Understanding our Baseline: Noise Mitigation and Modelling

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QUEST-DMC Collaboration Meeting
University of Liverpool
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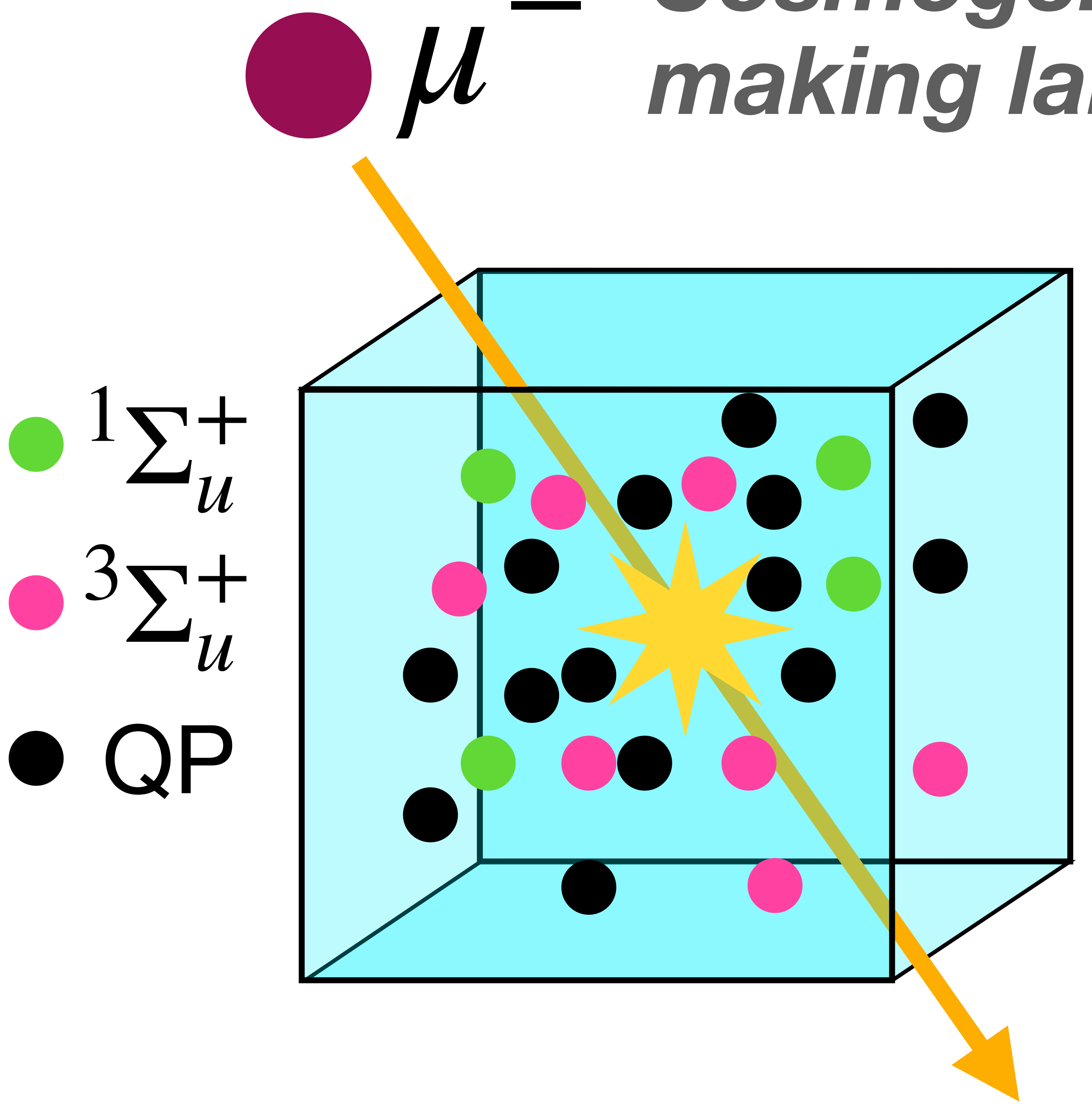
Cosmogenic Baseline Noise

Cosmogenic muons deposit a lot of energy, making large population of excimers



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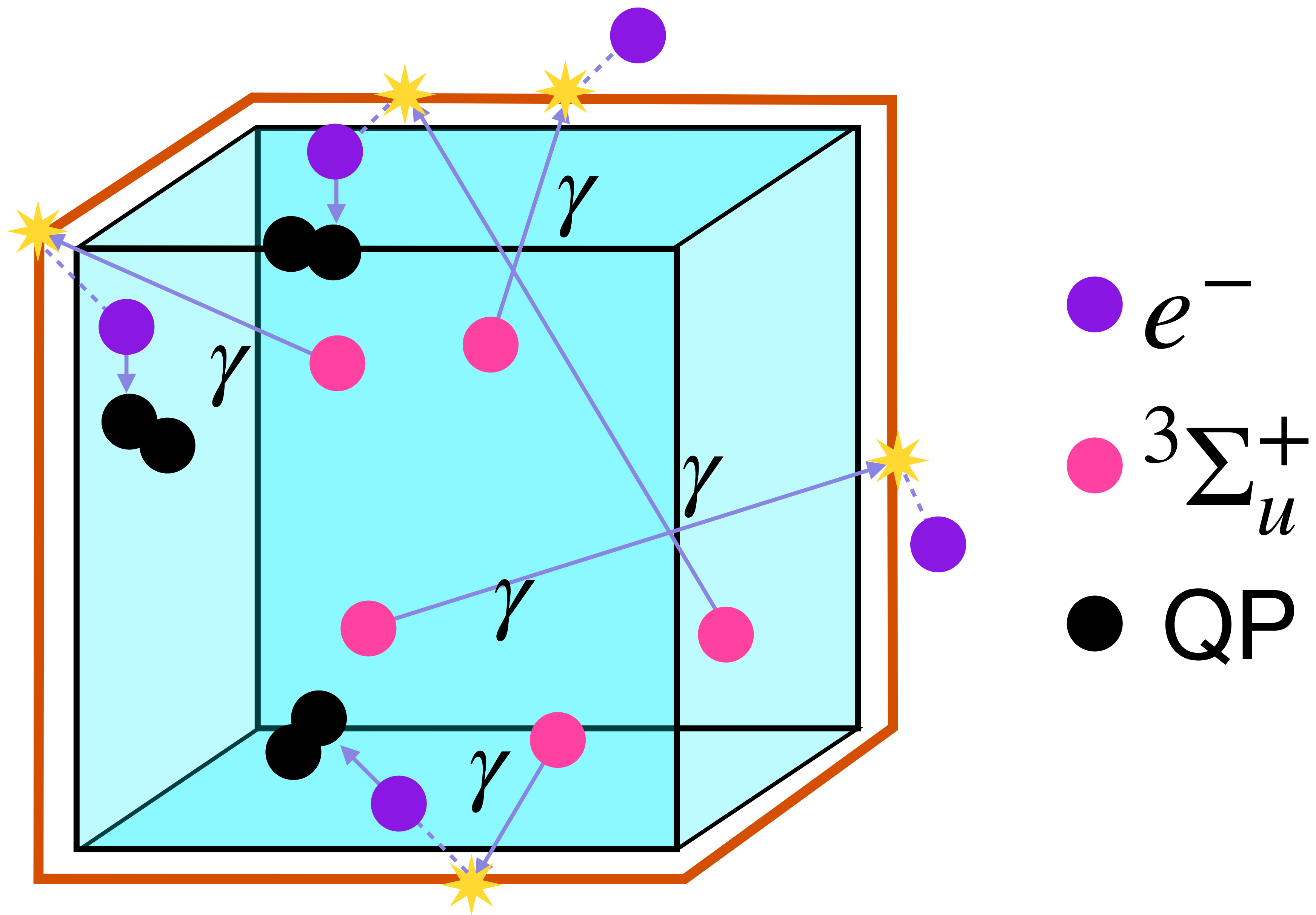
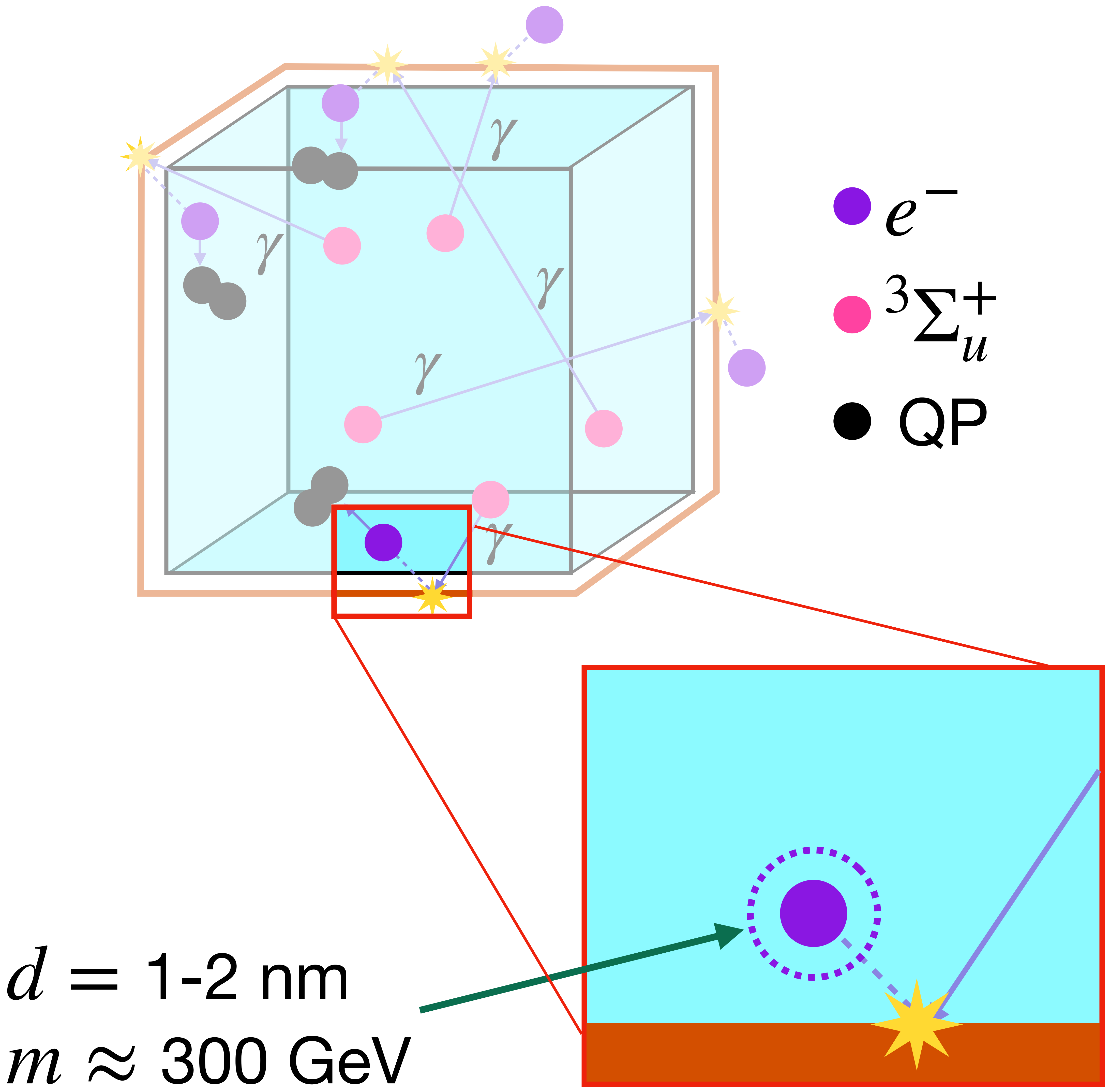


$$^1\Sigma_u^+ \xrightarrow{\sim\text{ns}} 2\ {}^3\text{He} + \gamma$$

$$^3\Sigma_u^+ \xrightarrow{\sim 13\text{s}} 2\ {}^3\text{He} + \gamma$$

Long lived excimers emit EUV photons, generating ~10 eV photoelectrons at He-Cu interface

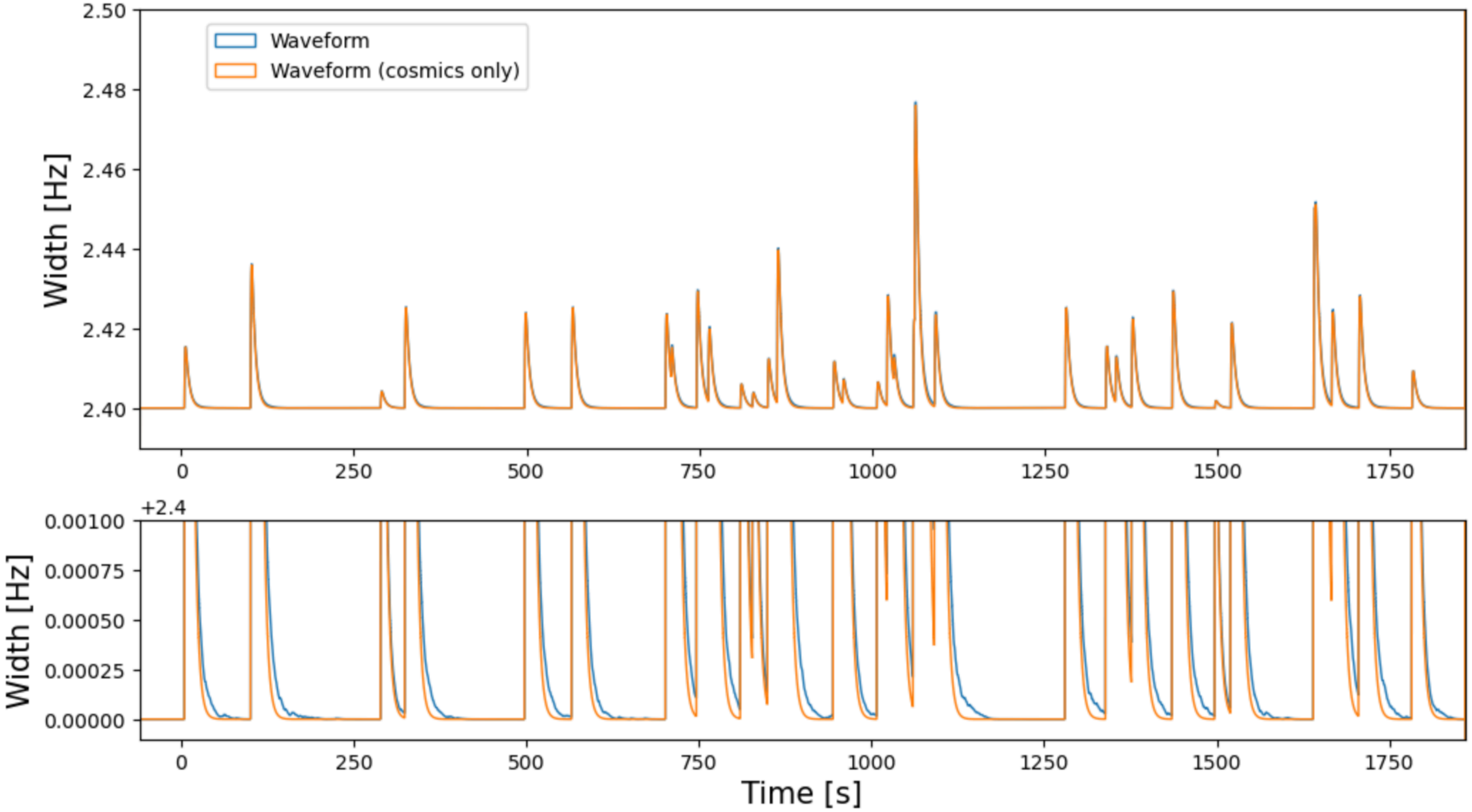
Cosmogenic Baseline Noise



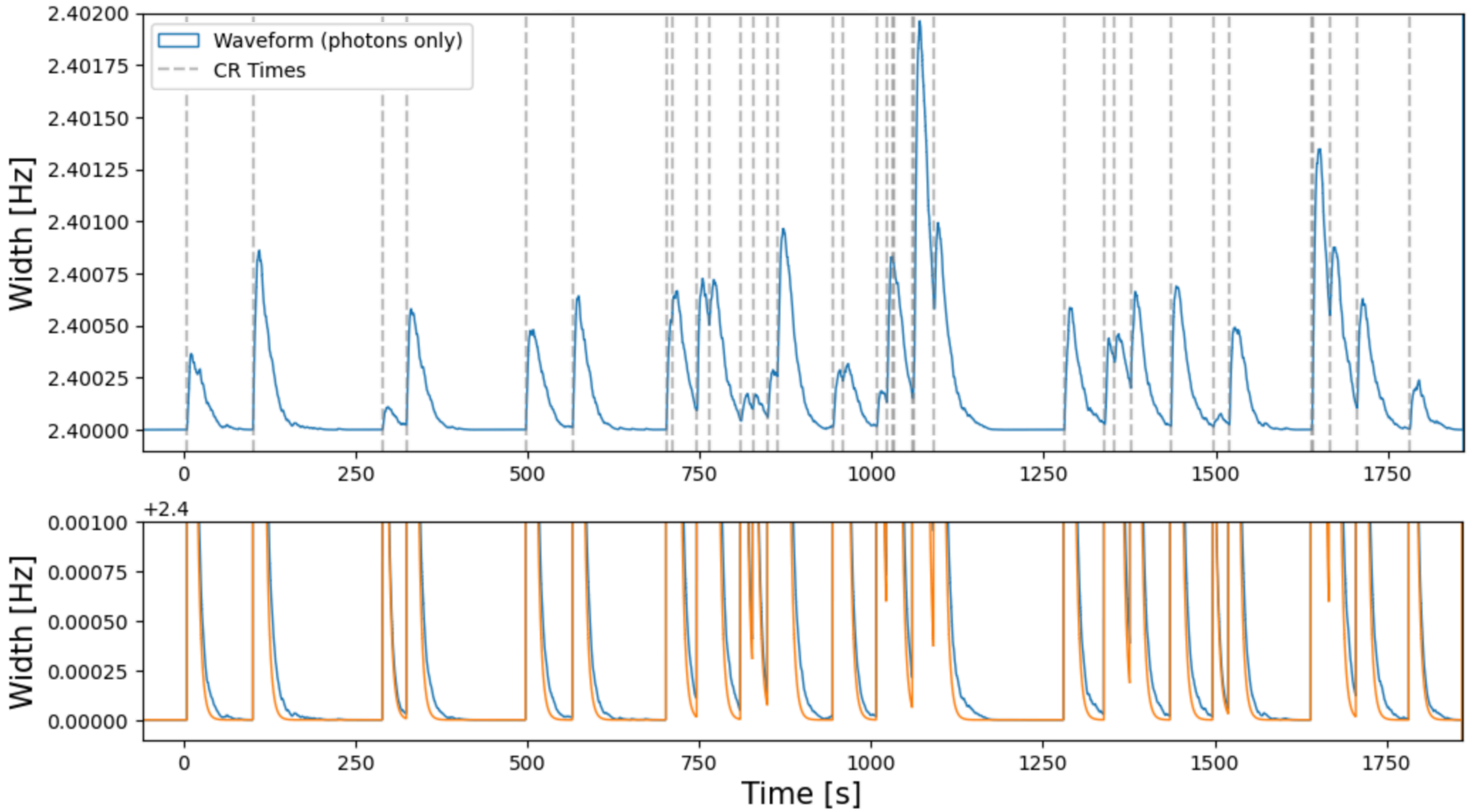
Electron Bubbles

- When electrons are injected into the superfluid ^{3}He, a "bubble" forms around it with an effective mass ~300 GeV
- Cu photoelectric work function is 5 eV, He scintillation photon energy is 15 eV, photoelectrons therefore have ~10 eV
- An electron bubble carrying 10 eV kinetic energy is moving at 2.4 km/s
- This is 4-5 orders of magnitude higher than the Landau critical velocity ($\mathcal{O}$(cm/s))
- Bubble energy dissipation should happen rapidly via quasiparticle generation

Cosmogenic Baseline Noise

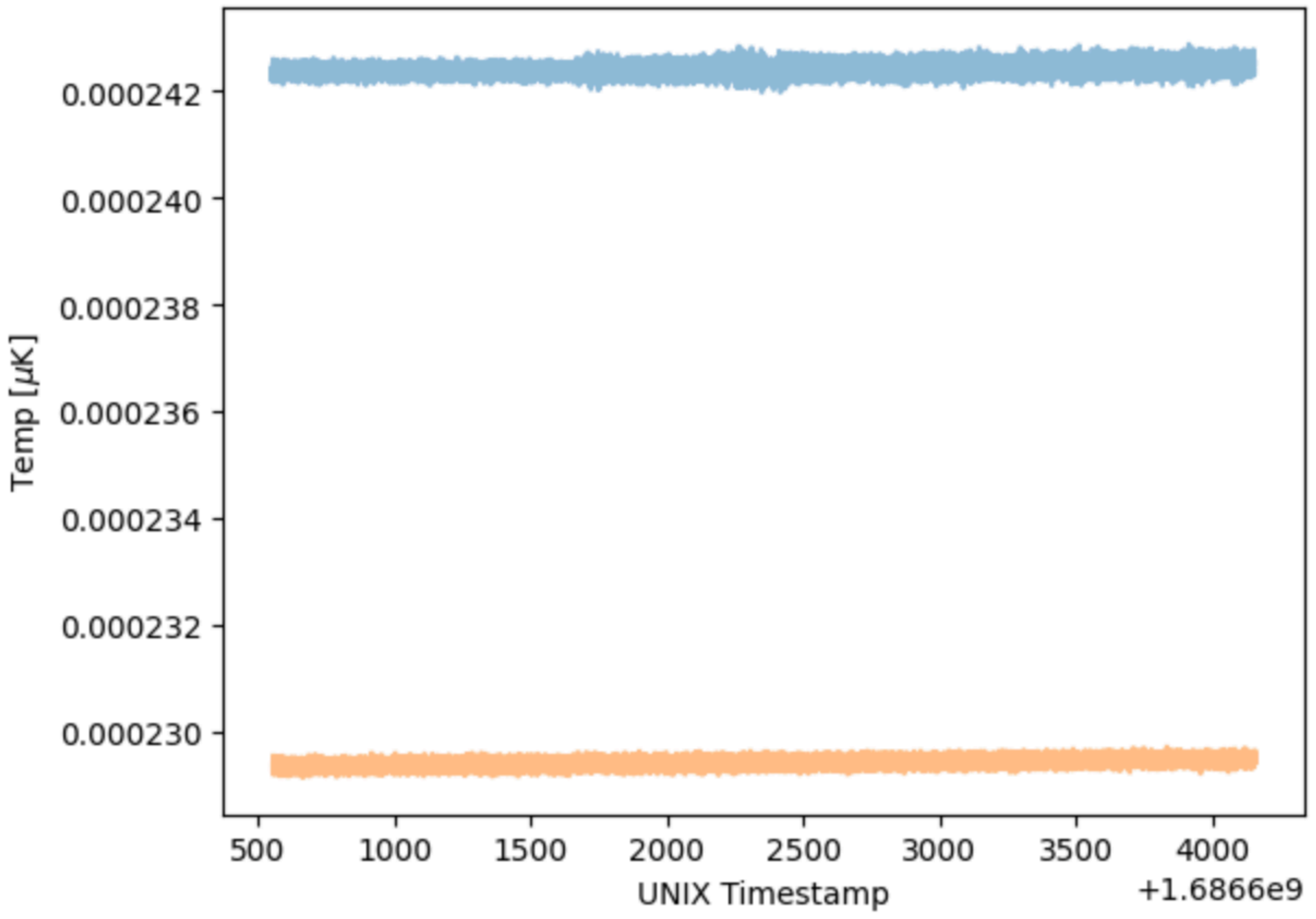


Cosmogenic Baseline Noise

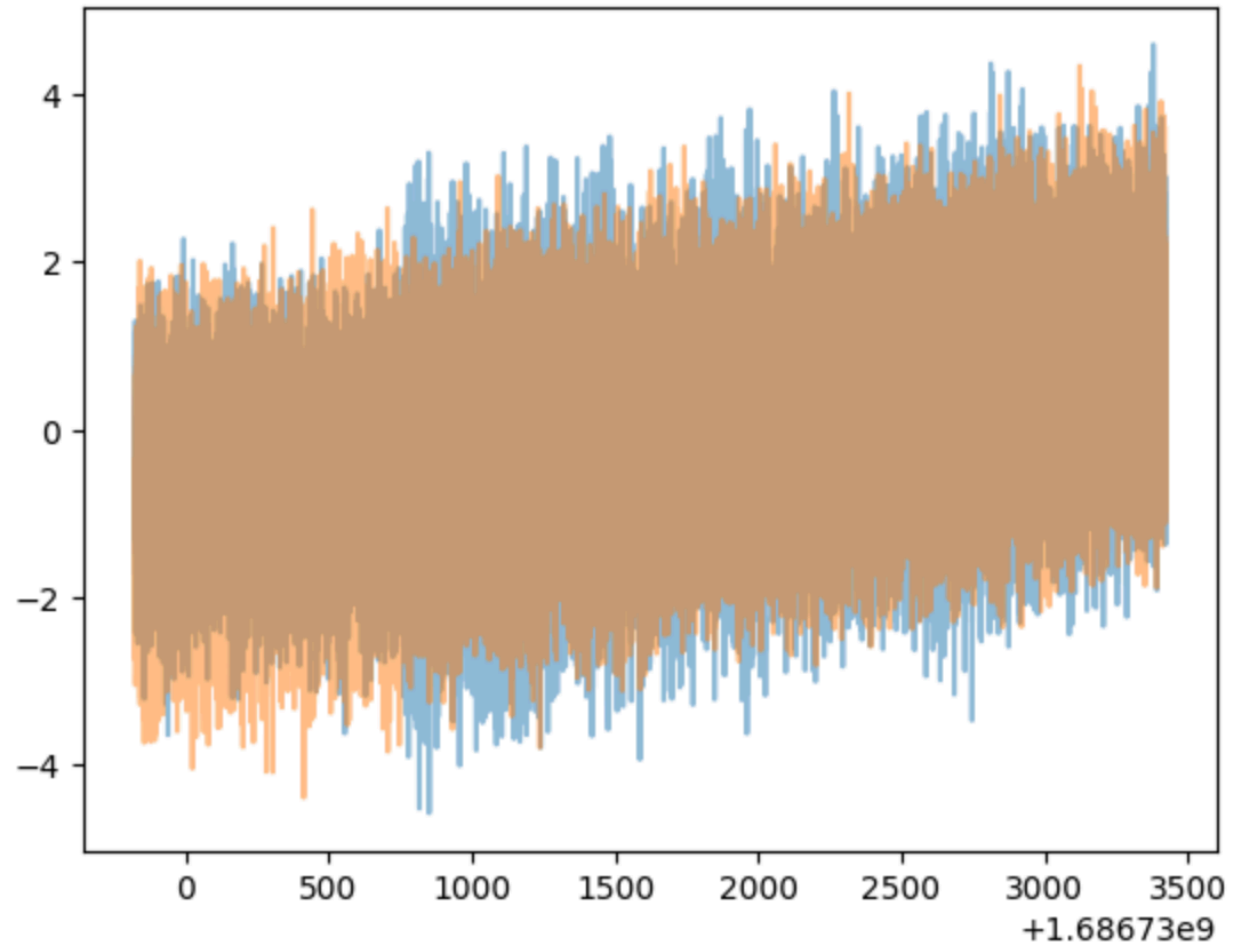


Acoustic/Vibrational Noise

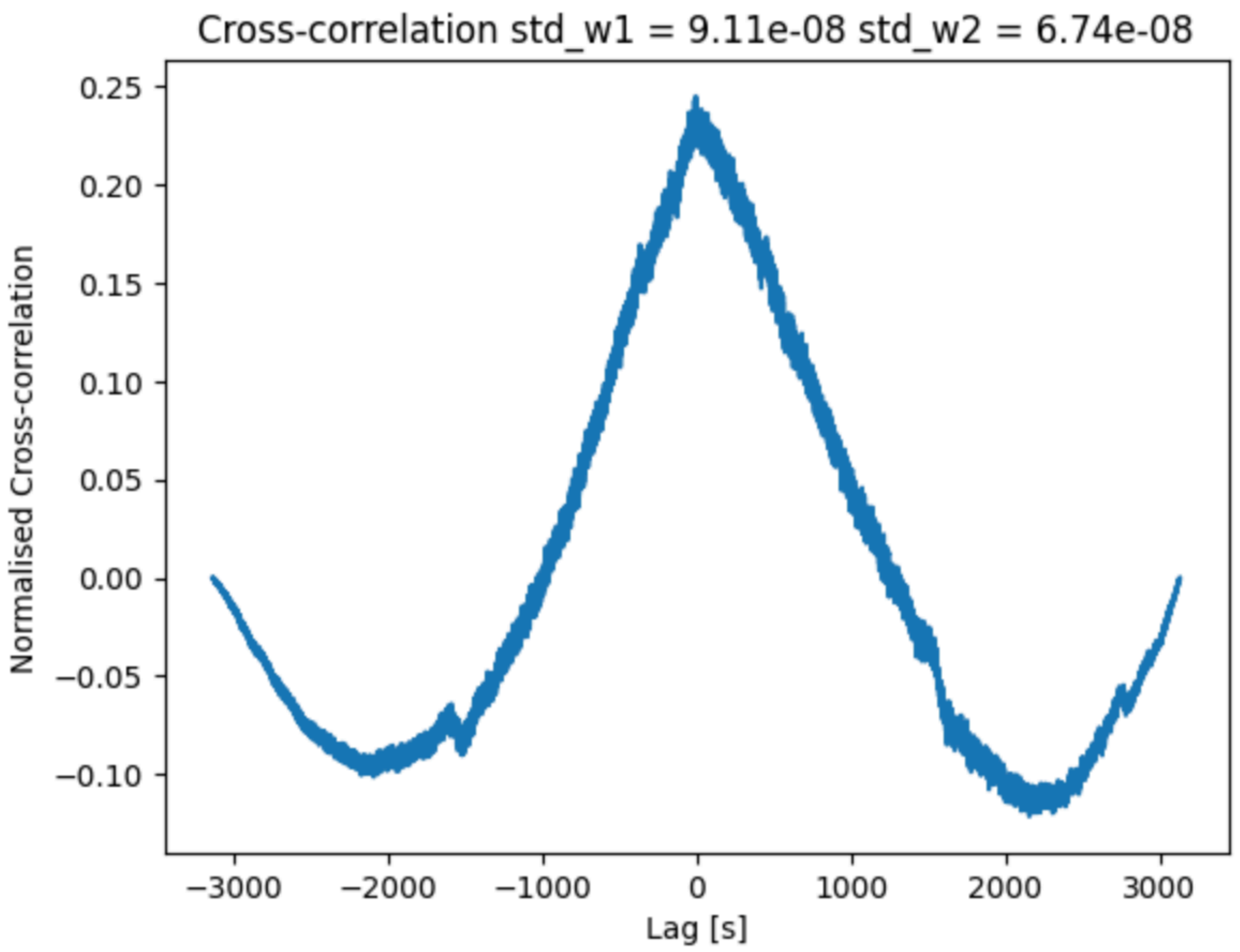
- Two bolometers in the same fridge will be subject to the same acoustic and vibrational environment
- If there is shared acoustic and vibrational noise, this will produce cross-correlation between channels



Start with two bolometer baseline signals



Subtract their means



Compute

$$R(l) = \frac{1}{(N-1)\sigma_x\sigma_y}\sum_{i}^{N} x_i y_{i-l}$$

All plots here, courtesy of Rob Smith 🙂

Principal Component Analysis

Intuitively:

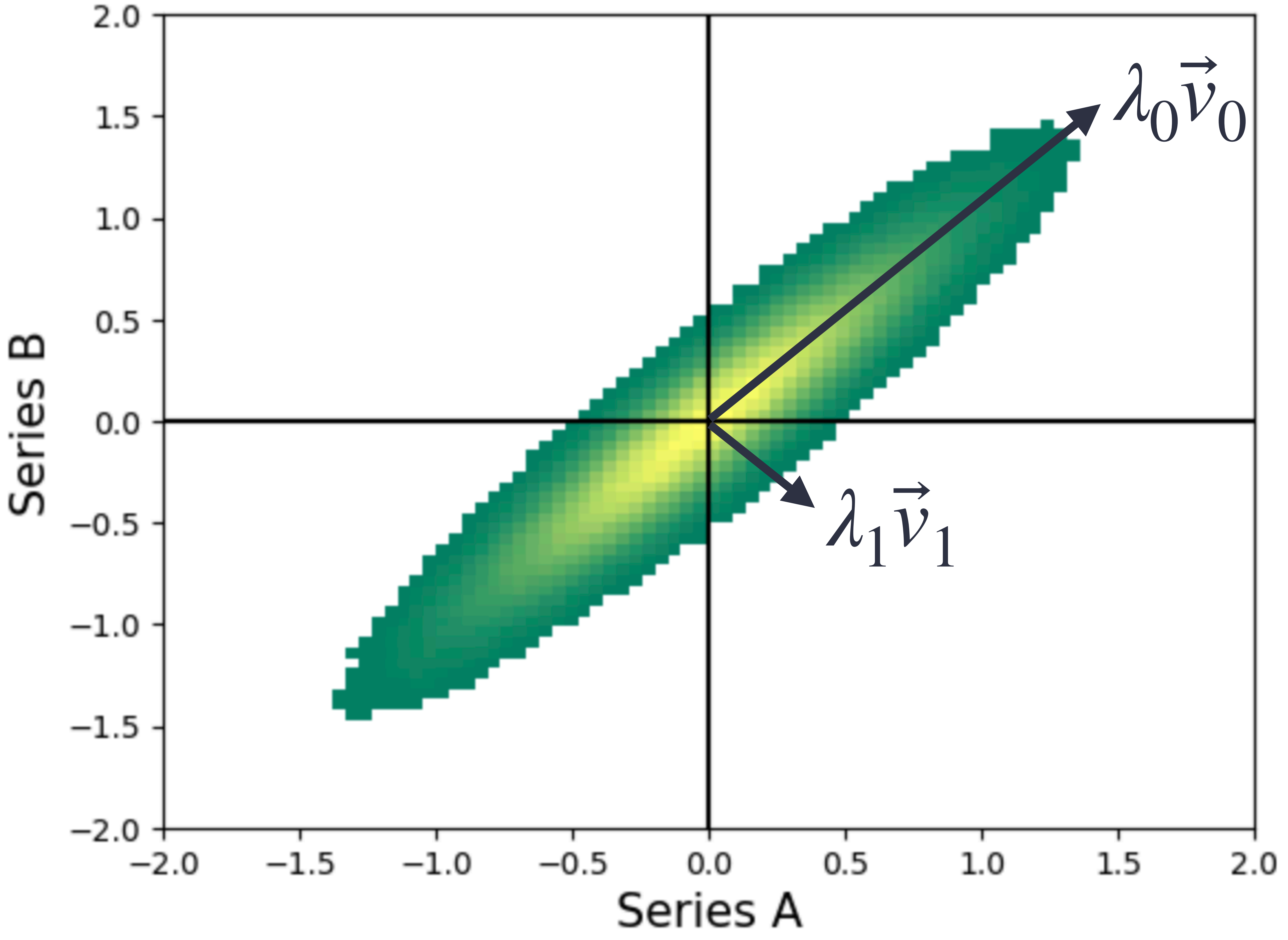
Principal component analysis (PCA) finds the dominant patterns of variation in multivariate data. In our case, we might consider time-series data from two bolometers ***A*****,** ***B***

$$\begin{aligned} A &= [a_1, a_2, a_3, \ldots, a_N] \\ B &= [b_1, b_2, b_3, \ldots, b_N] \end{aligned} \quad \Rightarrow \quad X = \begin{bmatrix} a_1 & a_2 & a_3 & \ldots & a_N \\ b_1 & b_2 & b_3 & \ldots & b_N \end{bmatrix}$$

Assuming:
$E[A] = E[B] = 0$

$$\frac{1}{N-1} X X^\top = \begin{bmatrix} \sigma_A^2 & \mathrm{cov}(A, B) \\ \mathrm{cov}(A, B) & \sigma_B^2 \end{bmatrix} = C$$

Principal Component Analysis



Eigen-decomposition:

The covariance matrix C can be factored into matrices constructed by its eigenvectors $\vec{v}$ and eigenvalues λ

$$C = V \Lambda V^\top$$

$$\underbrace{V = [\vec{v}_0, \vec{v}_1]} \qquad \Lambda = \mathrm{diag}(\lambda_0, \lambda_1)$$

Transformation matrix that mixes time series data into projections upon covariance eigenvectors

Principal Component Analysis

$$V^\top X = \begin{bmatrix} v_{00} & v_{10} \\ v_{01} & v_{11} \end{bmatrix}^\top \begin{bmatrix} a_1 & a_2 & a_3 & \dots & a_N \\ b_1 & b_2 & b_3 & \dots & b_N \end{bmatrix} = \begin{bmatrix} s_1 & s_2 & s_3 & \dots & s_N \\ t_1 & t_2 & t_3 & \dots & t_N \end{bmatrix}$$

Defines new series S and T; i.e. *principal components* of X

Quick example with:

$$A = \cos(t) \;\&\; B = \cos(t)$$

$$X = \begin{bmatrix} \cos(t_1) & \cos(t_2) & \dots & \cos(t_N) \\ \cos(t_1) & \cos(t_2) & \dots & \cos(t_N) \end{bmatrix}$$

$$C = \frac{1}{2}\begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \Rightarrow \Lambda = \frac{1}{\sqrt{2}}\begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$$

$$\therefore \; S = \frac{1}{\sqrt{2}}\big(\cos(t) + \cos(t)\big) = \sqrt{2}\cos(t)$$

$$T = \frac{1}{\sqrt{2}}\big(\cos(t) - \cos(t)\big) = 0$$

Principal Component Analysis

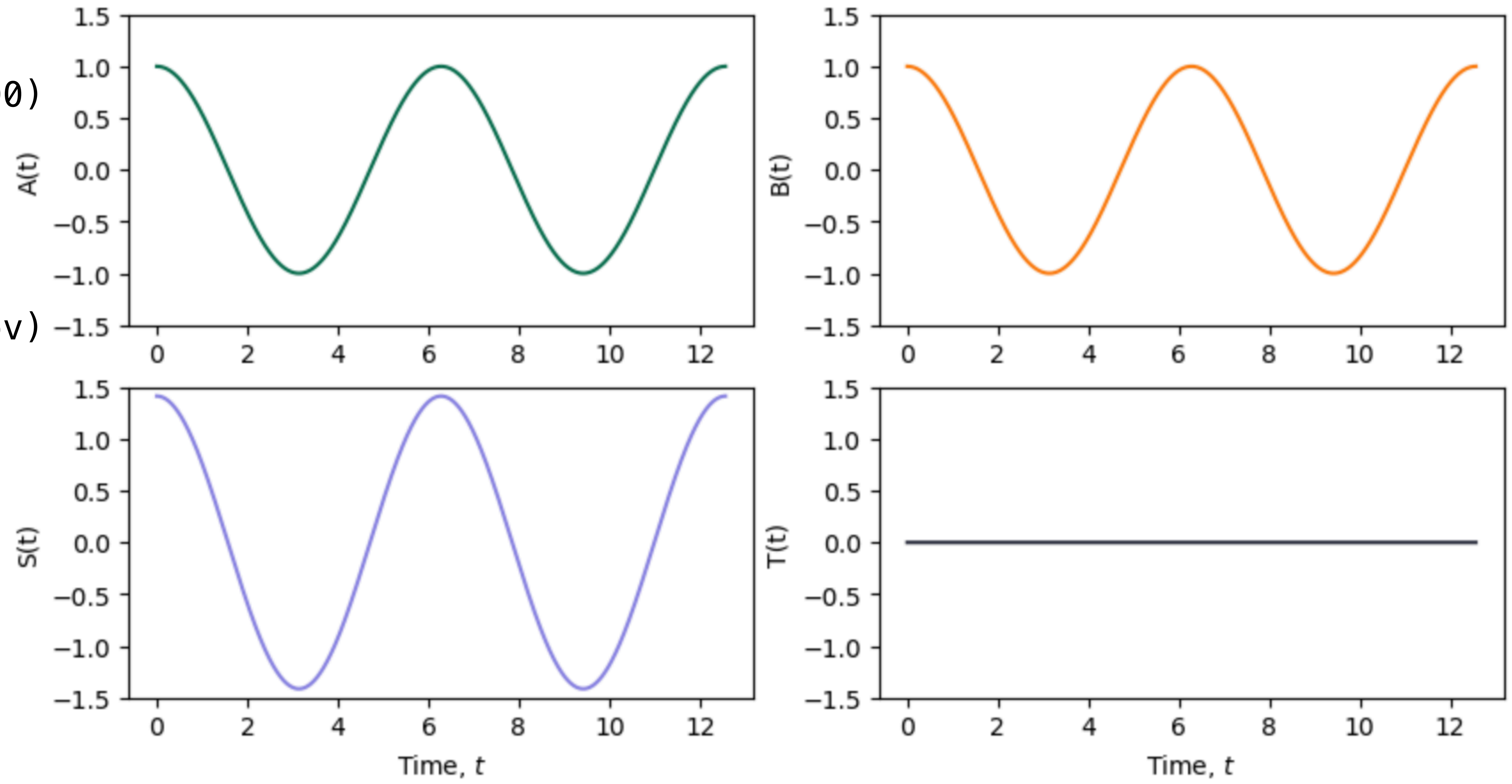
Et voila!

```
import numpy as np

t = np.linspace(0,4.*np.pi,100)
A = np.cos(t)
B = np.cos(t)

X = np.stack([A,B])
cov = np.cov(X)
Lambda, V = np.linalg.eigh(cov)

S, T = V.T @ X
```

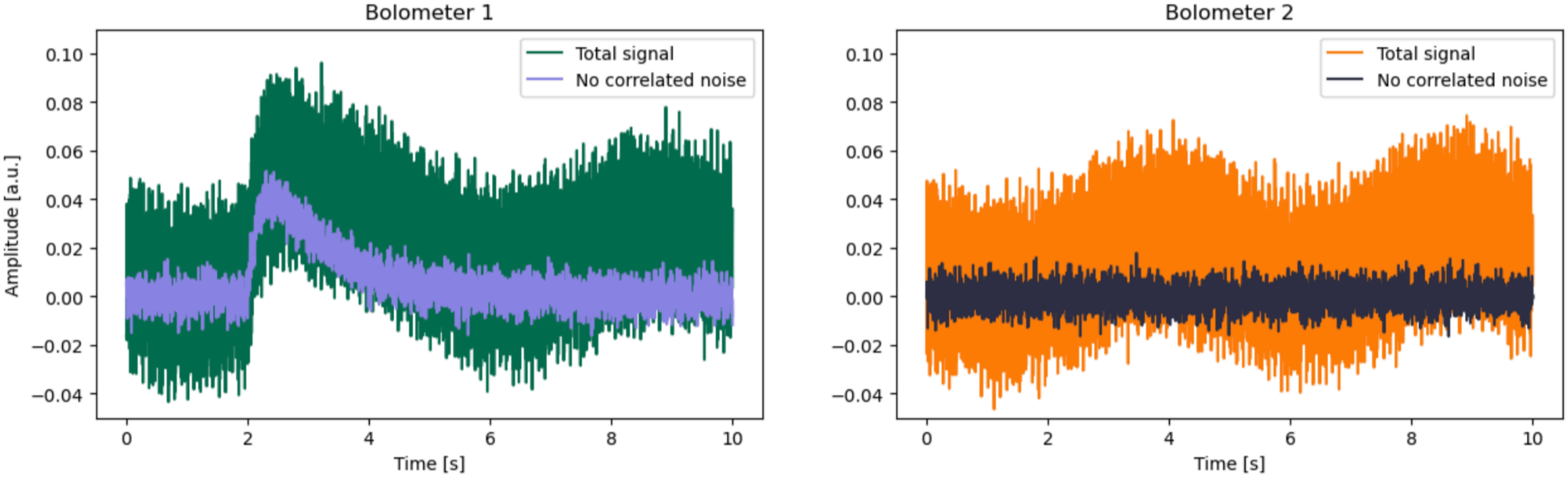


Principal Component Analysis

Now let's make something a little more realistic

Two bolometer time series over 10s with 3 components:

I. Gaussian baseline fluctuations as a proxy for Johnson-Nyquist noise (independent in each channel)
II. Sinusoidal acoustic/vibrational noise components at several frequencies (shared between channels)
III. Small Winkelmann pulse at 2s (only appearing in one channel)



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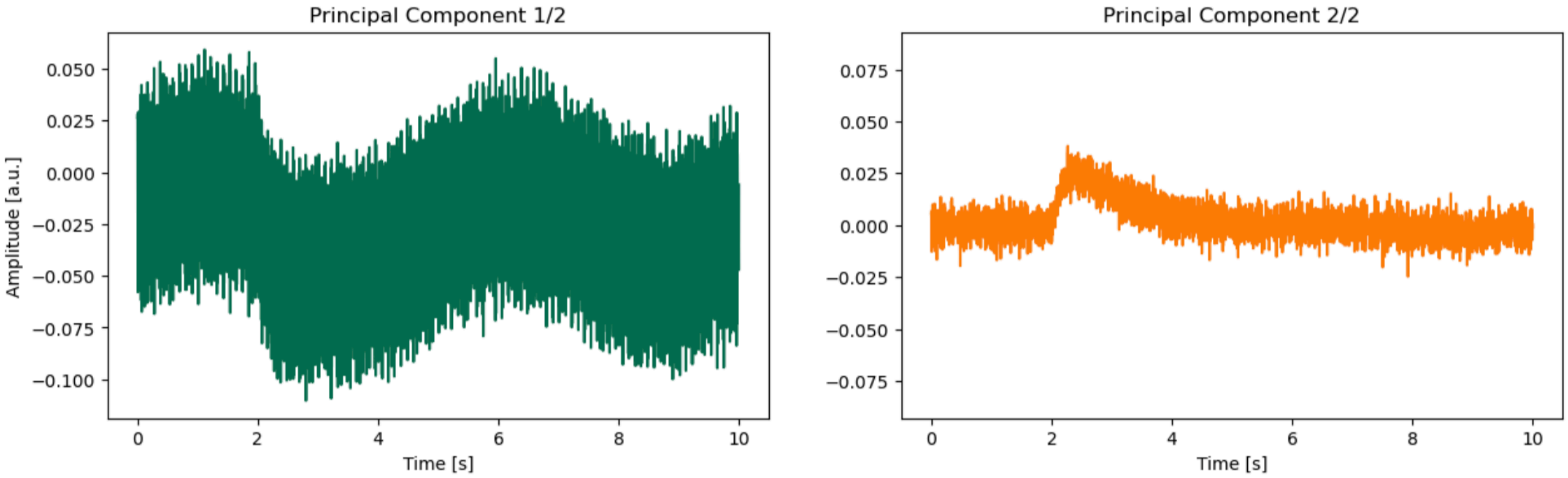

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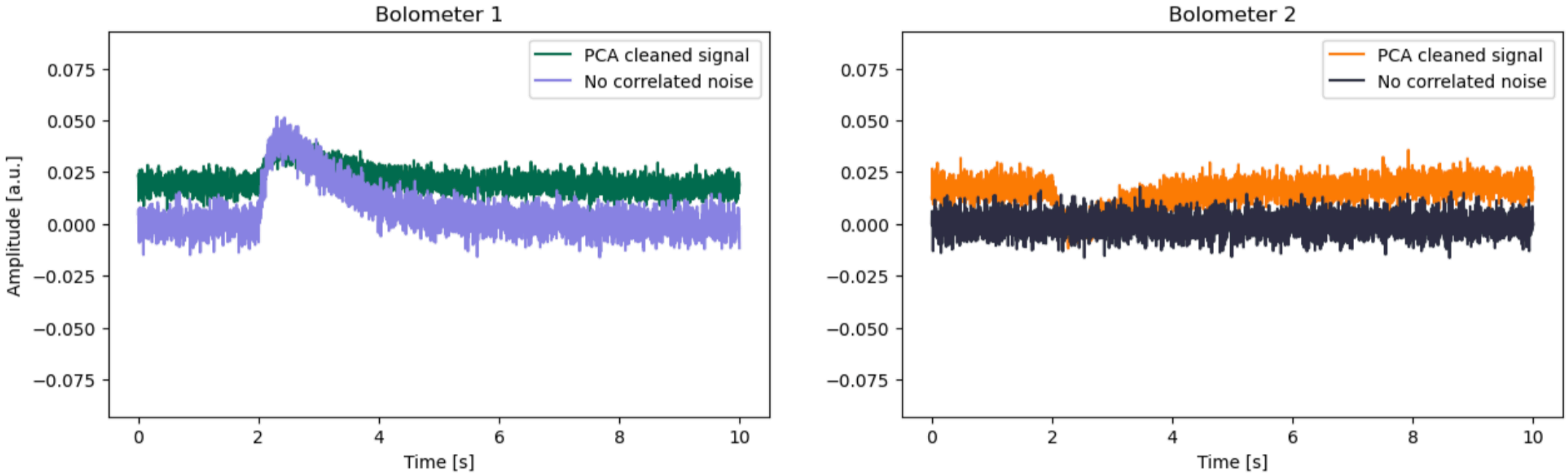
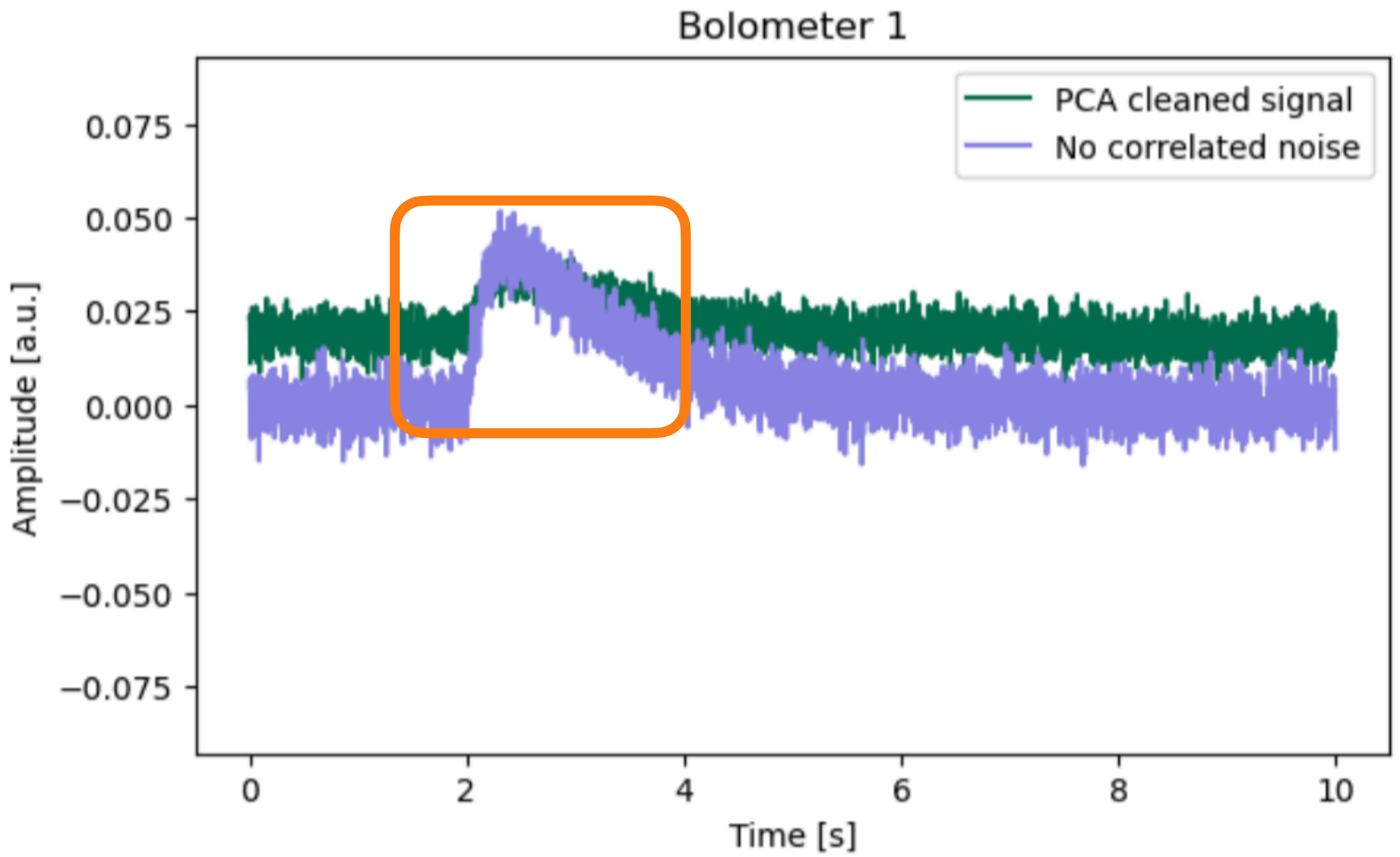
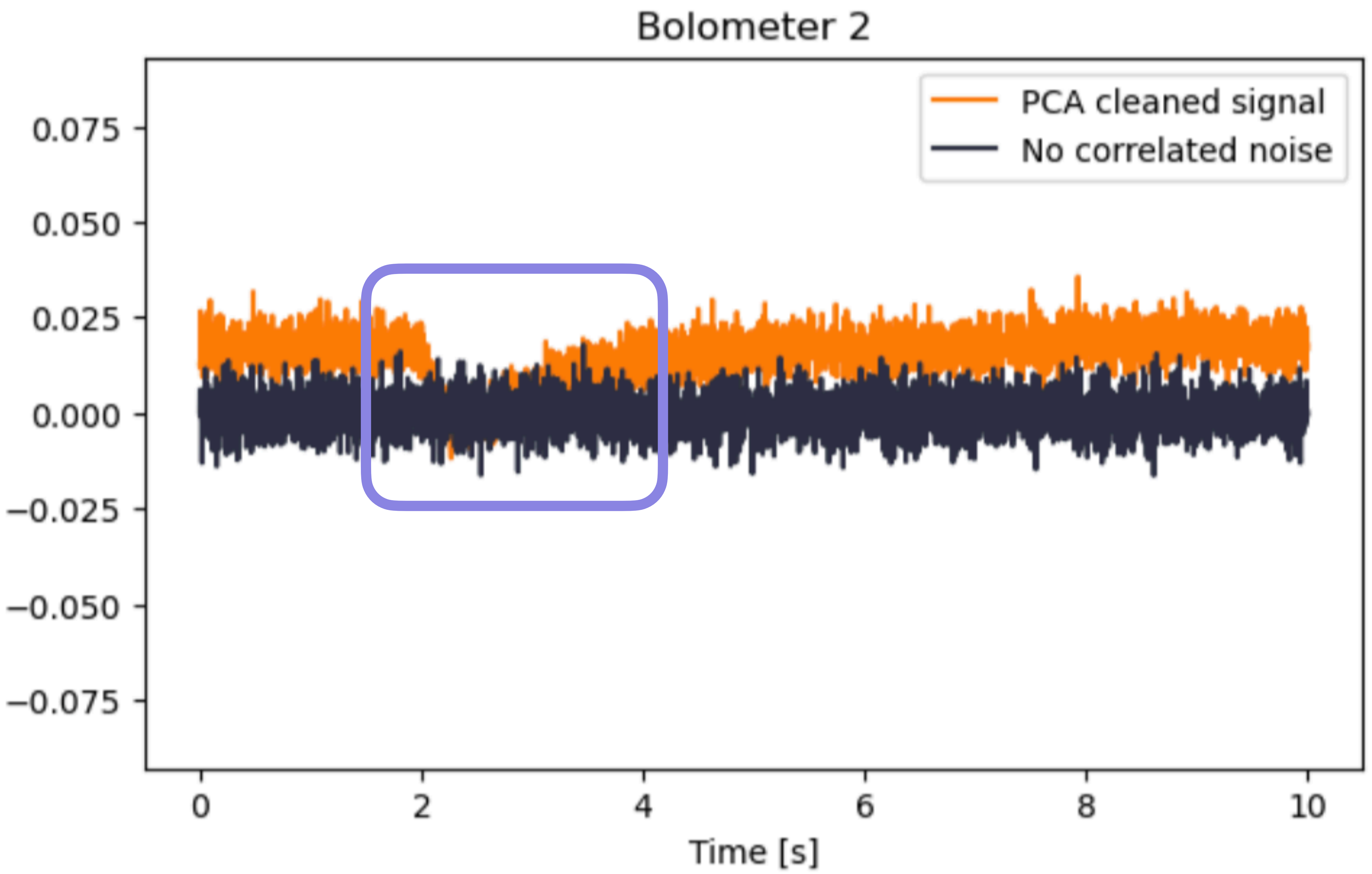


Principal Component Analysis

Why does this happen?

- Essentially because the Winkelmann pulse happens to rise and fall on somewhat similar timescales as one or more of the acoustic noise sinusoid modes
- Some of that correlation ends up being attributed to the acoustic noise and is removed from both bolometer signals when we filter it out





Independent Component Analysis

Intuitively:

Independent component analysis (ICA) is similar to PCA, but with an additional condition that components must be statistically independent (i.e. not just uncorrelated). Start by proposing that observed data ***X*** *is the sum of physical sources* ***S*** *with some mixing* ***M***

$$X = \begin{bmatrix} a_1 & a_2 & a_3 & \dots & a_N \\ b_1 & b_2 & b_3 & \dots & b_N \end{bmatrix} = M\,S$$

Where $$S = \begin{bmatrix} \eta_1 & \eta_2 & \eta_3 & \dots & \eta_N \\ \zeta_1 & \zeta_2 & \zeta_3 & \dots & \zeta_N \end{bmatrix}$$

Pure, independent physics signals

Independent Component Analysis

As with PCA:

Assuming:

$E[\eta] = E[\zeta] = 0$

$SS^\top = I$

$$\frac{1}{N-1}XX^\top = C = \frac{1}{N-1}MM^\top = V\Lambda V^\top$$

Independent Component Analysis

As with PCA:

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But now we go further:

Because C *is symmetric and positive definite, we can write*

$$C = (V\Lambda^{1/2}V^\top)(V\Lambda^{1/2}V^\top)^\top \Rightarrow \text{So } M = V\Lambda^{1/2}V^\top?$$

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Yes, but not uniquely

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Yes, but not uniquely

More generally:

For <u>any</u> orthogonal matrix Q

$$C = (V\Lambda^{1/2}Q)(V\Lambda^{1/2}Q)^\top = V\Lambda V^\top \Rightarrow \therefore M = V\Lambda^{1/2}Q$$

Independent Component Analysis

The goal with ICA:

$$
\begin{aligned}
X &= M\,S \\
&= \left(V\Lambda^{1/2}Q\right) S \\
\therefore S &= \left(Q^{\top}\Lambda^{-1/2}V^{\top}\right) X
\end{aligned}
$$

Independent Component Analysis

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$$X = M\,S$$
$$= \left(V\Lambda^{1/2}Q\right)\,S$$
$$\therefore S = \left(Q^\top\Lambda^{-1/2}V^\top\right)\,X$$

Solve for $Q^\top$ such that components in data matrix S are statistically independent

- A number of algorithms already exist that handle this, including `FastICA` in the `scikit-learn` package

Independent Component Analysis

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\end{aligned}
$$

Solve for $Q^{\top}$ such that components in data matrix S are statistically independent

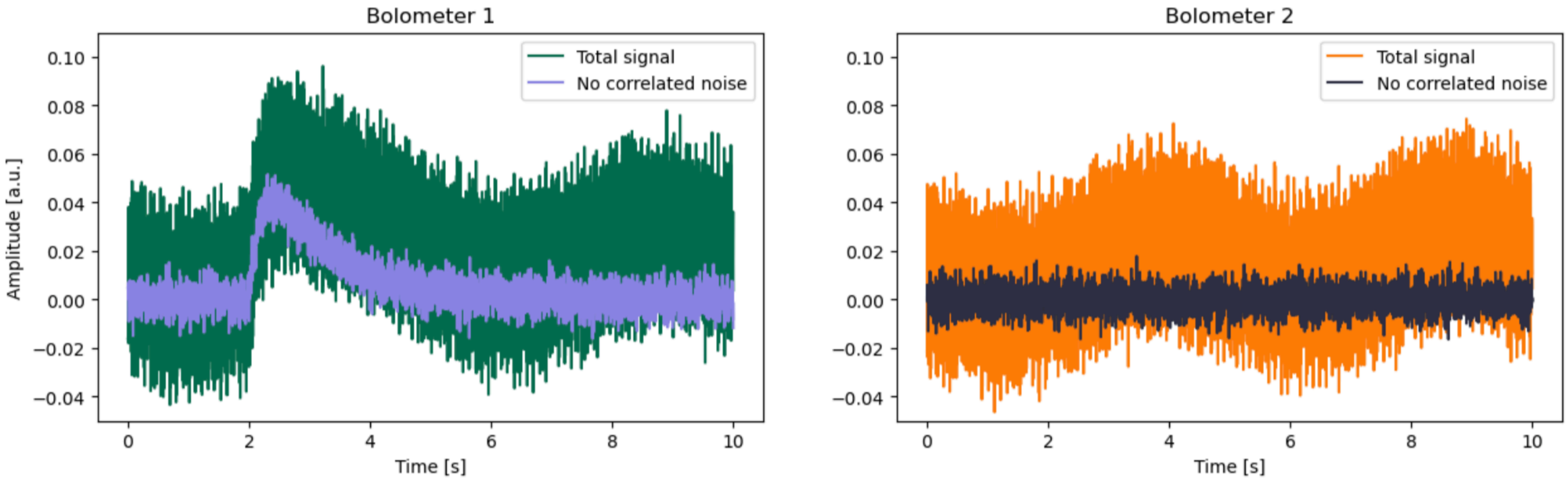
- A number of algorithms already exist that handle this, including `FastICA` in the `scikit-learn` package

What does this mean?

In PCA, we rotate into a data-space where variance is maximised (i.e. minimising off-diagonal elements of the covariance matrix), resulting in principal components that are *uncorrelated* but not necessarily *independent*. To achieve the latter, we need to maximise higher-order central moments alongside variance.

Independent Component Analysis

Let's try ICA on the same test setup as PCA



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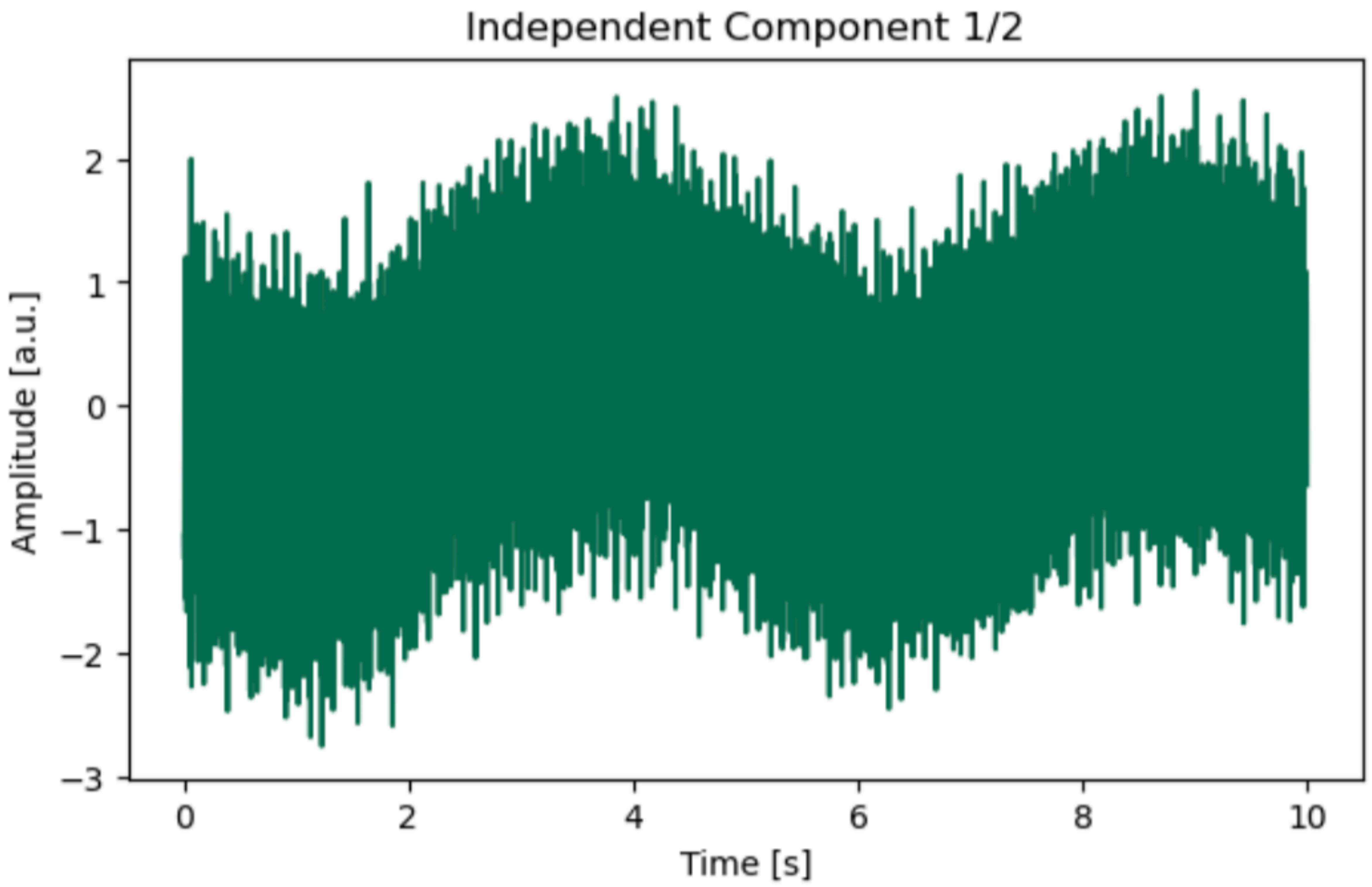

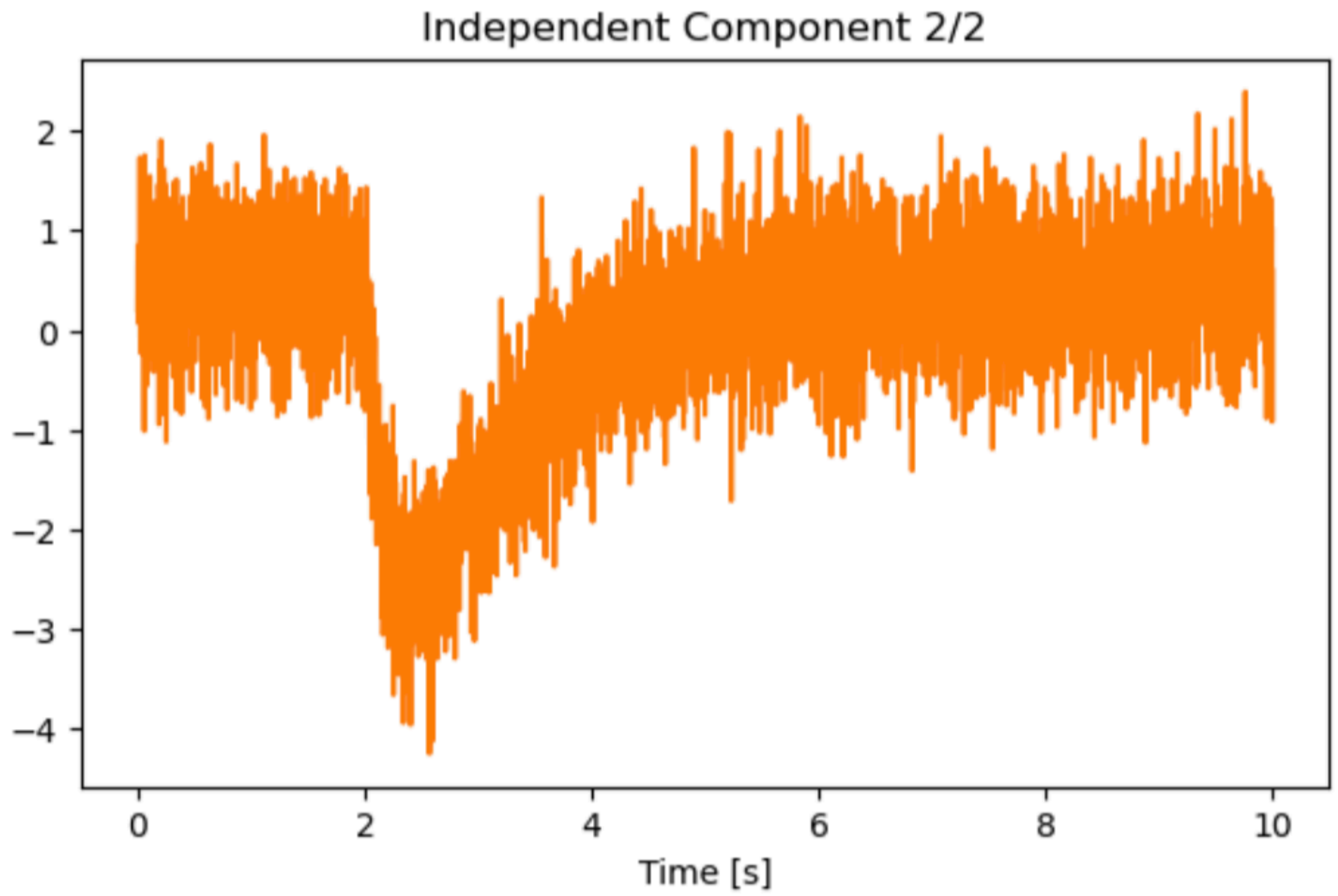

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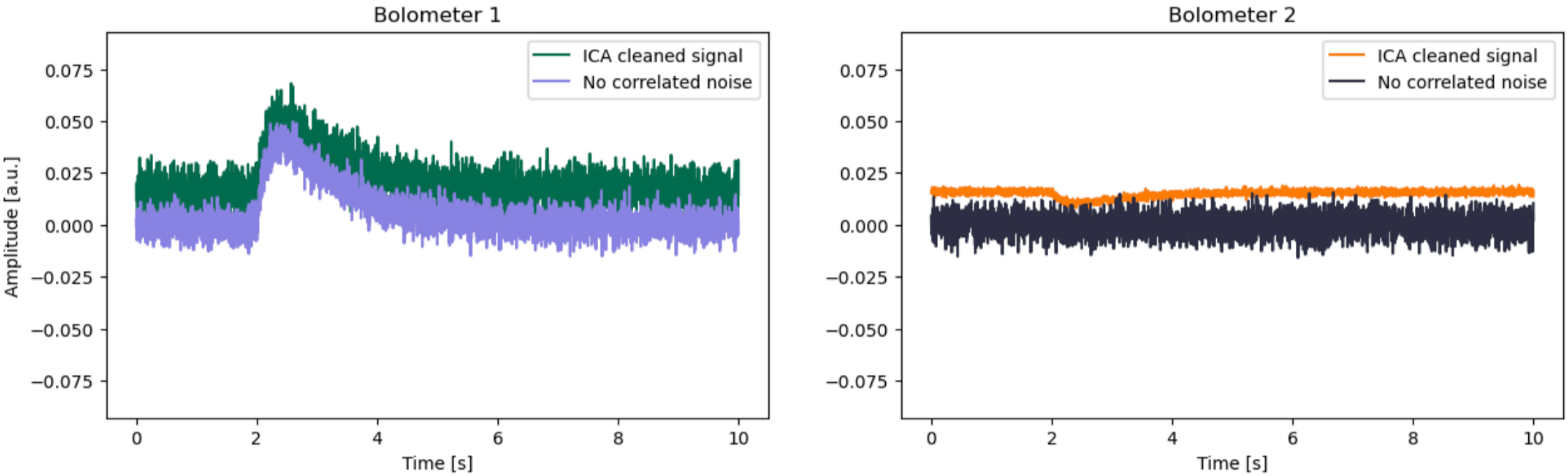
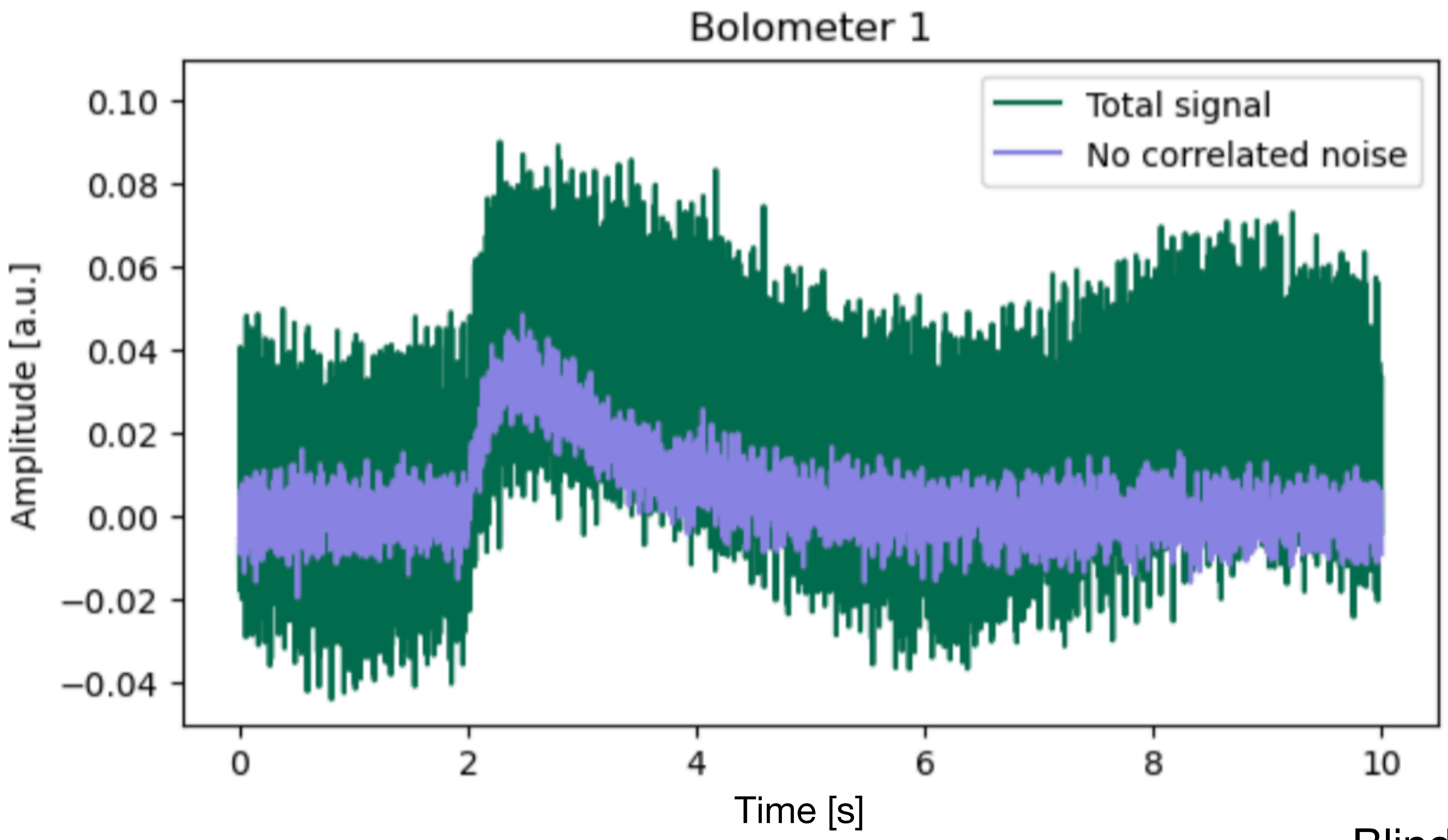
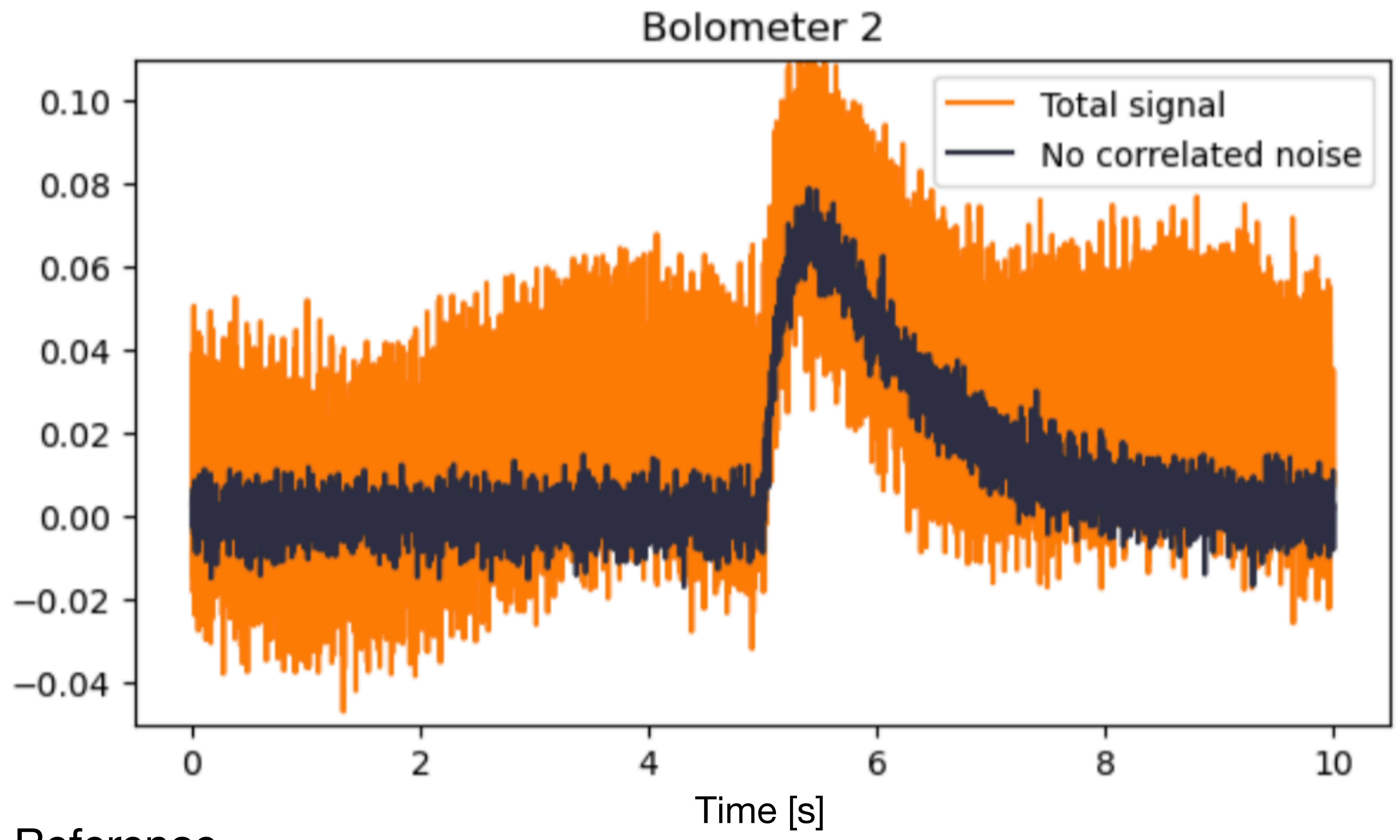
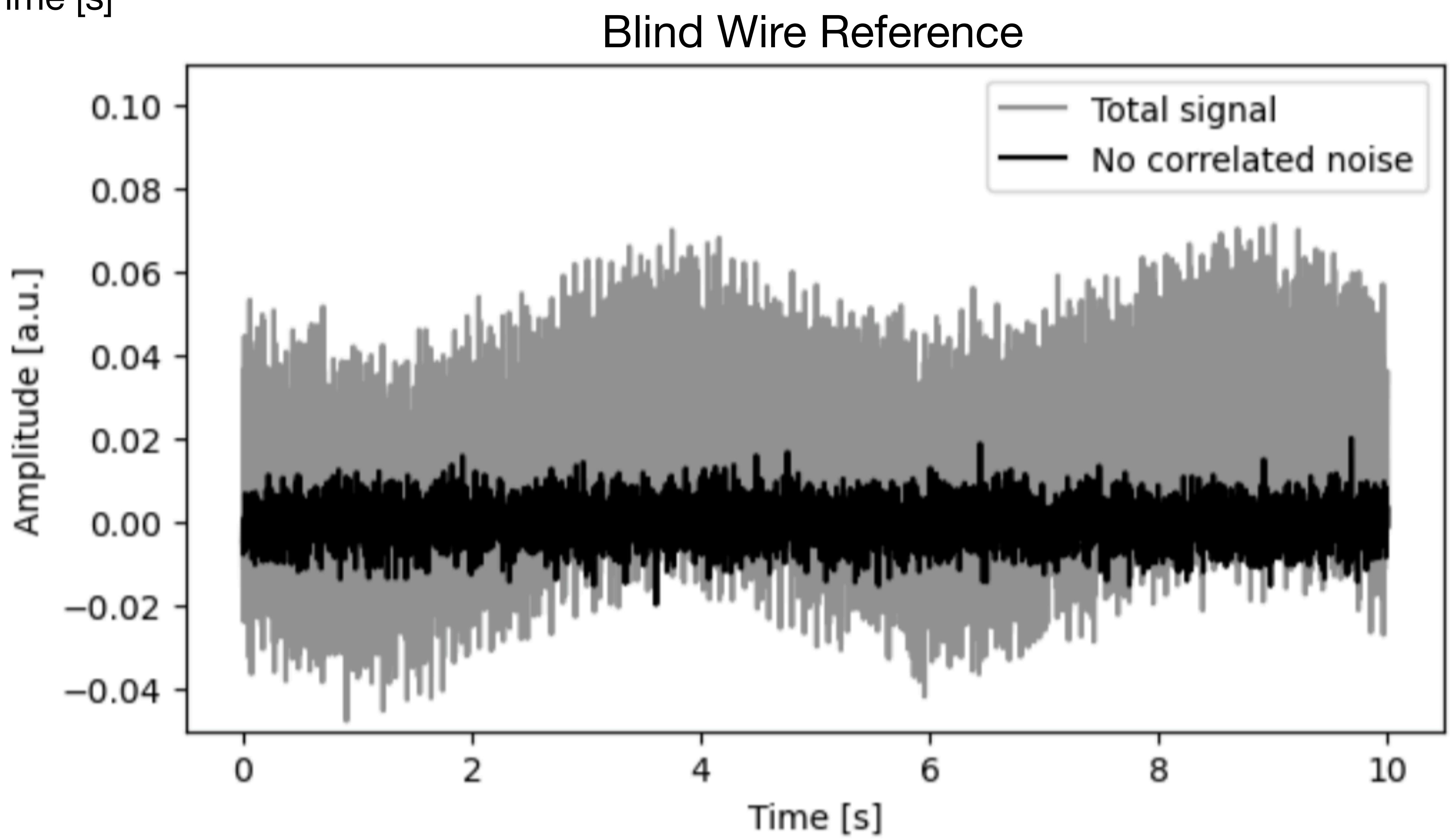


Independent Component Analysis



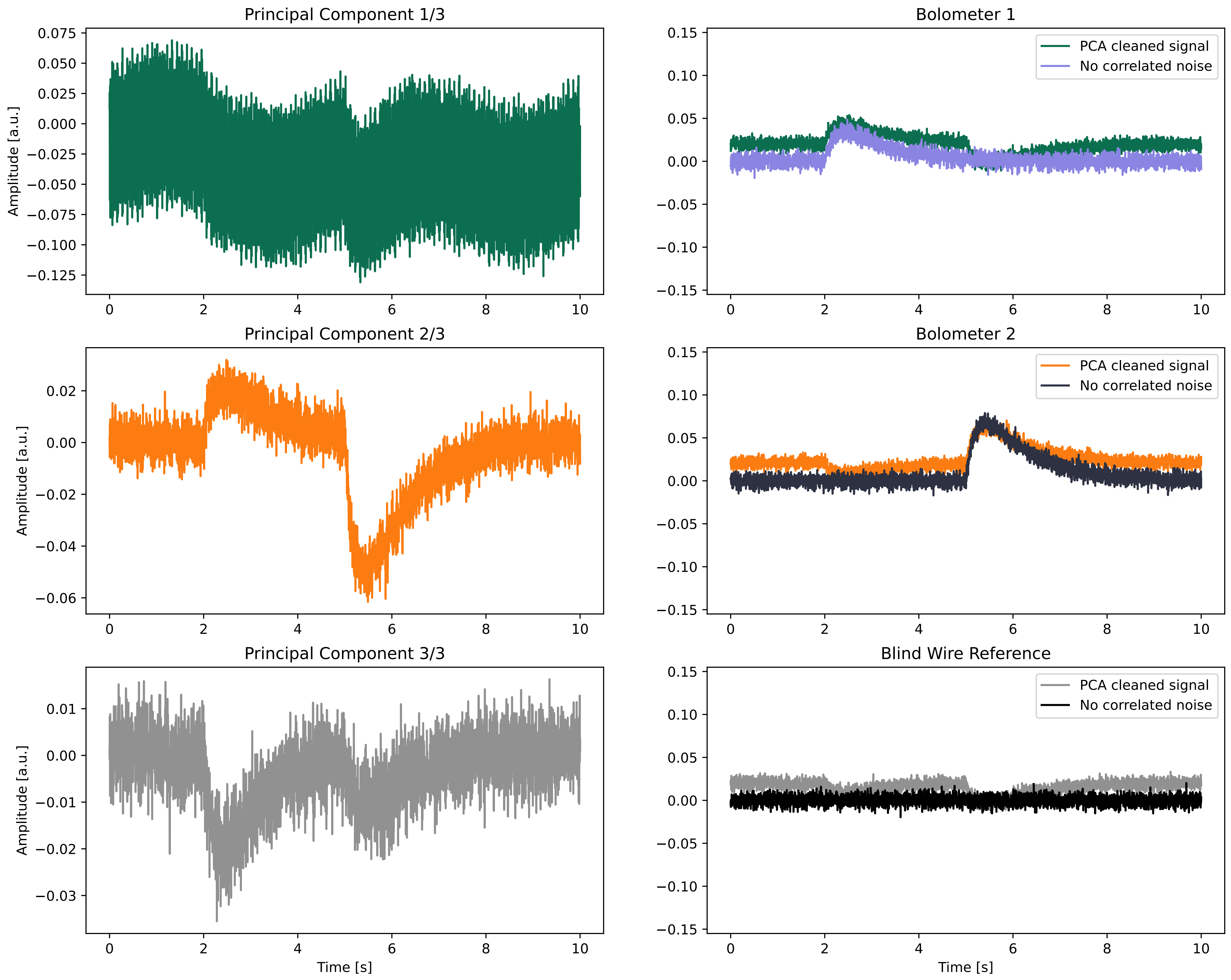


Now let's try adding a 3rd signal

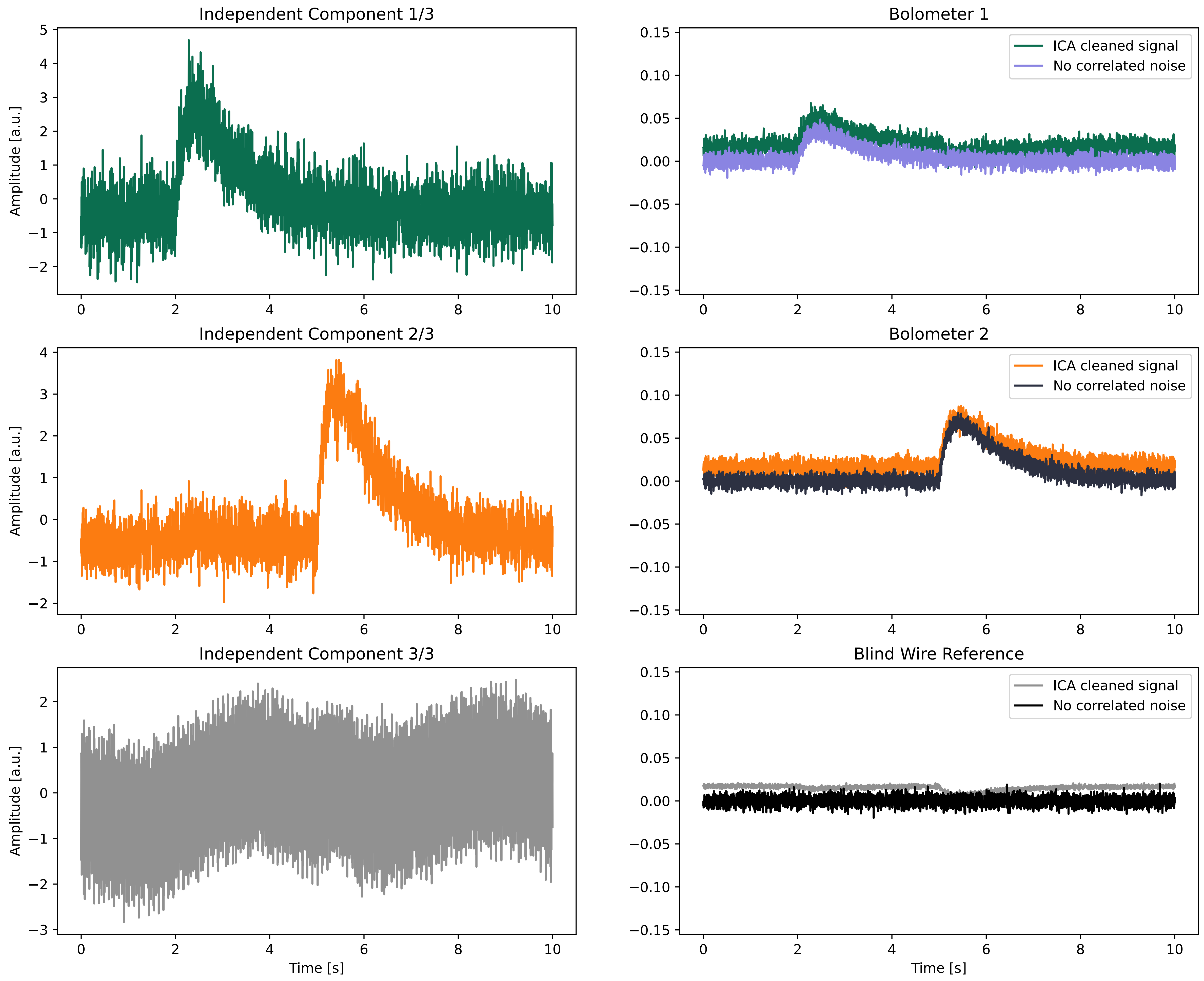


Independent Component Analysis

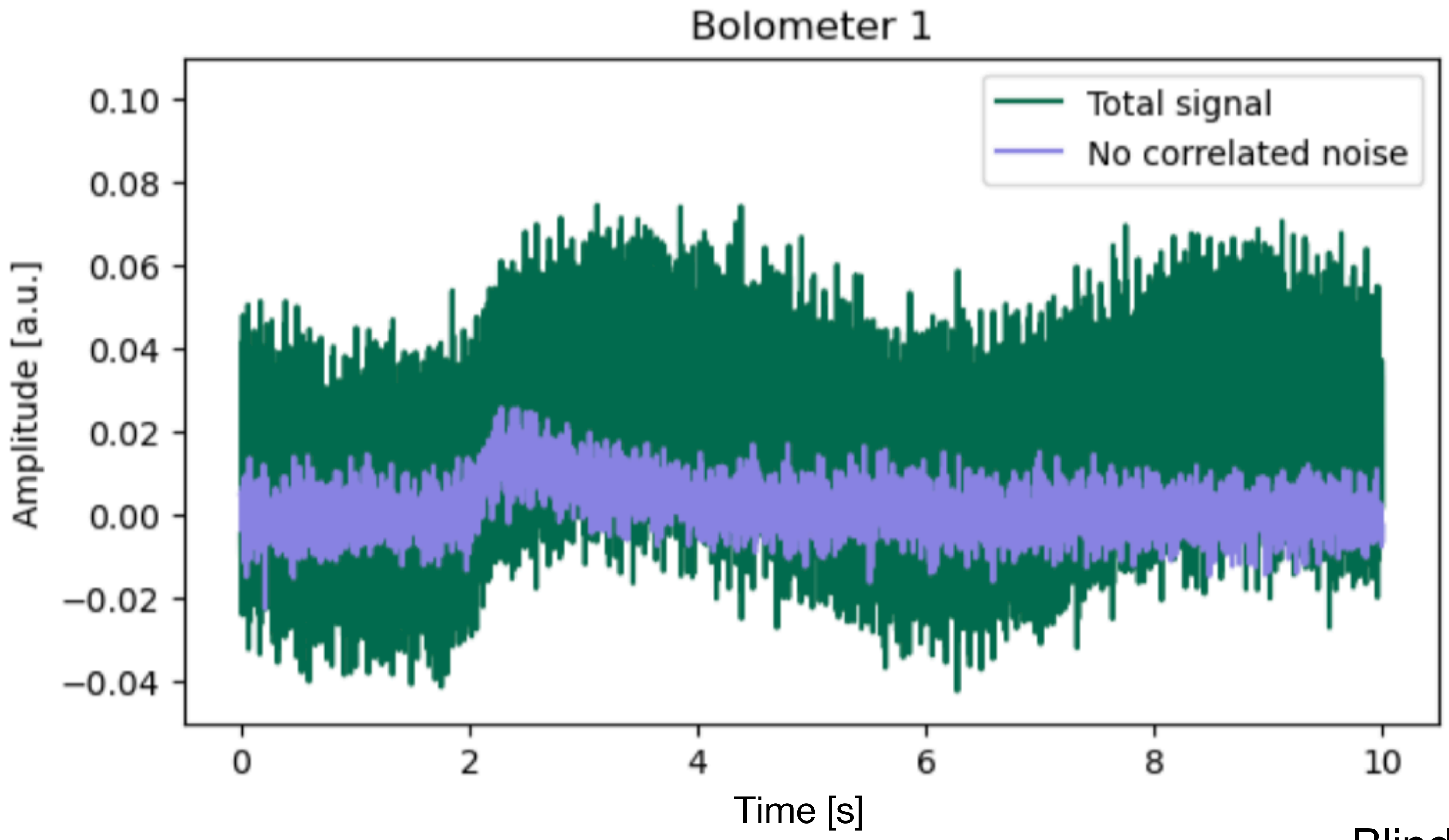
With PCA

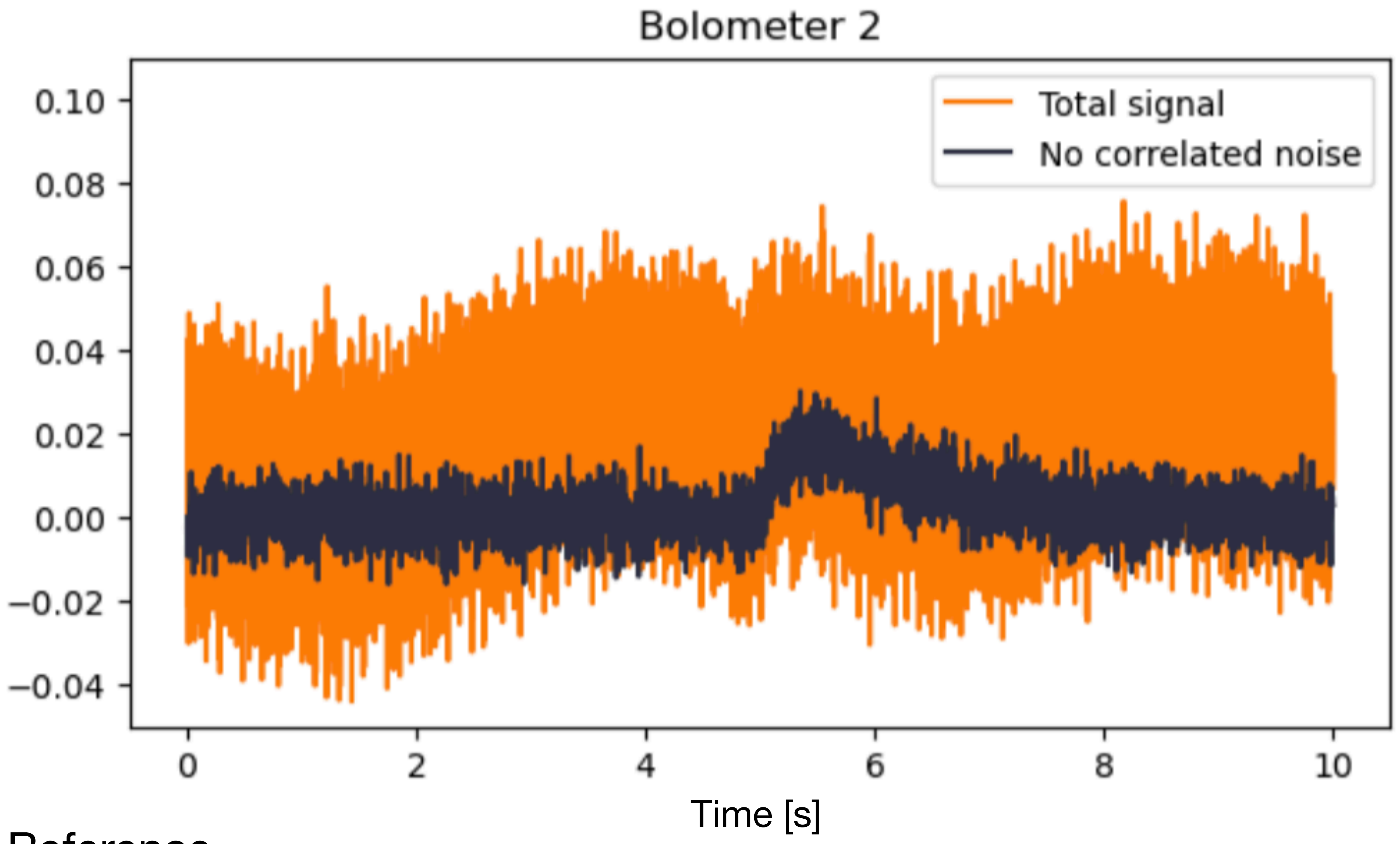


With ICA

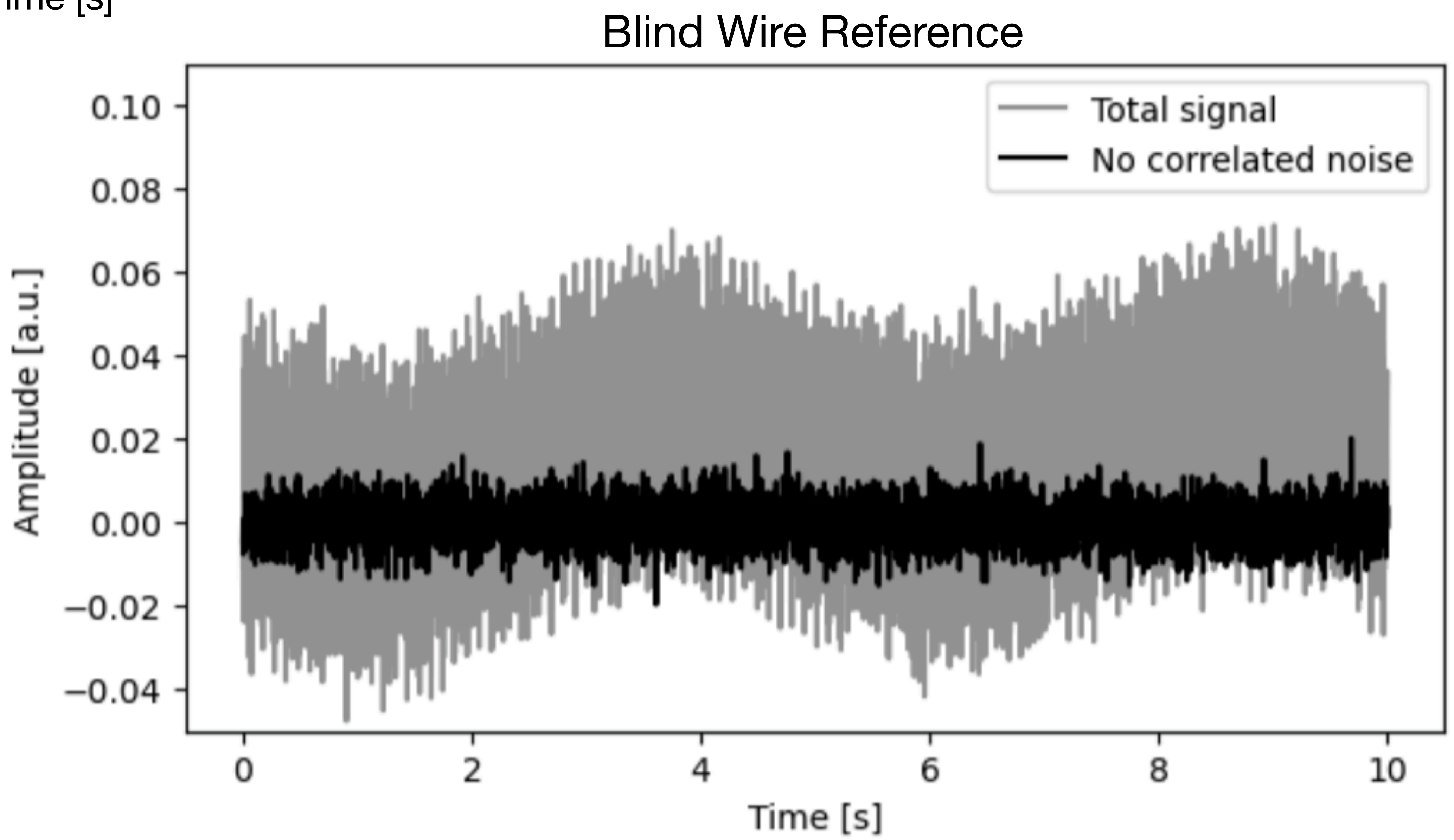


Independent Component Analysis



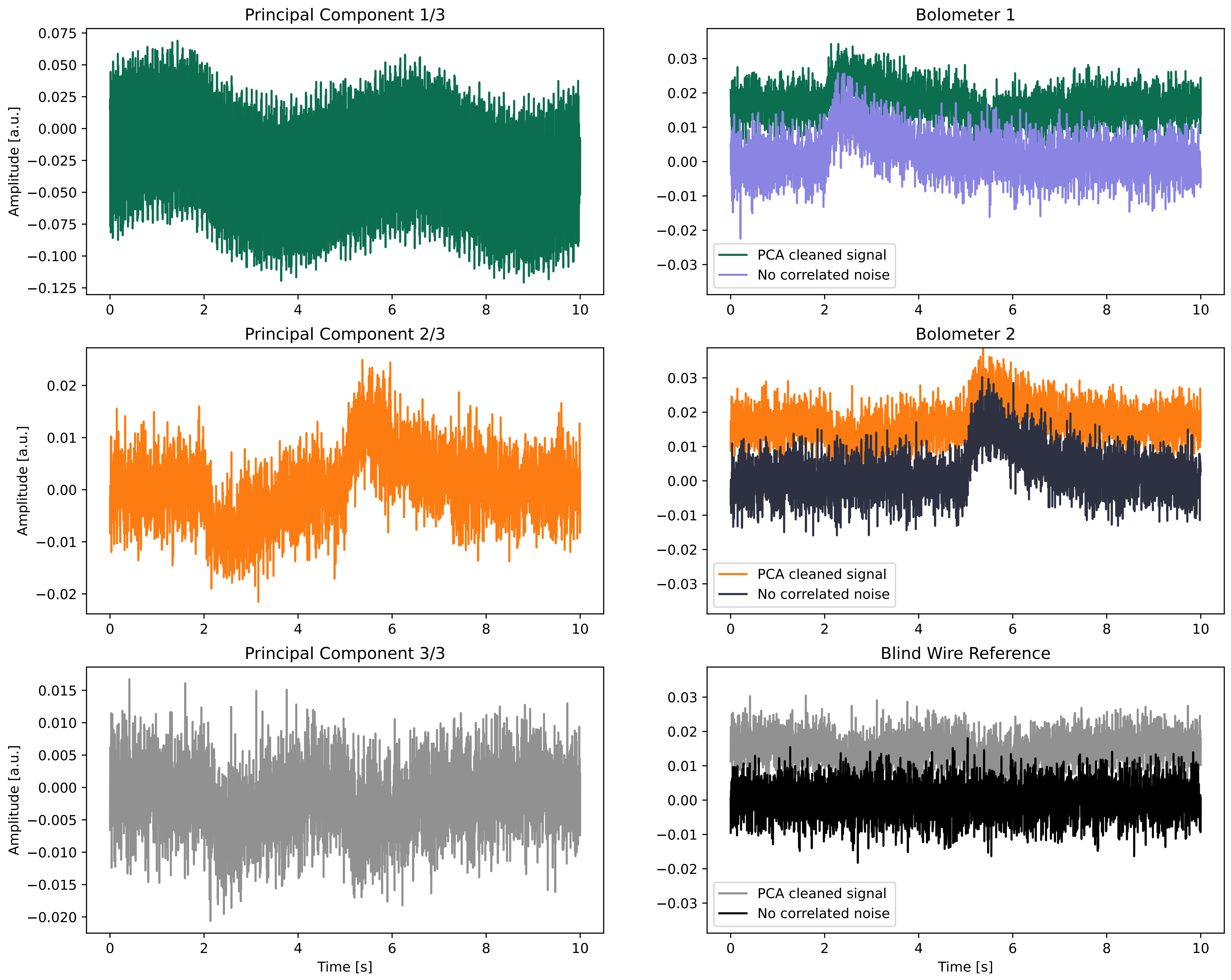


Now let's try smaller signals

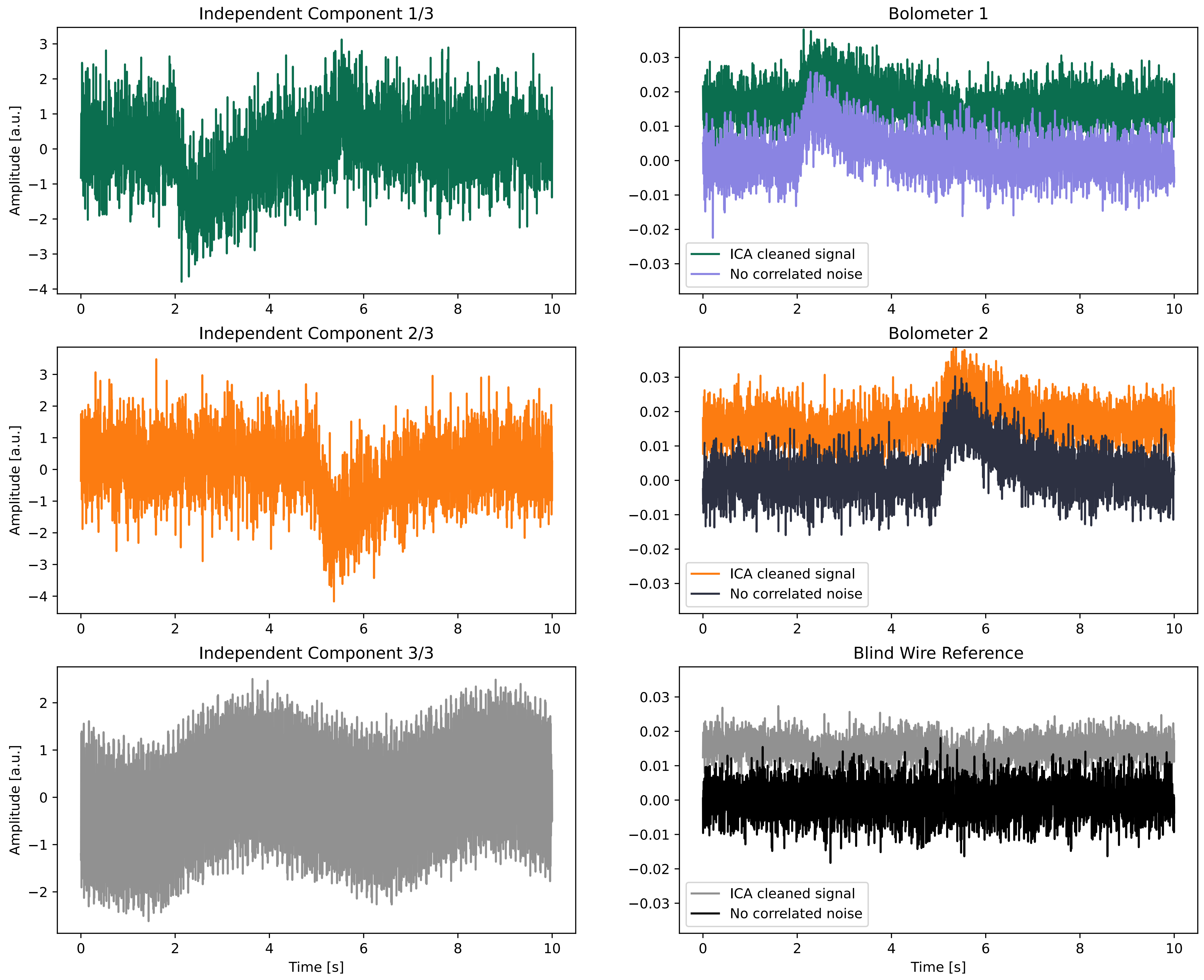


Independent Component Analysis

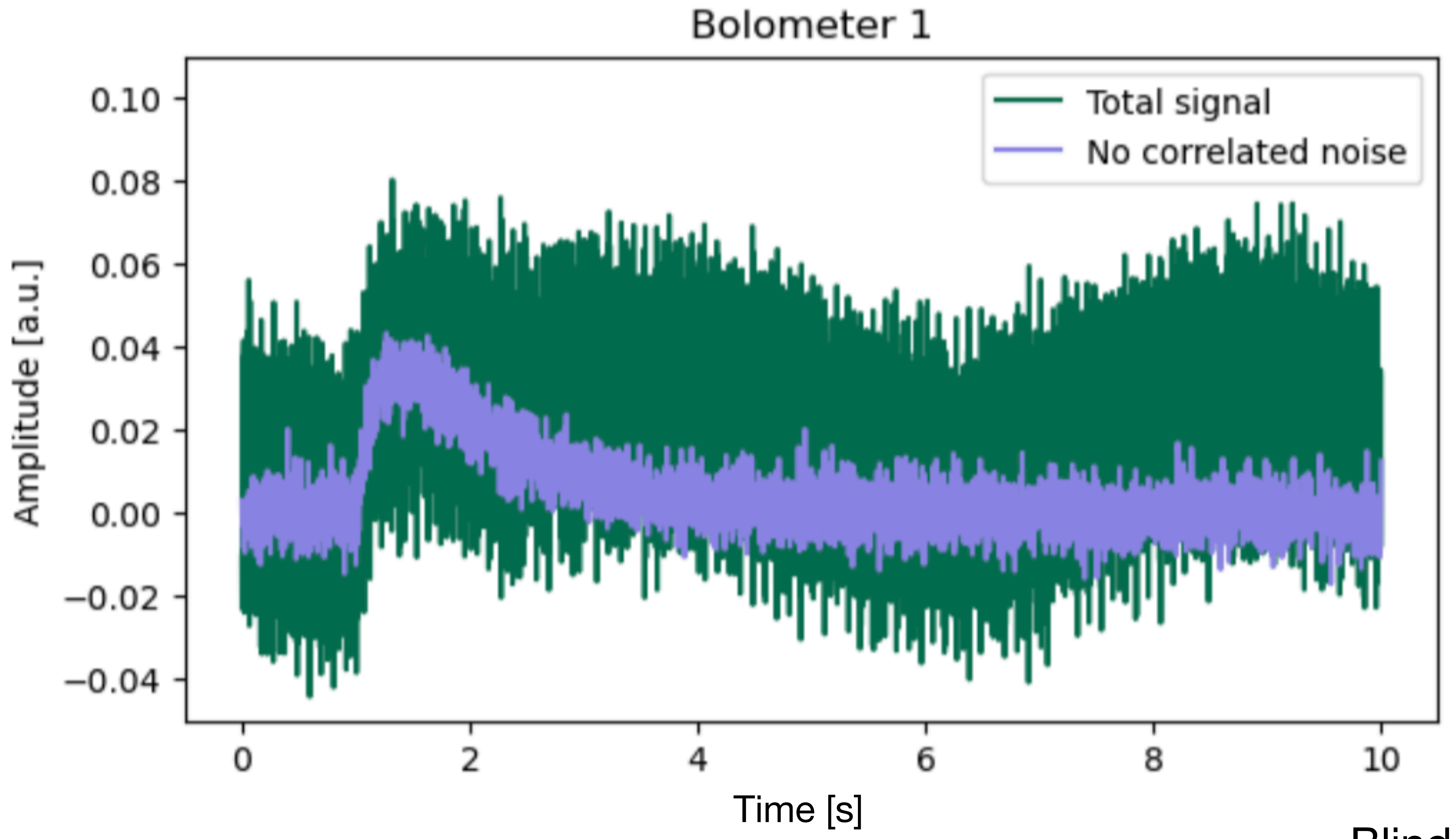
With PCA

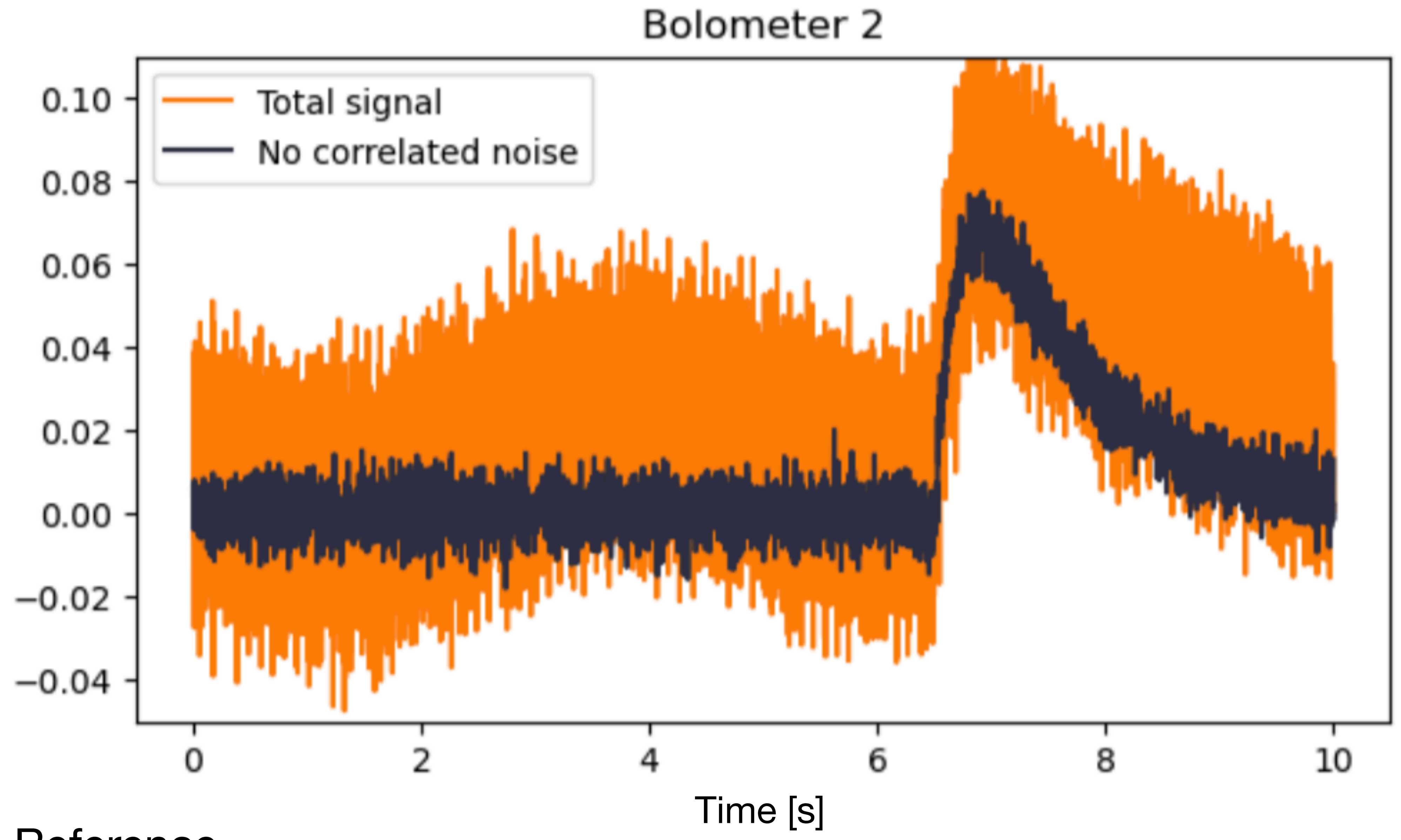


With ICA

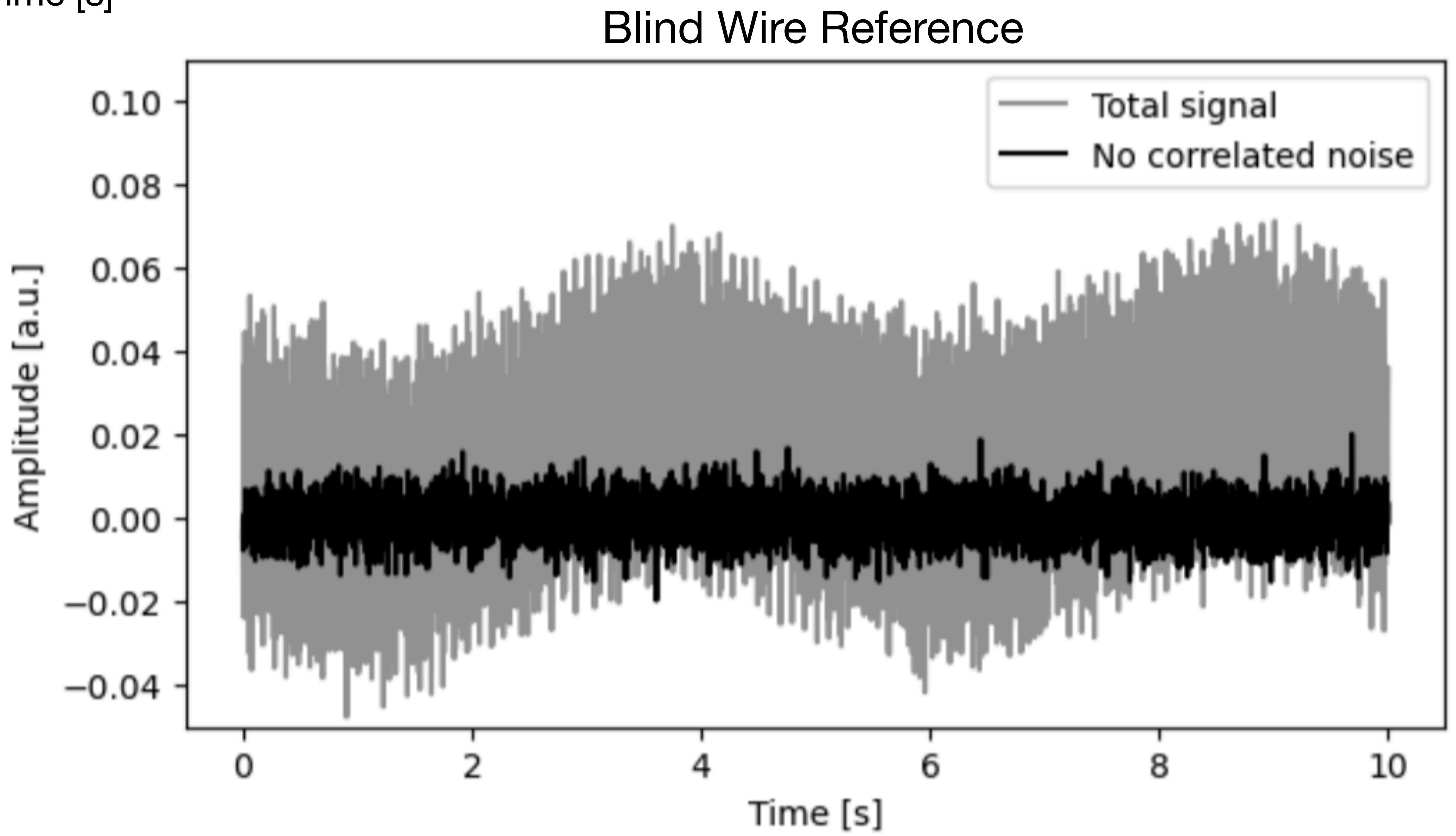


Independent Component Analysis



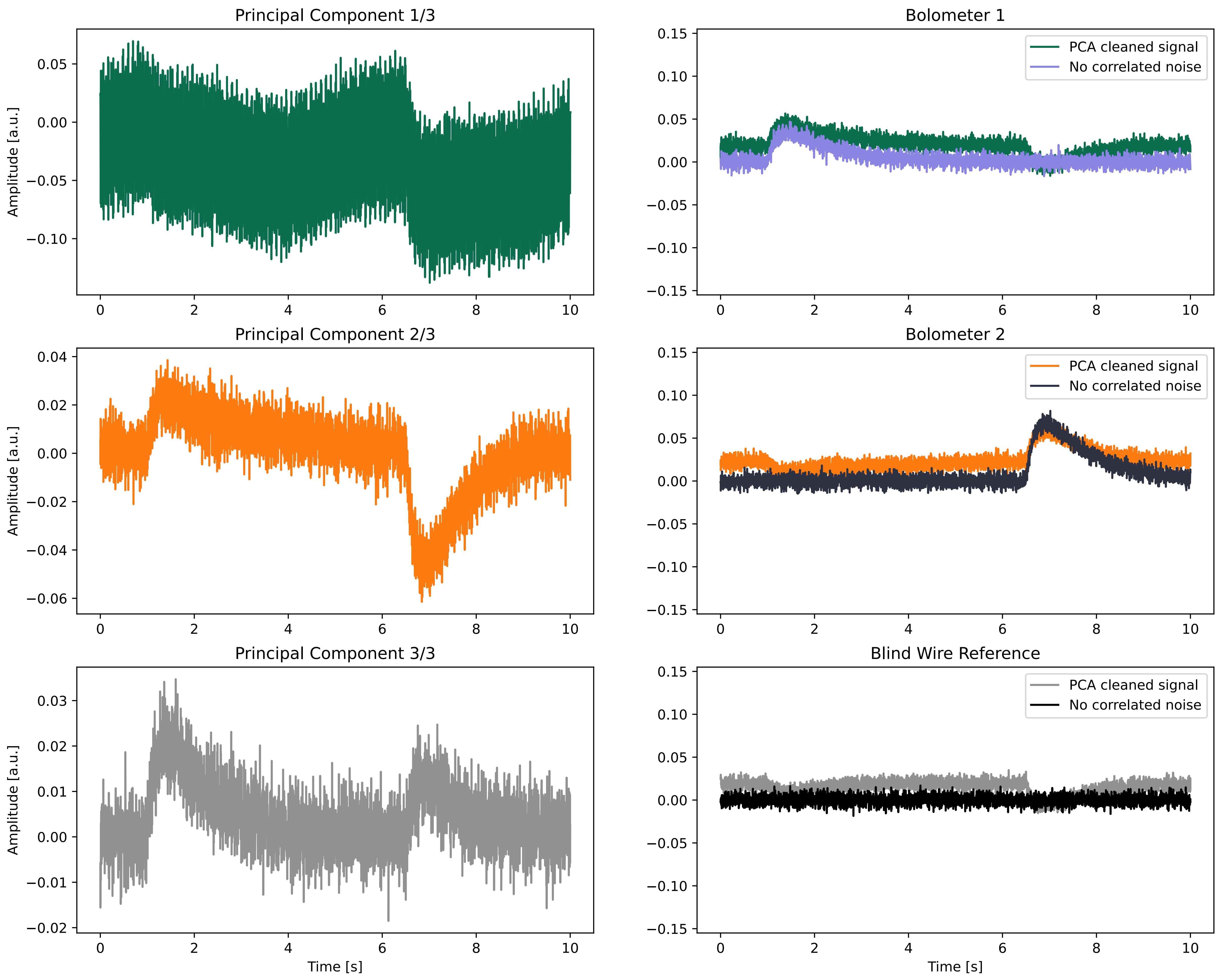


Now let's moving the signals



Independent Component Analysis

With PCA



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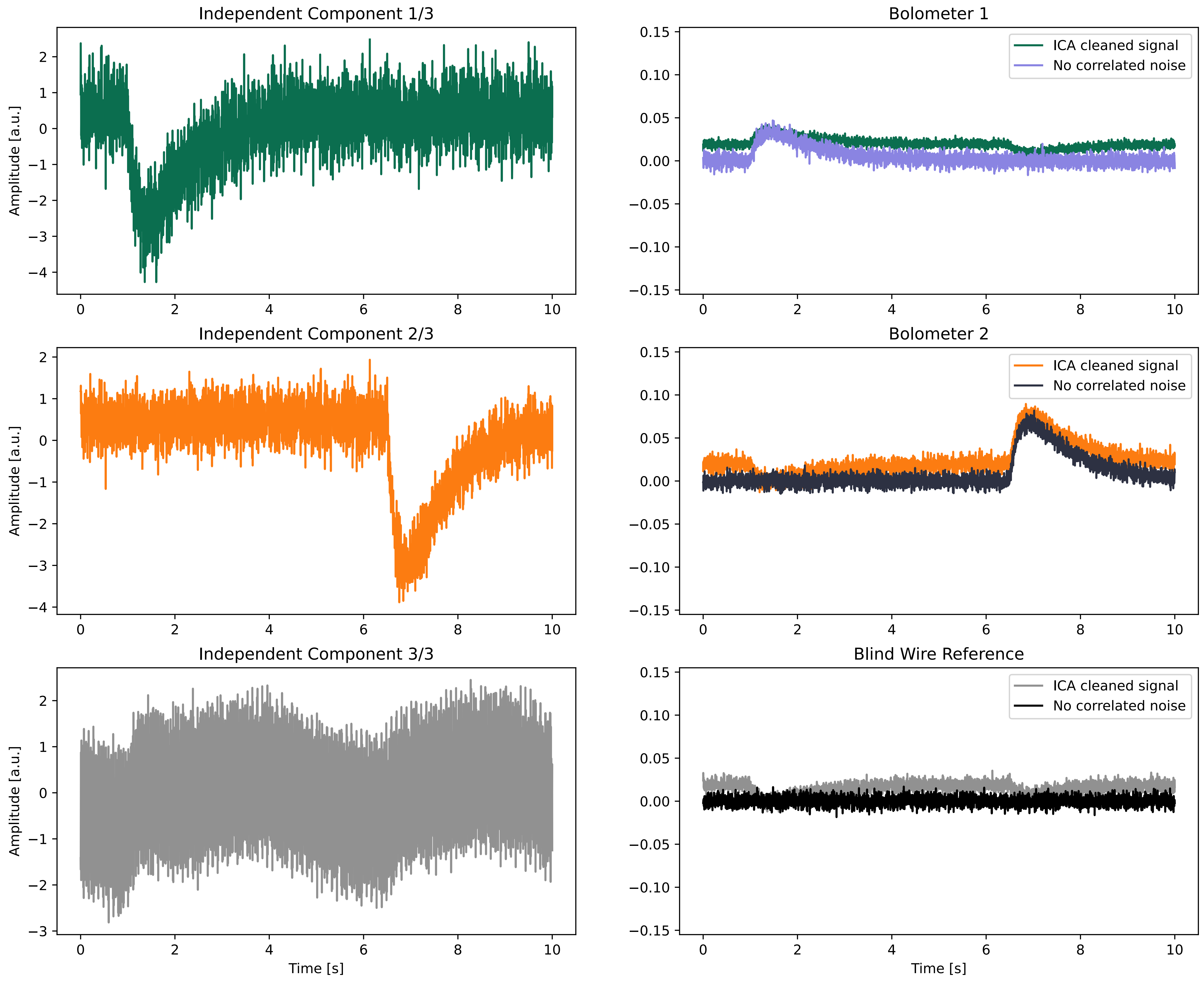
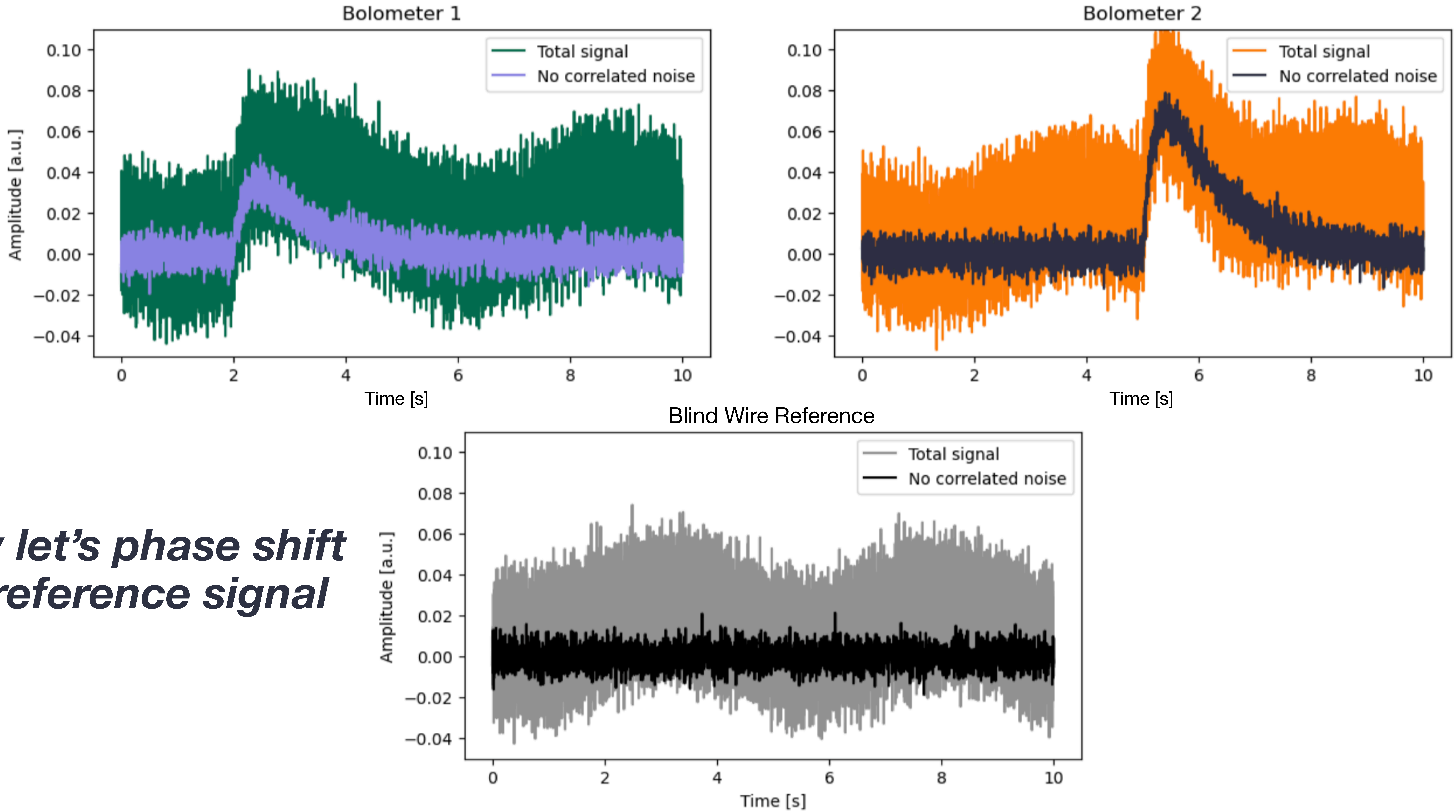


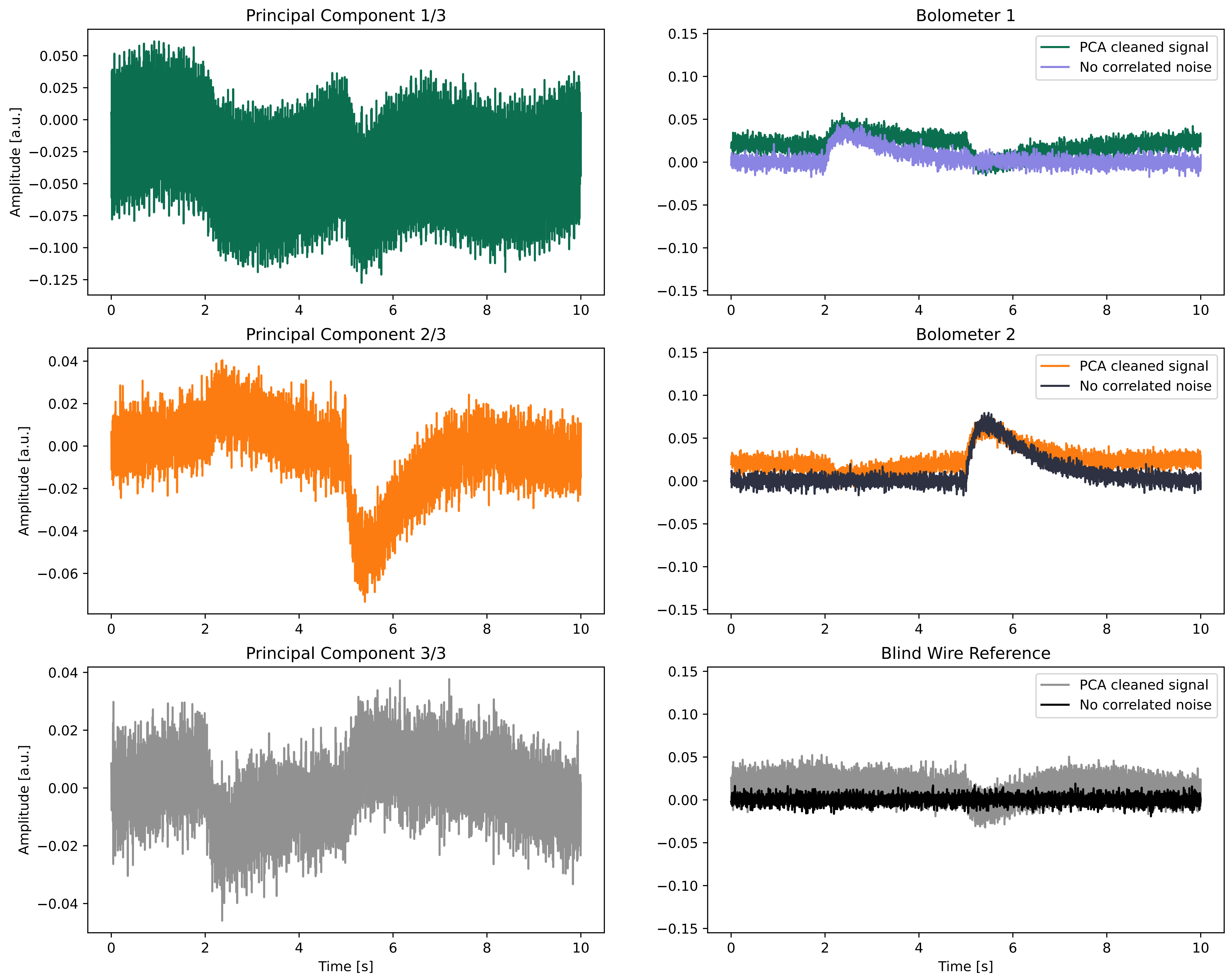
Independent Component Analysis



Now let's phase shift the reference signal

Independent Component Analysis

With PCA



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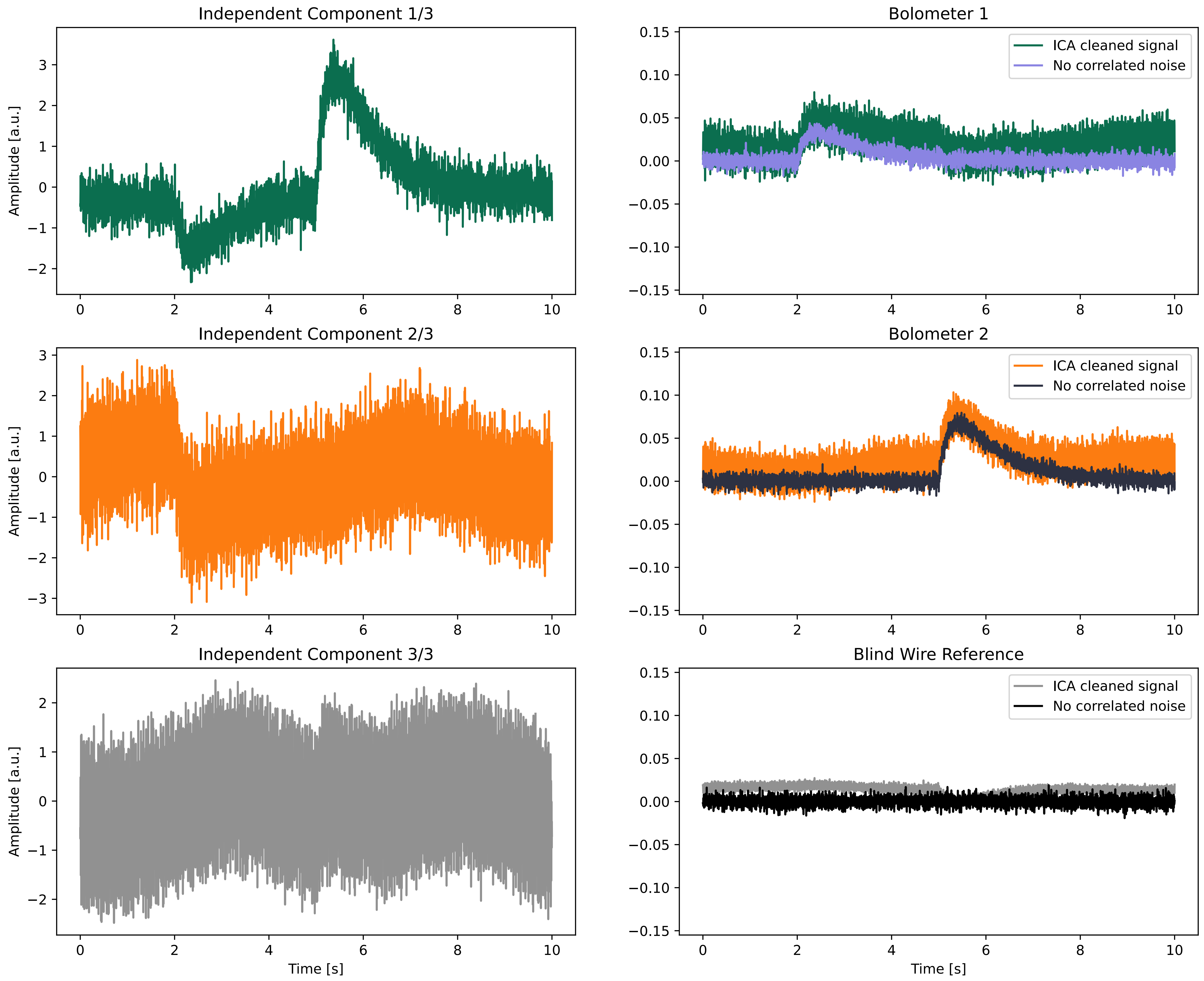

Summary

- Scintillation photons can produce photoelectrons inside the bolometer leading to many small heating events
- Acoustic/vibrational noise can be picked up in multiple wires in the same dilution fridge: can we subtract this out? Yes!
    - Caveat 1: using ICA may not be perfect at isolating correlated noise, so we'd have to add data quality cuts
    - Caveat 2: we have to make sure signals are in phase with each other, which can be done using Rob's work
- Extending ICA to Spectral Matching ICA (SMICA) also provides us an opportunity to cleanly measure acoustic/vibrational noise in-situ