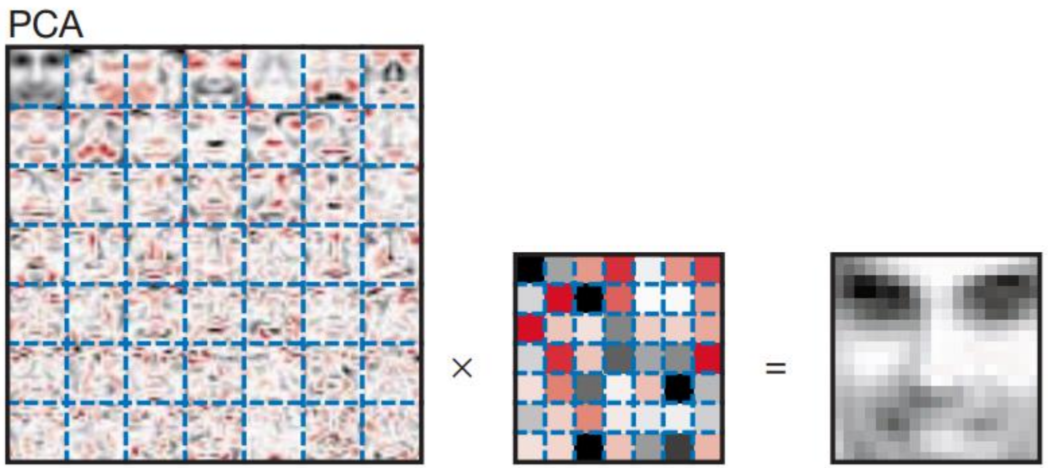
Receptive field ➔ Noise pattern
Other noisy stimulus ➔ Original Ephy signals
Each spike timestamp ➔ Each chunk scan timestamp

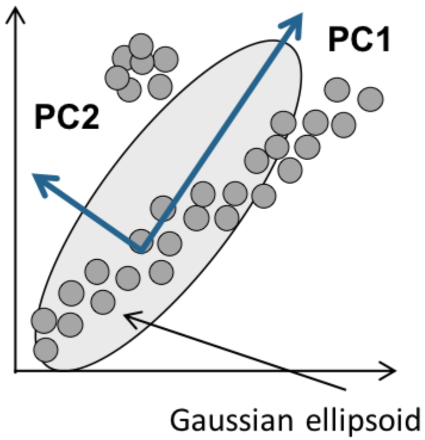
1. **Align** (chunks = slices * segments) in volumes
2. **Average** (precise synchronization in MRI-Ephy)
3. **Subtract** (compared with reference noise pattern)

Software Solution: PCA, NMF

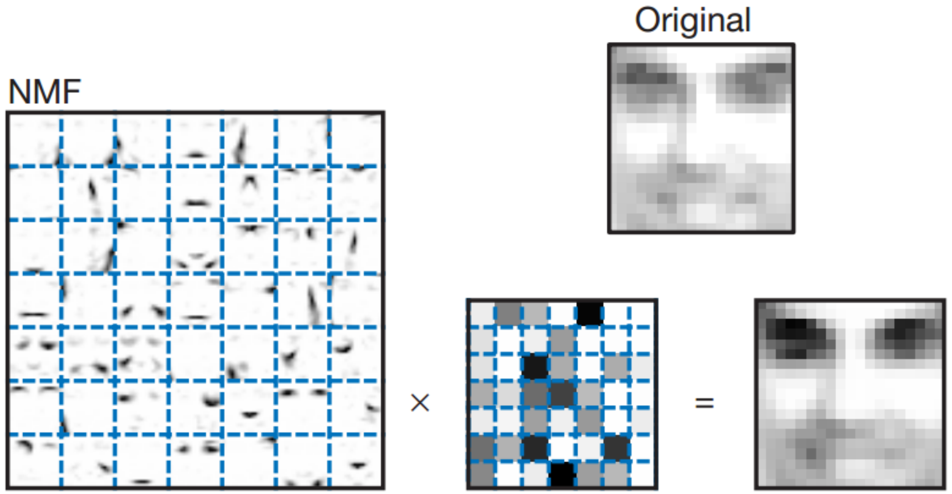
(Lee et al., 1999) [6]
PCA and NMF picture from wiki and deconICA

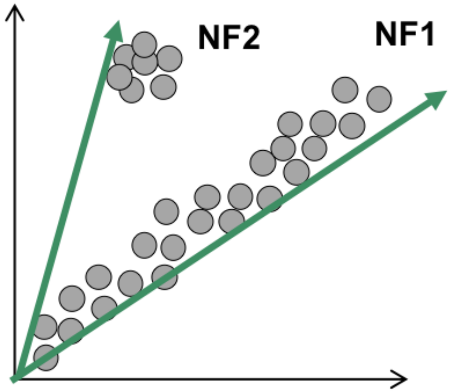




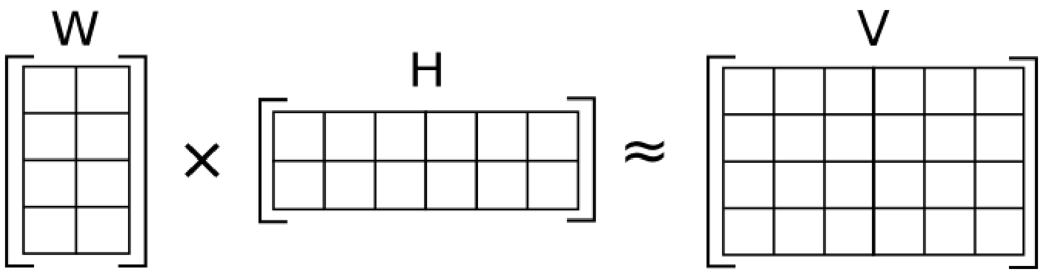


PCA,





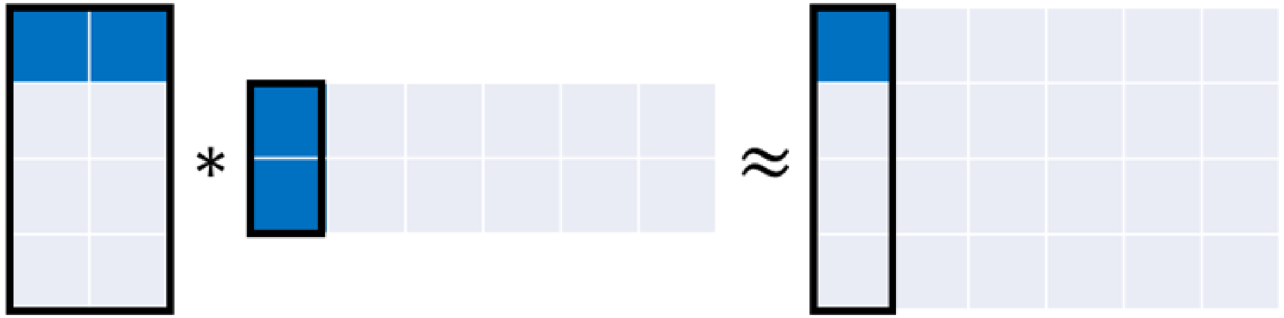
Software Solution: Nonnegative matrix factorization



$$H * H^T = I$$
$$W * H * H^T \approx V * H^T$$
$$V * H^T \approx W$$

$$W * H \approx V$$

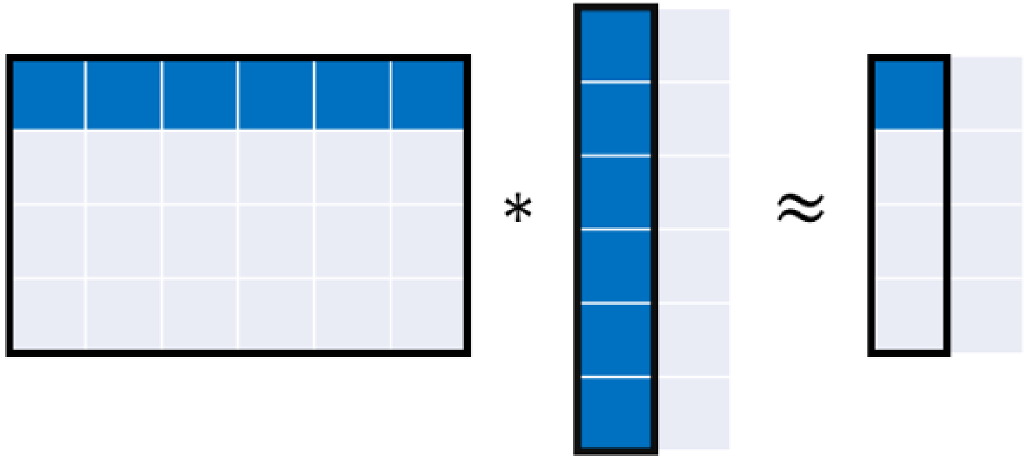
(4*2) (2*6) (4*6)



2 prototypes

activation coefficients

Rows: observation direction
Columns: features direction



Columns of W: transformation of V
Rows of H (columns of H^T): contribution of V to W

Software Solution: Itakura-Saito divergence

(Févotte et al., 2009) [7]

The optimization problem:

$$\min_{\mathbf{W},\mathbf{H}\geq \mathbf{0}} \; D(\mathbf{V} \mid \mathbf{WH}),$$

where $D(\mathbf{V} \mid \mathbf{WH})$ is a cost function defined by

$$D(\mathbf{V} \mid \mathbf{WH}) = \sum_{f=1}^{F} \sum_{n=1}^{N} d([\mathbf{V}]_{fn} \mid [\mathbf{WH}]_{fn}),$$

and where $d(x \mid y)$ is a scalar cost function.

(1) Euclidean distance:

$$d_{EUC}(x \mid y) = \frac{1}{2}(x-y)^2$$

(2) Kullback-Leibler (KL) divergence:

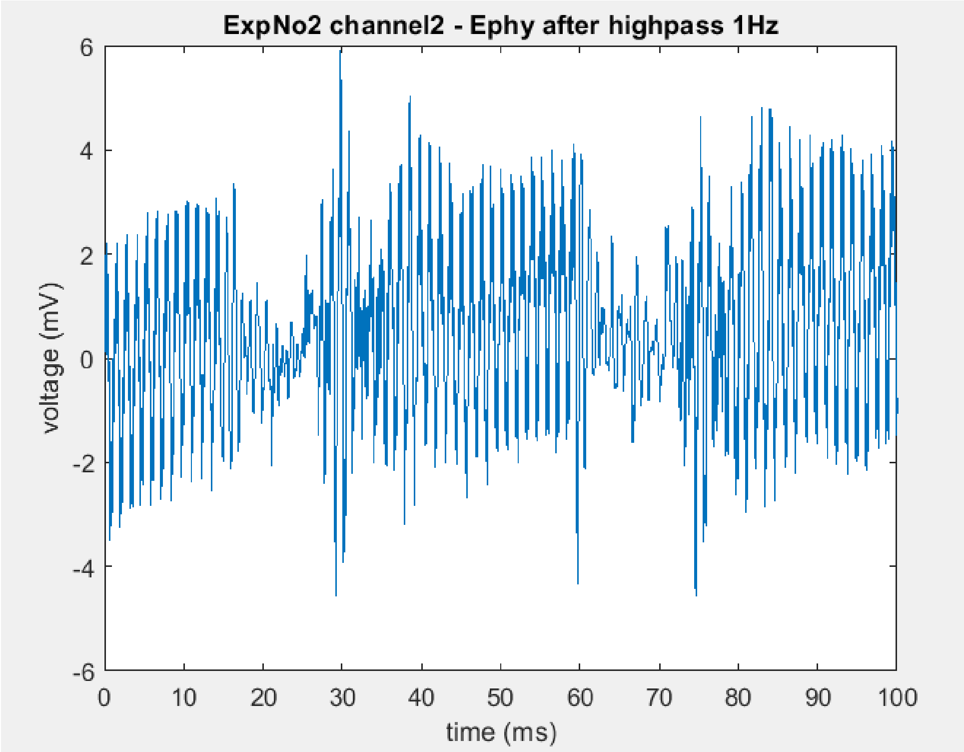
$$d_{KL}(x \mid y) = x \log \frac{x}{y} - x + y$$

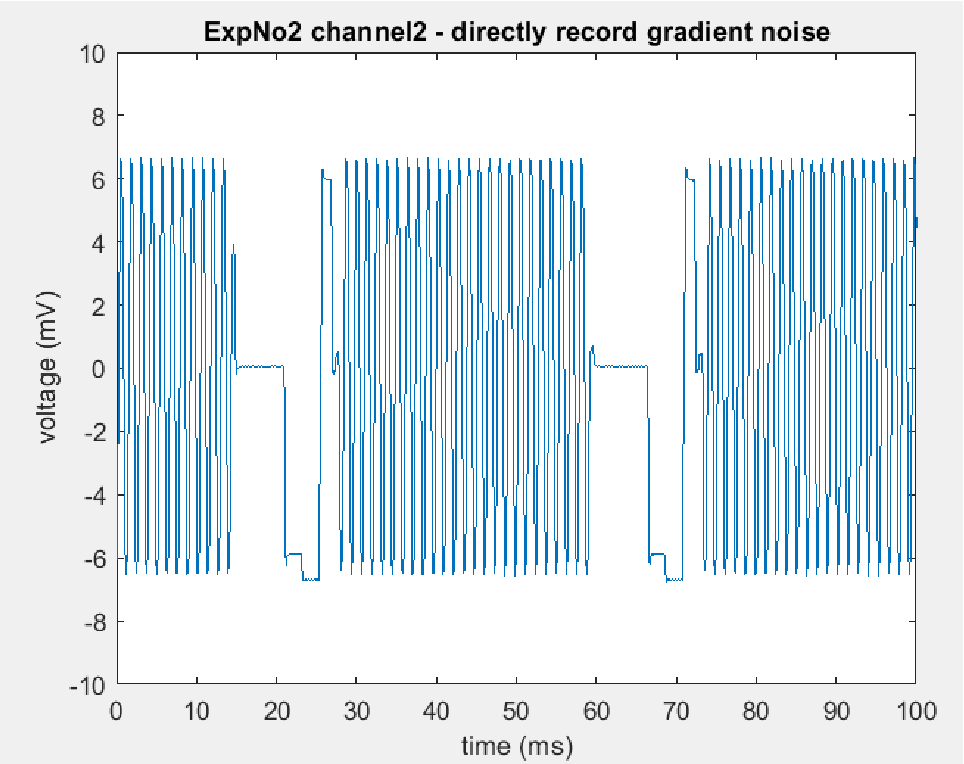
(3) Itakura-Saito (IS) divergence:

$$d_{IS}(x \mid y) = \frac{x}{y} - \log \frac{x}{y} - 1$$

Results: IS-NMF denoising workflow

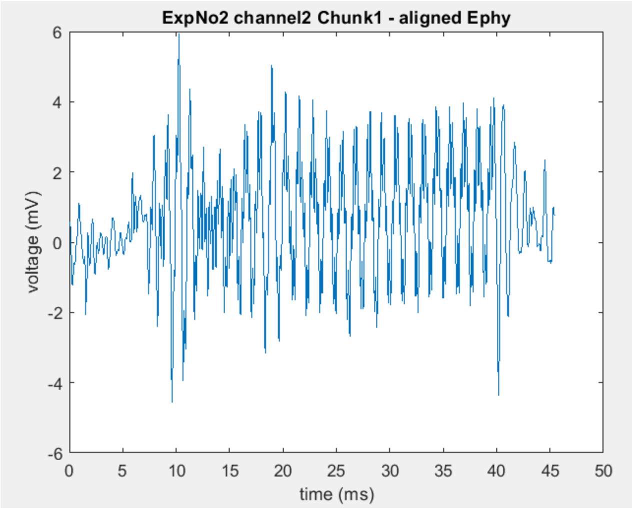
1. **Synchronize** MRI-Ephy;
2. **Highpass filtering** (1Hz);
3. **Align** Ephy chunks for each unique noise pattern;

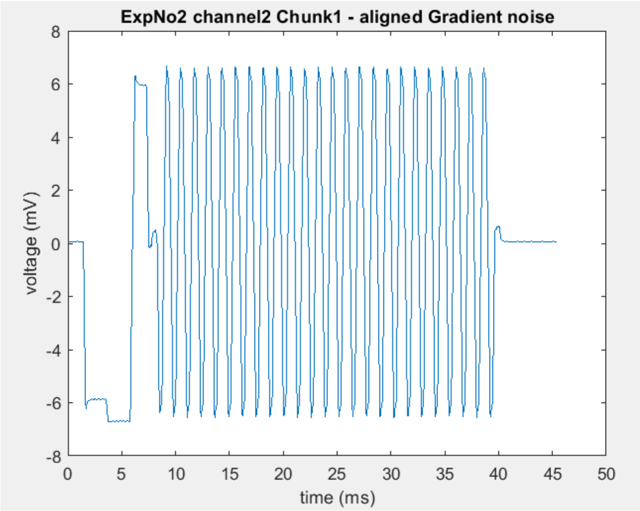


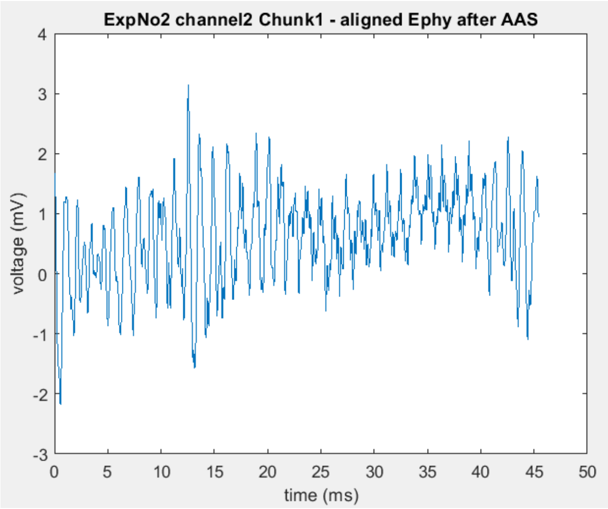


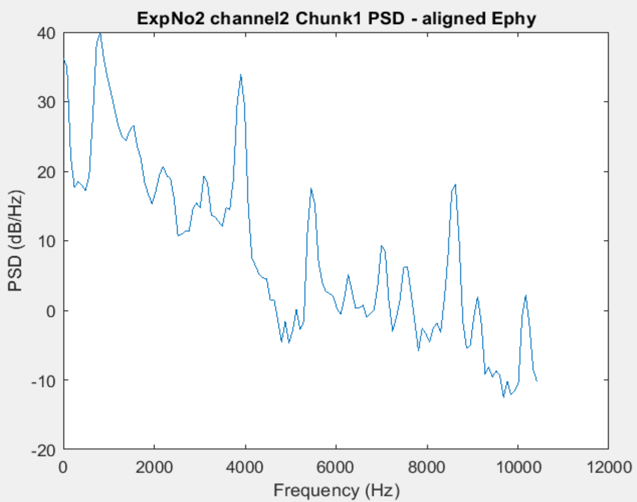
Results: IS-NMF denoising workflow

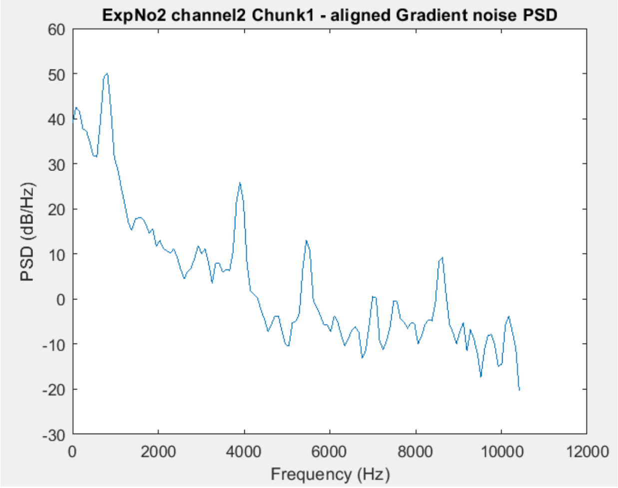
4. **Perform AAS**, and construct gradient noise pattern list;
5. **Perform IS-NMF**
   5.1 Preprocess

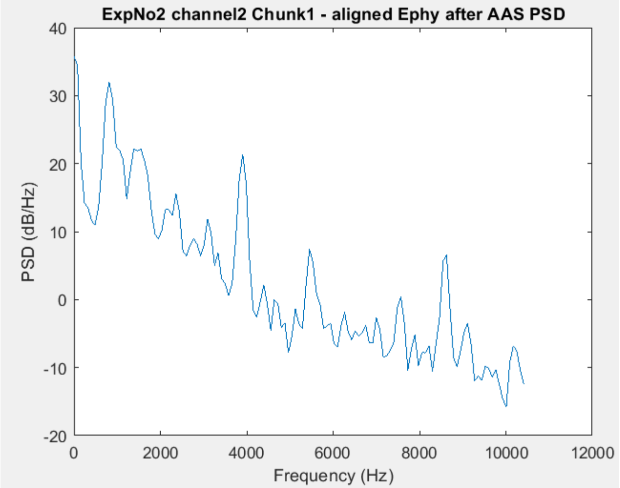








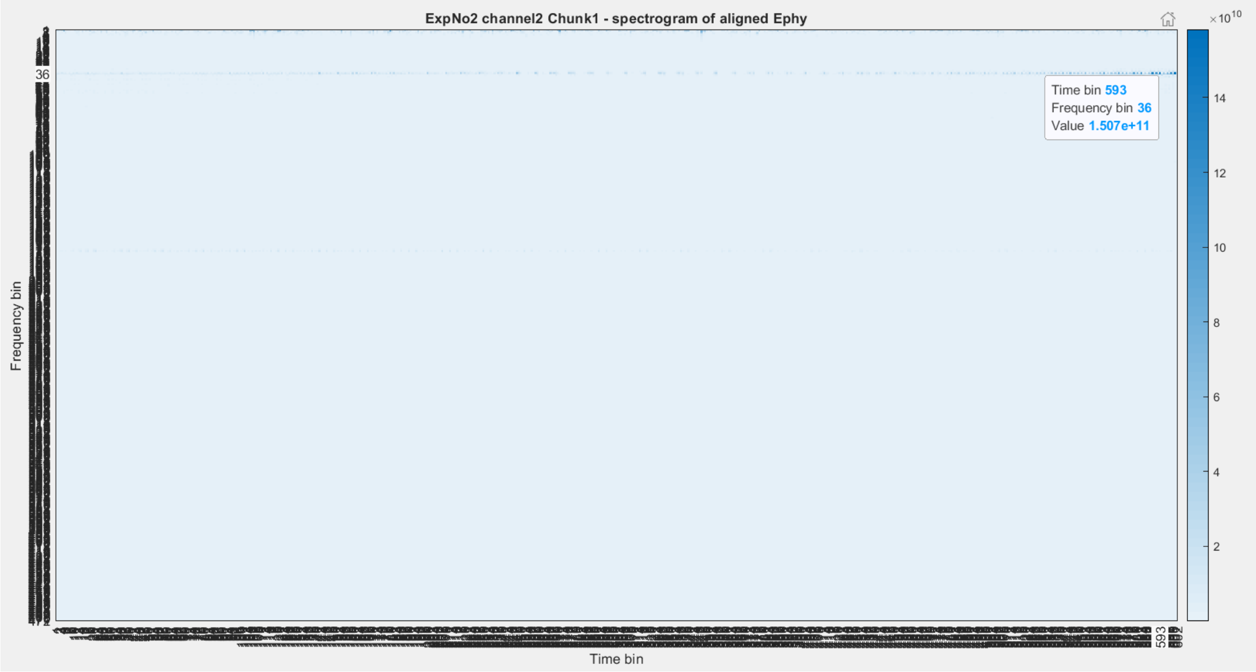


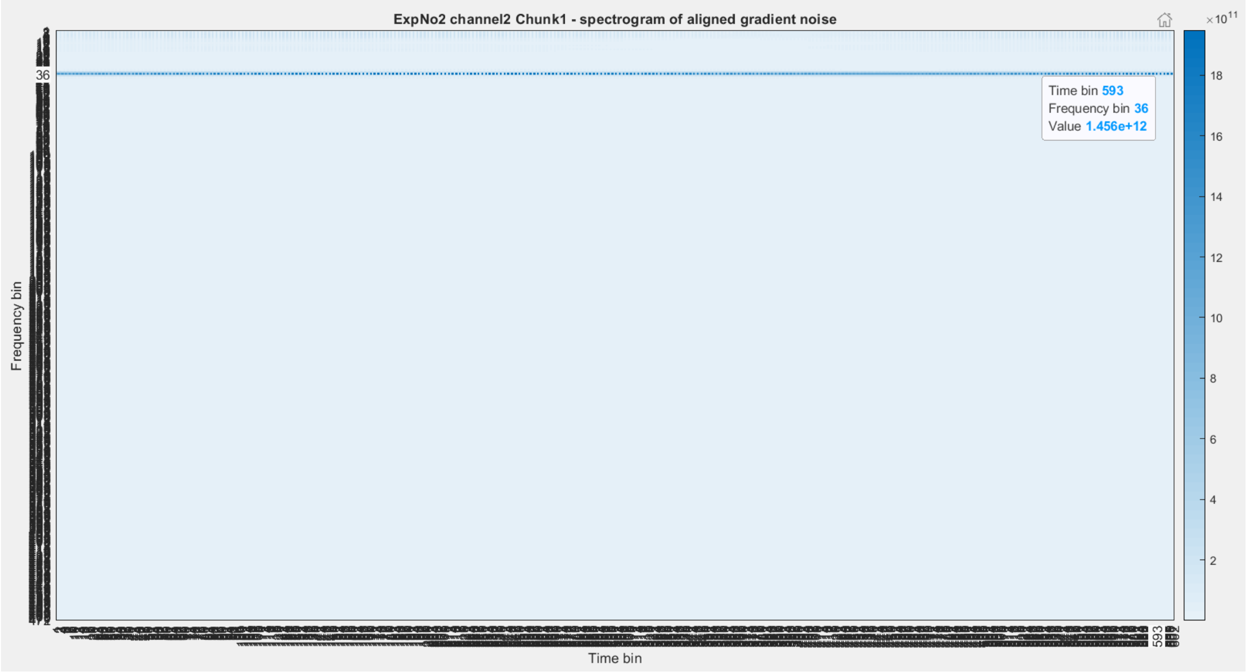


Results: IS-NMF denoising workflow

5.2 Do **STFT**

5.3 Do IS-NMF on **Spectrogram** (**V** matrix)





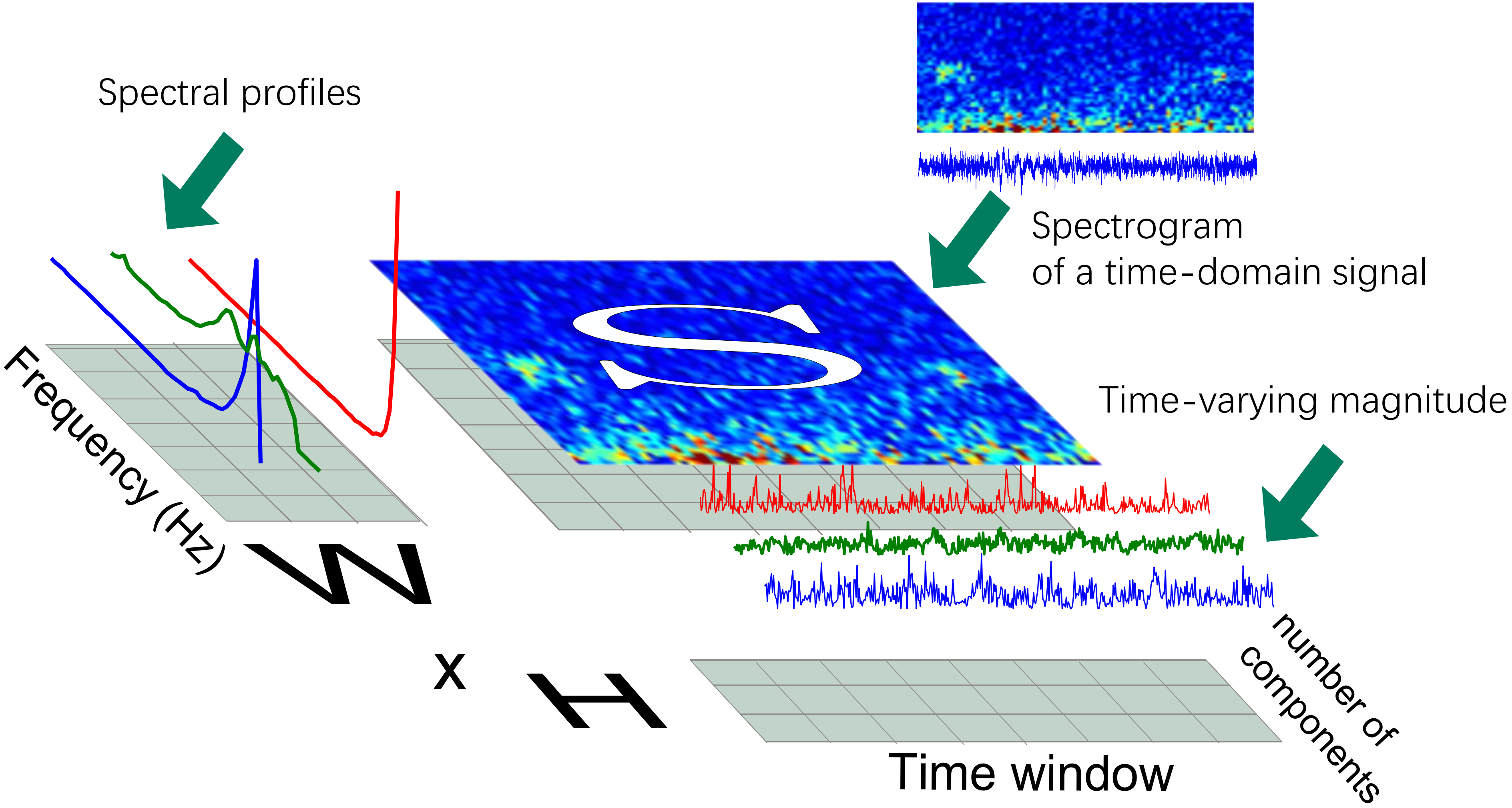
Results: IS-NMF denoising workflow

Assumptions of IS-NMF:
The **spectrum** of the **chunk-unfolded Ephy signal** (matrix **V**) is a time varying linear combination of components associated to **neural activity** and **gradient noise**:

$$S(f,t) = w_{neur}(t).S_{neur}(f) + w_{grad}(t).S_{grad}(f) + \cdots.$$

Objective:
Identify these components,
and remove the time varying contribution of **gradient noise**.

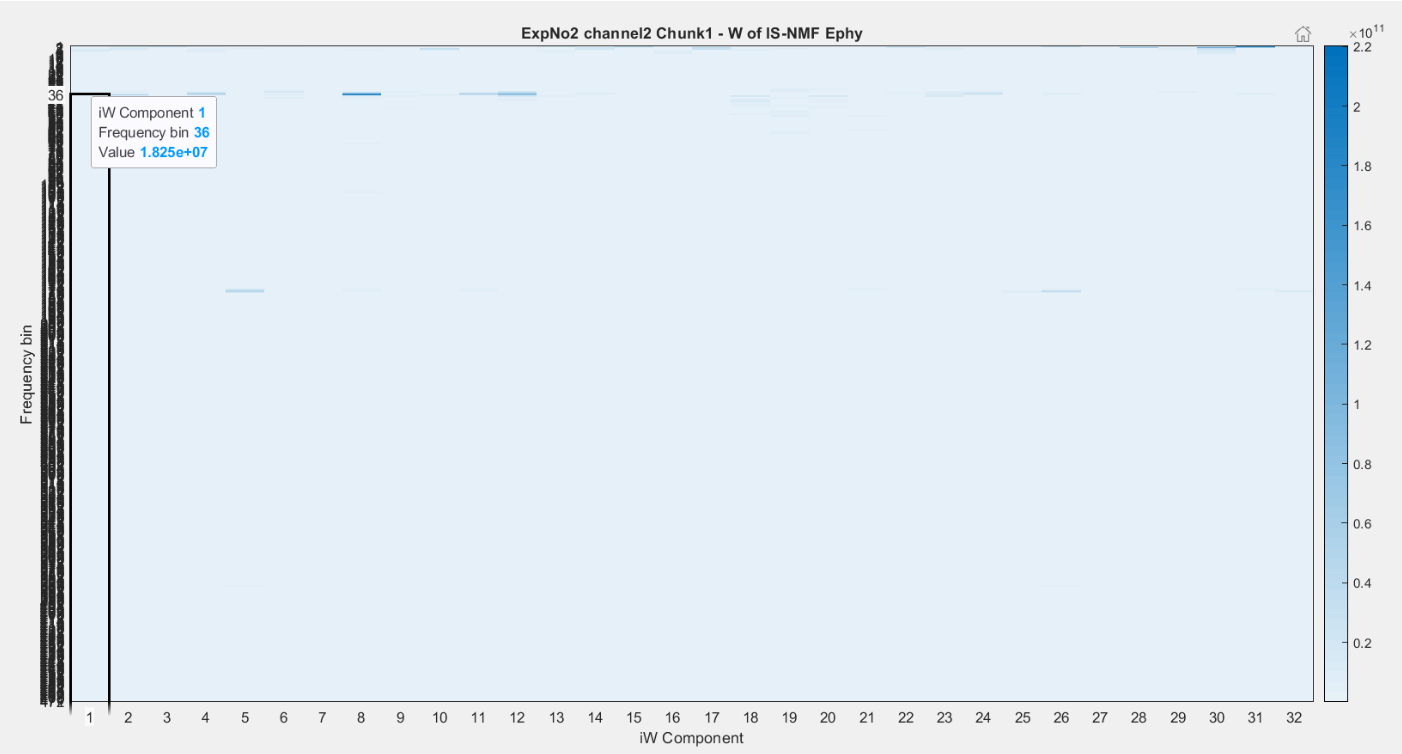
Results: IS-NMF denoising workflow

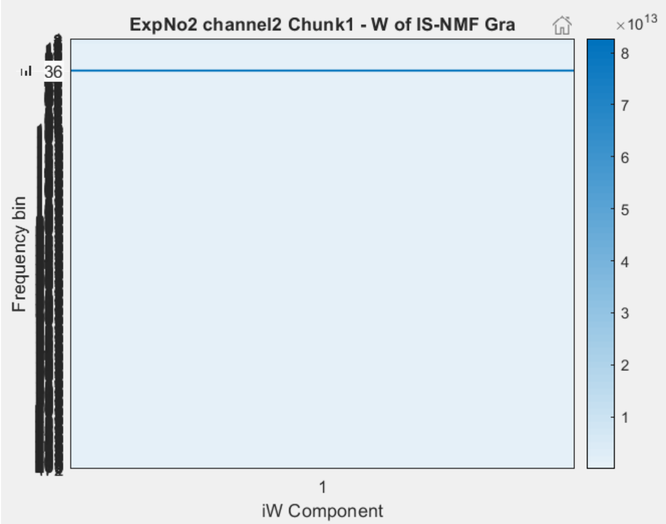


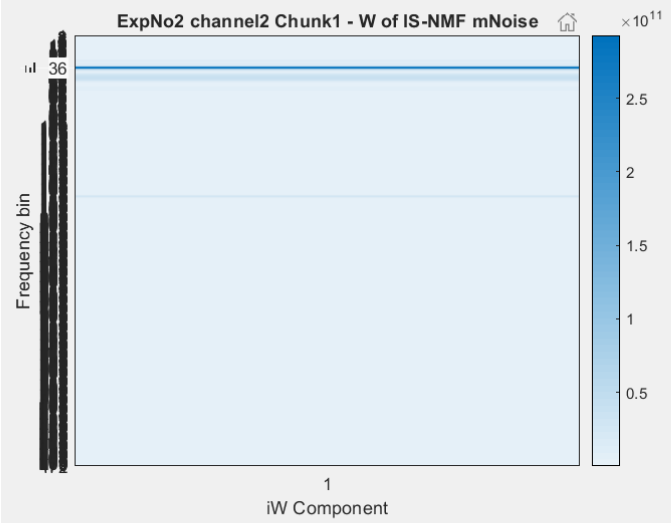
$$S \approx WH$$

Results: IS-NMF denoising workflow

5.4 Remove best **noise-correlated components** (columns in **W** matrix)







Correlated iWs (coeff threshold 0.5) are

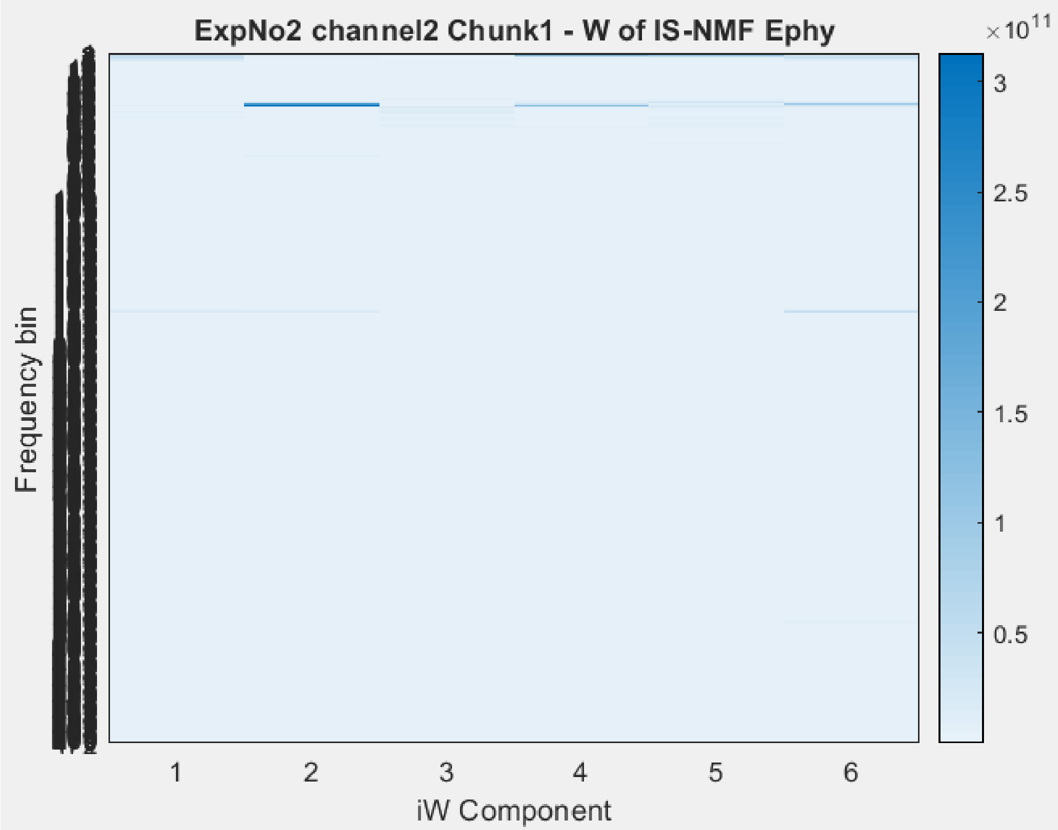
[2 4 6 8 9 11 12 18 19 20 23 24]

Gradient noise pattern list

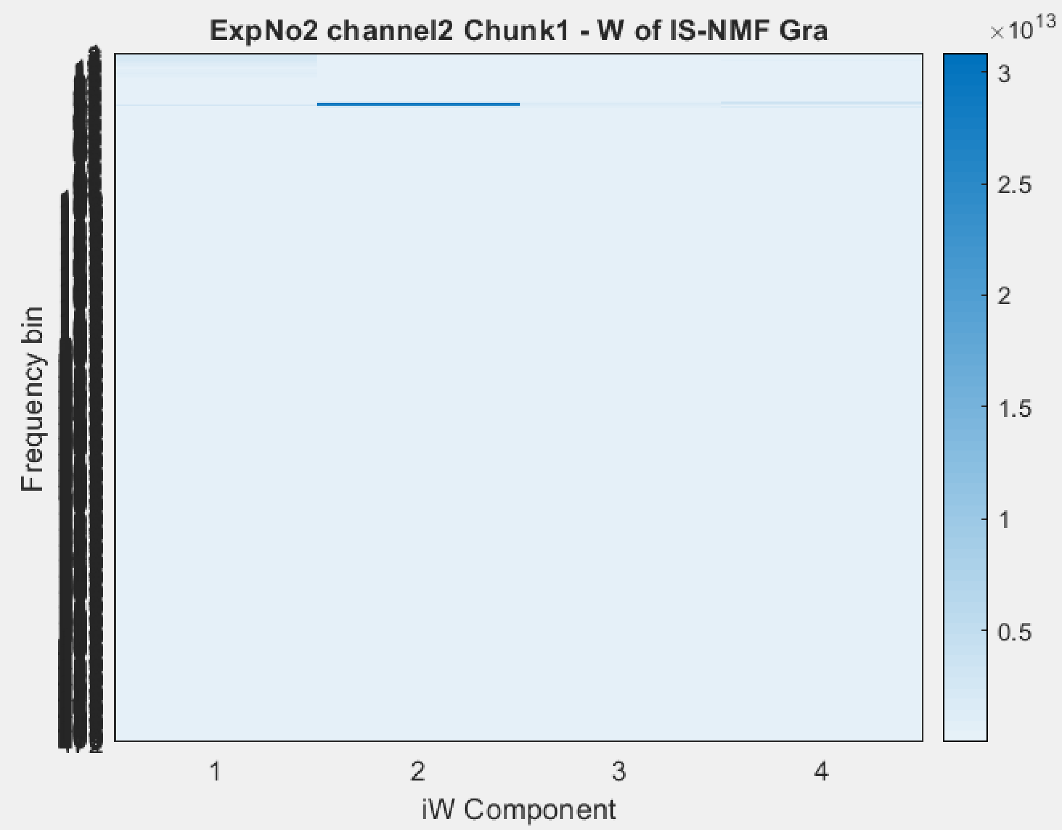
Results: IS-NMF denoising workflow

Depends on the data itself:

The **number of hidden components** can not **too small** or **too large**.



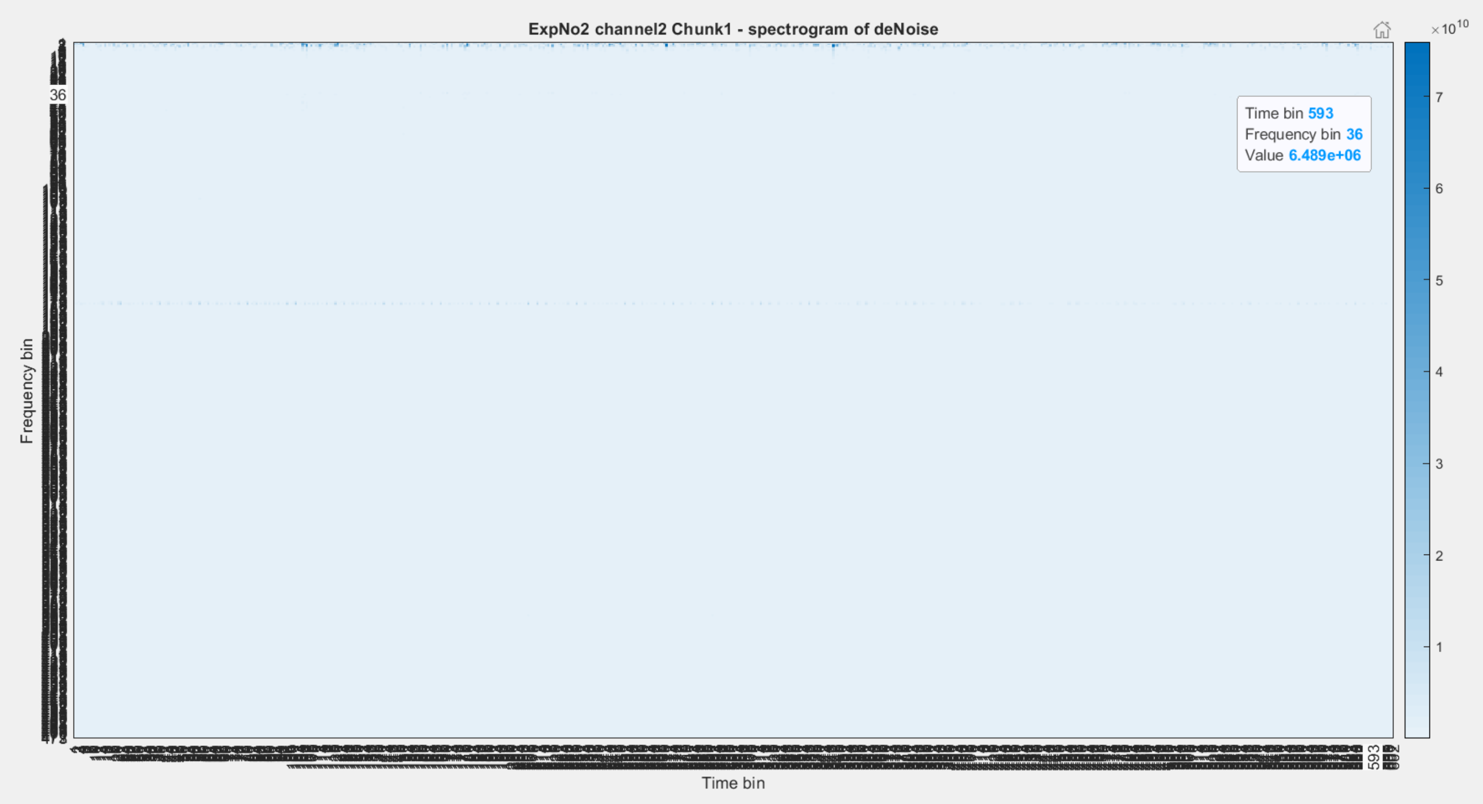
Too little components in the **Ephy Signal** case

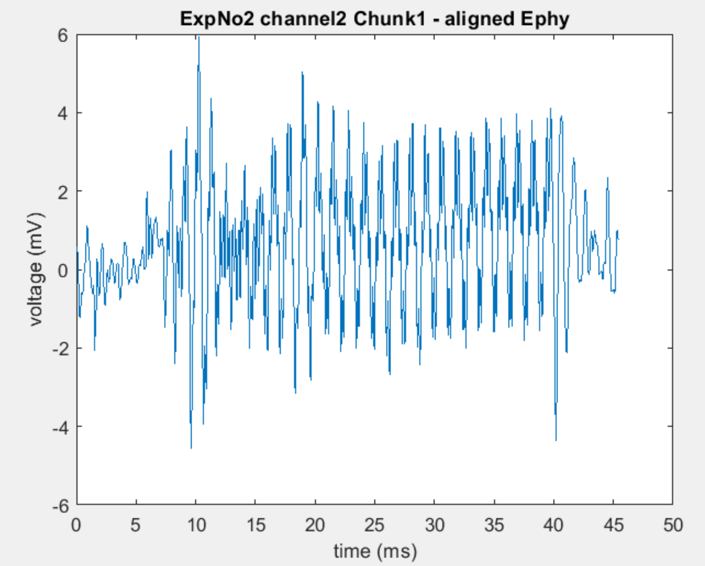


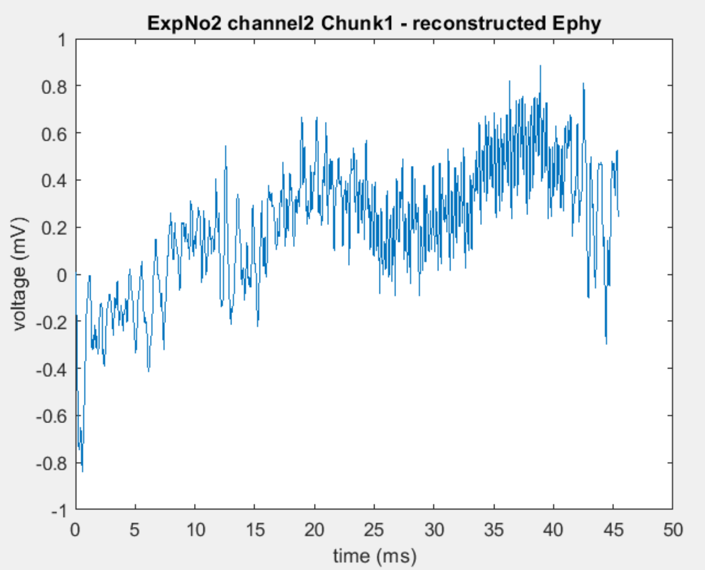
Too many components in the **Gradient Signal** case

Results: IS-NMF denoising workflow

5.5 Reconstruct via **Wiener filter** (**H** matrix as coefficients) and **Inverse STFT**

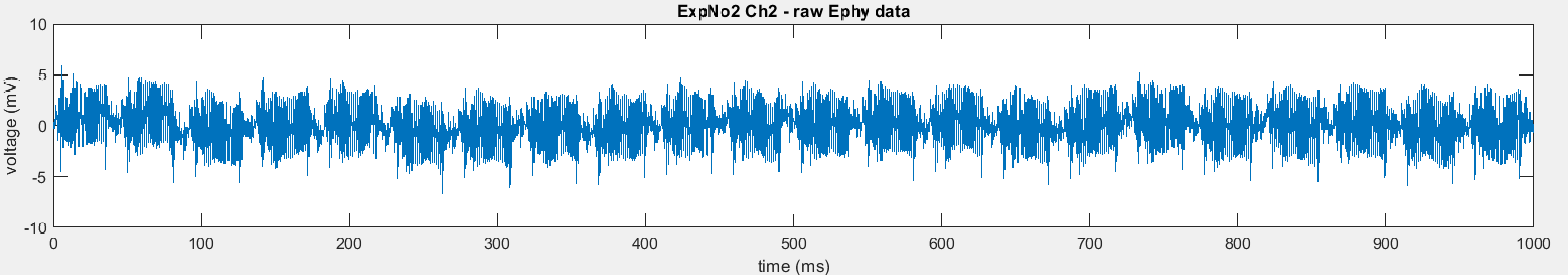


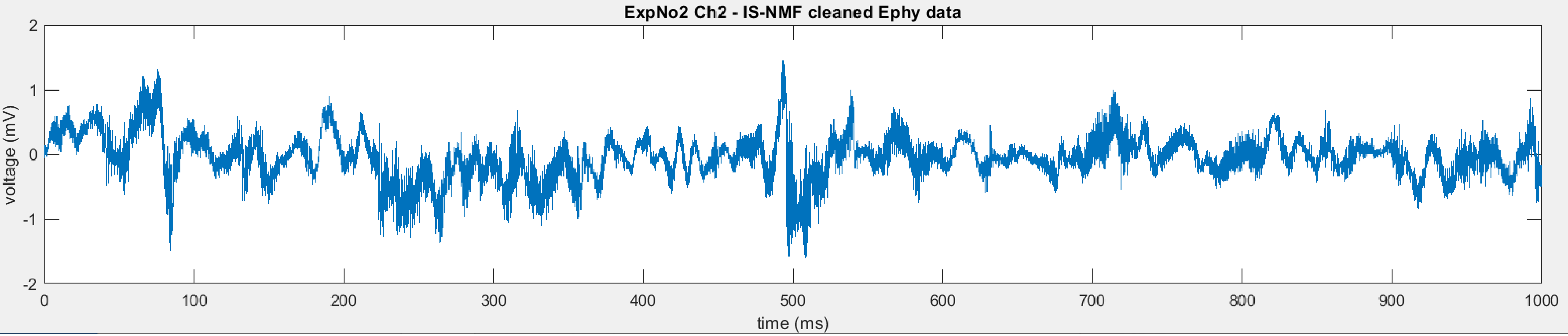




Results: IS-NMF denoising workflow

6. Postprocess
7. Evaluation





Summary and Future Work

Summary

- **Noise source:** fMRI gradient artifacts
- **Solutions:**
  - **Hardware:** compensation circuits;
  - **Software:** AAS, PCA, **IS-NMF**.
- **Results:** IS-NMF denoising workflow

Future Work

1. Choose **N hidden components**

2. Local minima and **convergence**

3. Ground truth for **feedback learning**

References

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Thank you
Q&A