# 3 new methods for signal analysis and denoising


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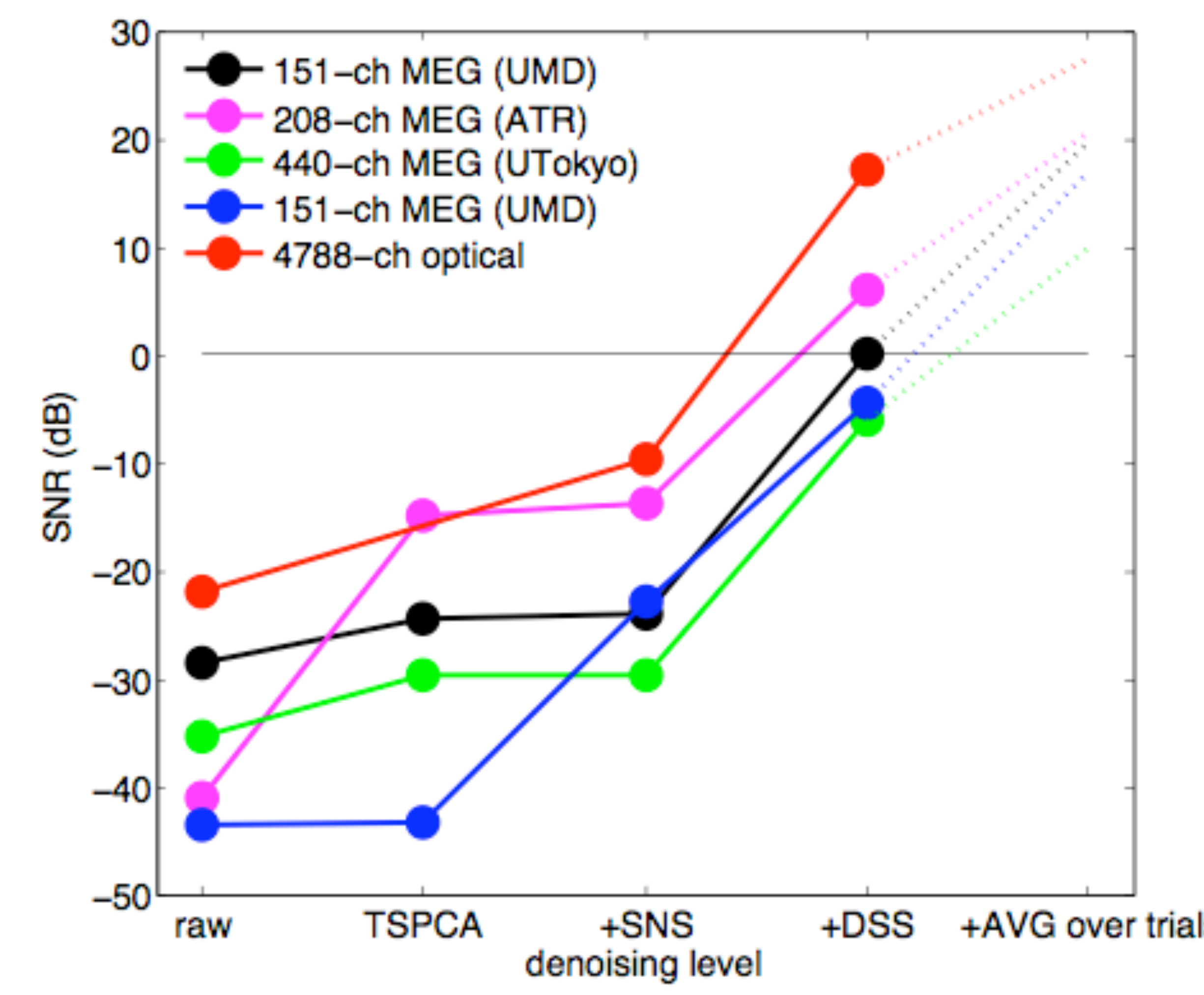
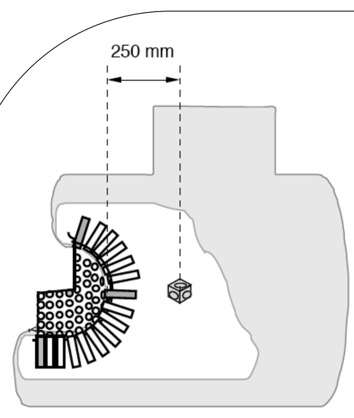
## SUMMARY AND CONCLUSIONS


Noise degrades data from electrophysiological recordings such as EEG, MEG, optical, multielectrode array, etc. Three new denoising methods target three main sources: *environmental*, *sensor*, and *physiological* noise. **TSPCA** uses signals from reference sensors as regressors to remove environmental noise, with *time shifts* to compensate for convolutional mismatch between reference and brain sensor pathways. **SNS** replaces each sensor channel by its projection on the subspace spanned by other channels, thus removing sensor-specific noise. The **DSS** algorithm takes advantage of high density recordings to form a spatial filter that maximizes a target criterion (e.g. proportion of evoked response) while minimizing noise components. An improvement in SNR on the order of **40 dB** is obtained with minimal distortion of brain patterns.Denoising is complementary with other standard techniques of brain signal analysis.


SNR improvement on several systems:




## Time-Shift PCA (TSPCA)

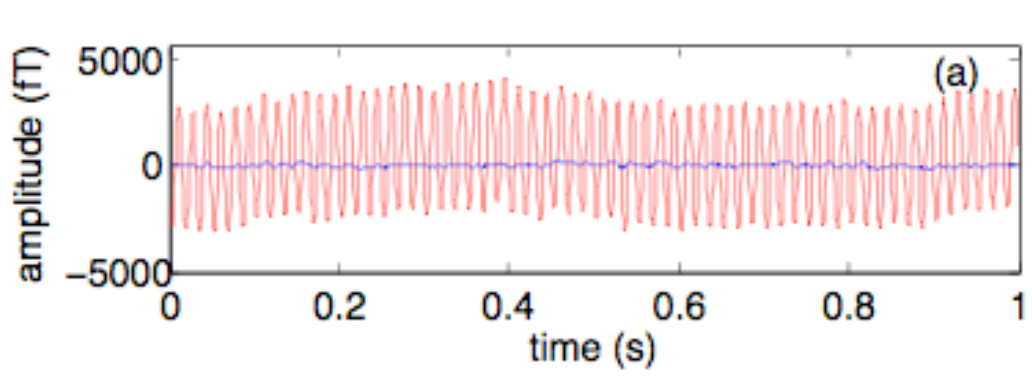


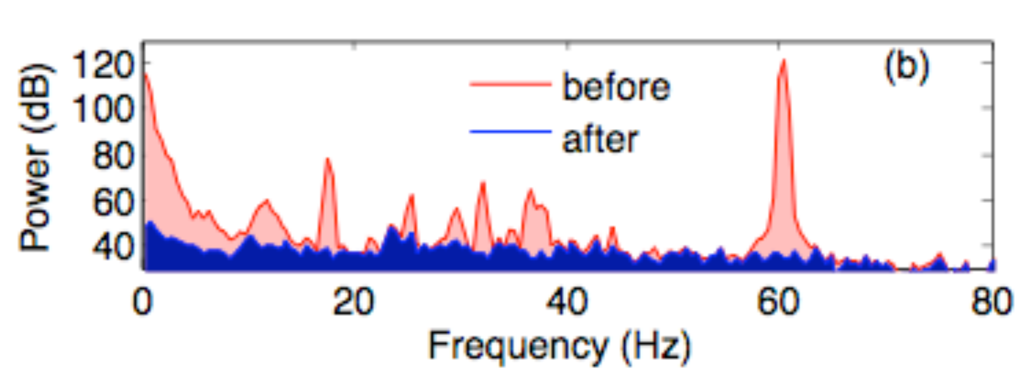

**Assumption**: environmental noise observed by reference sensors, but with possible ***convolutional distortion*** (filtering, delay).

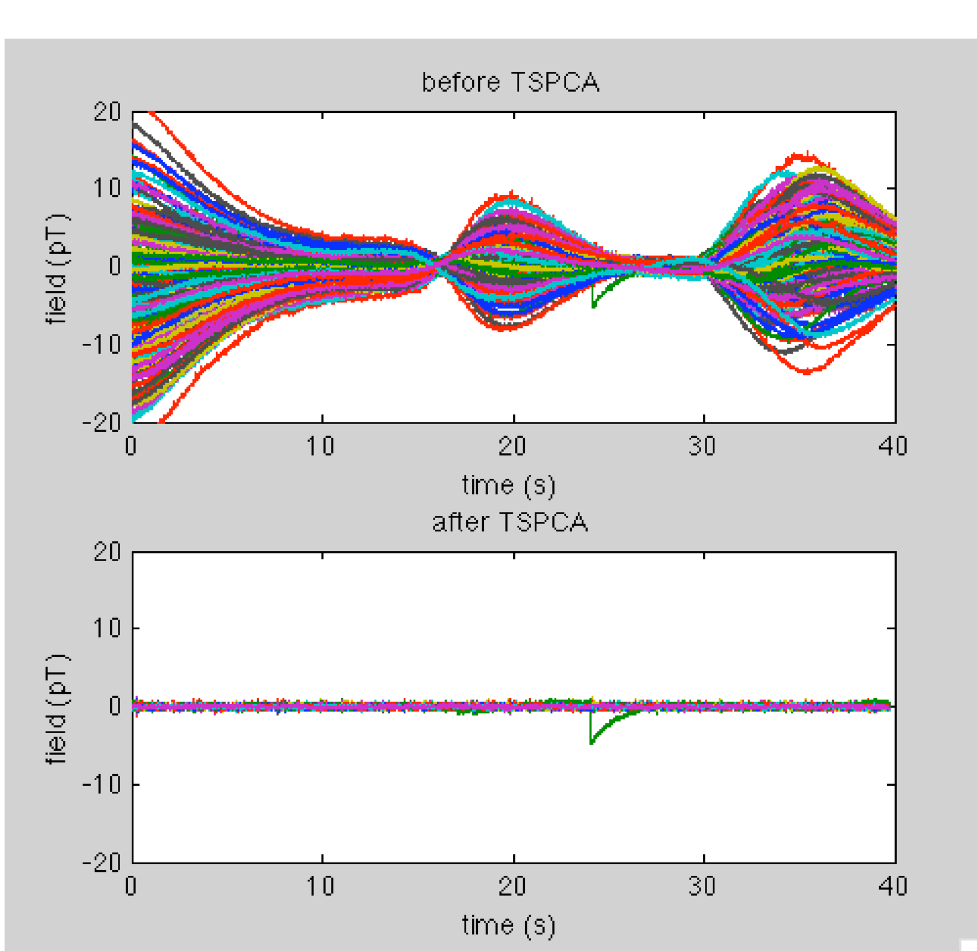
**Algorithm**:

(1) take set of ***delayed*** reference signals
(2) orthogonalize to obtain basis
(3) project brain signal on reference basis, subtract projection

$$s_k(t) \rightarrow \tilde{s}_k(t) = s_k(t) - \sum_j \sum_\tau \alpha_{kj\tau} r_j(t-\tau)$$



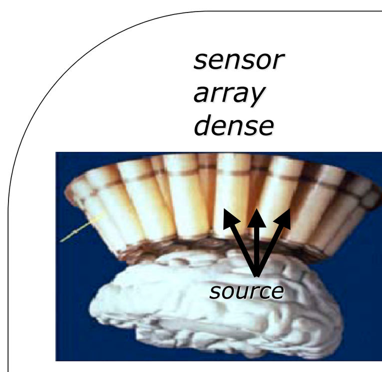





de Cheveigné, A. and Simon, J. Z. (2007). "Denoising based on Time-Shift PCA." *Journal of Neuroscience Methods* 165: 297-305.


## Sensor Noise Suppression (SNS)



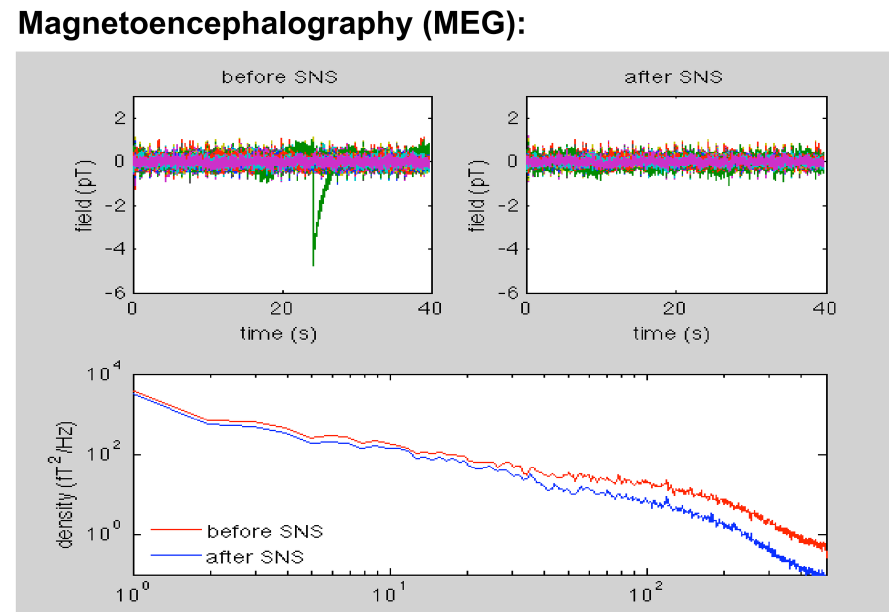

**Assumption**: every source of interest is picked up by several sensors ==> a component specific to one sensor is artifact.

**Algorithm**:

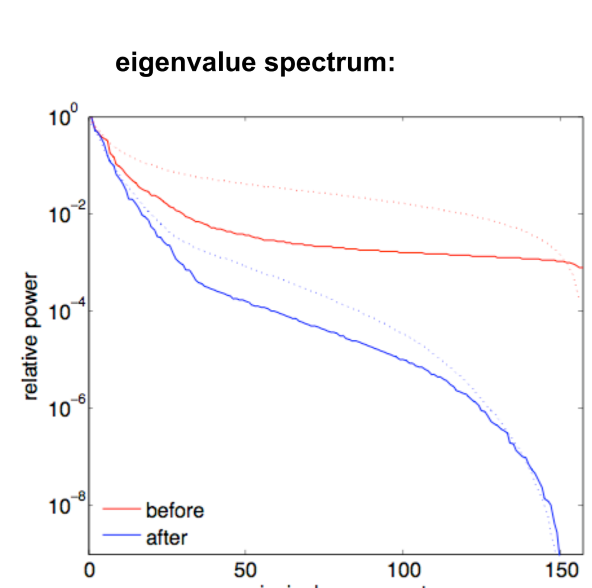
(1) project each sensor on subspace spanned by ***other*** sensor signals
(2) replace by projection

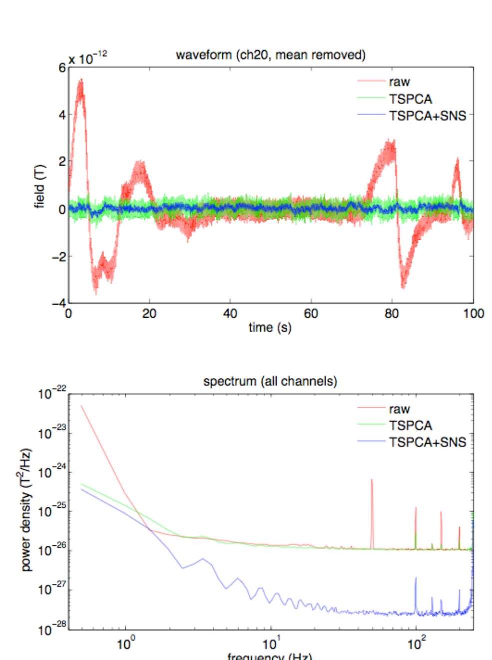
$$s_k(t) \longrightarrow \tilde{s}_k(t) = \sum_{k' \neq k} \alpha_{k'} s_{k'}(t)$$

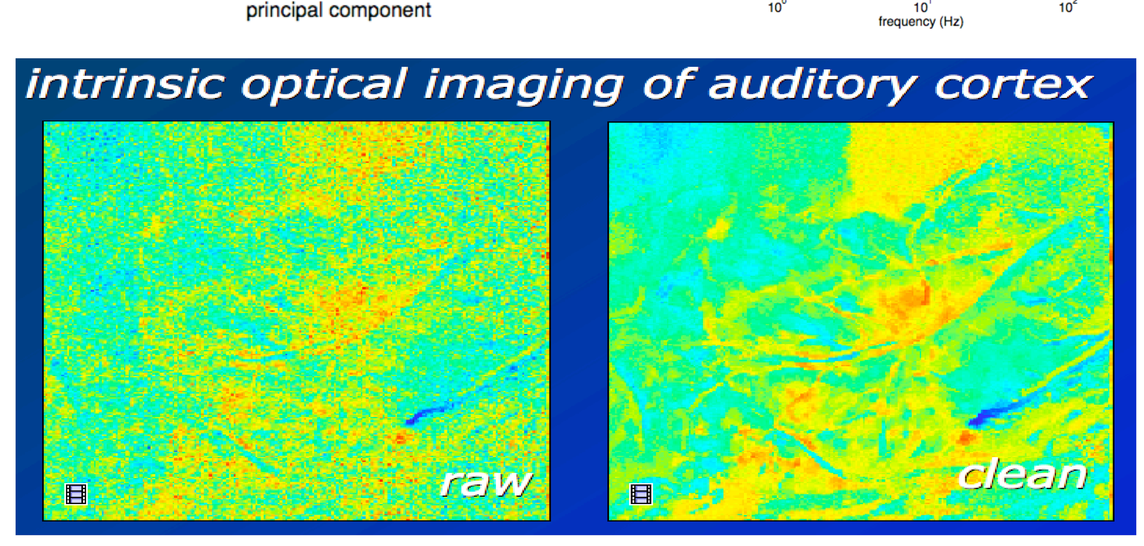
**Magnetoencephalography (MEG):**




**eigenvalue spectrum:**







de Cheveigné, A. and Simon, J. Z. (2008). "Sensor Noise Suppression." *Journal of Neuroscience Methods* 168: 195-202.


## Optimal Spatial Filter (DSS)

**Assumption**: (1) Target and noise sources are spatially distinct (may overlap) and temporally distinct (may be correlated). (2) There exists an objective criterion to distinguish target and noise (here: evoked power).

**Algorithm** (based on Denoising Source Separation, DSS, Särelä J, Valpola H. Denoising source separation. *J Mach Learn Res* 2005; 6:233-72.):

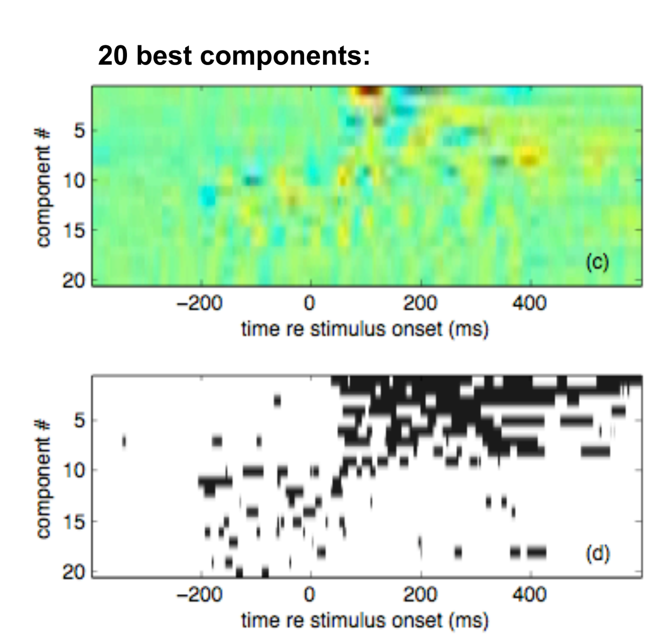
(1) PCA, normalize (spatial whitening)
(2) apply bias function (average over trials)
(3) PCA to align data with maximum bias (--> rotation matrix)
(4) Apply rotation matrix to whitened data (-->DSS components)
(5) Select best DSS components, discard others
(6) Project back to sensor space

$$s_k(t) \rightarrow \tilde{s}_k(t) = \sum_{j=1}^{J_{MAX}} \beta_j c_j(t), \qquad c_j(t) = \sum_k \alpha_k s_k(t)$$

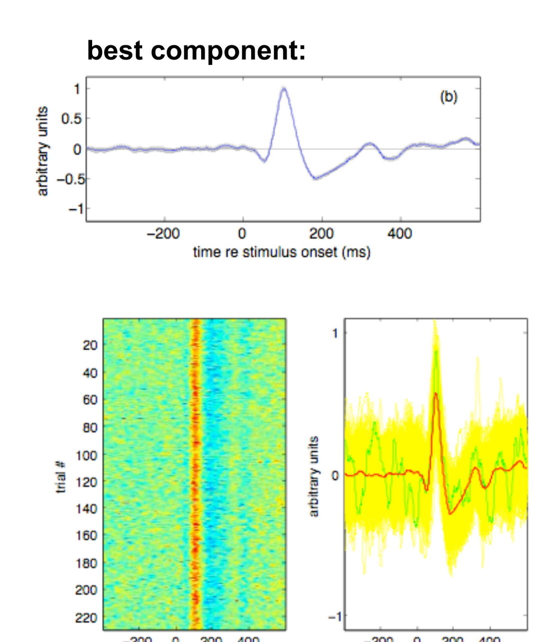
**$c_1(t)$: best linear combination of sensors**
**$c_2(t)$: best linear combination orthogonal to c1(t), etc.**

$$\tilde{\mathbf{S}}(t) = \mathbf{PQR_2N_2R_1N_1S}(t)$$

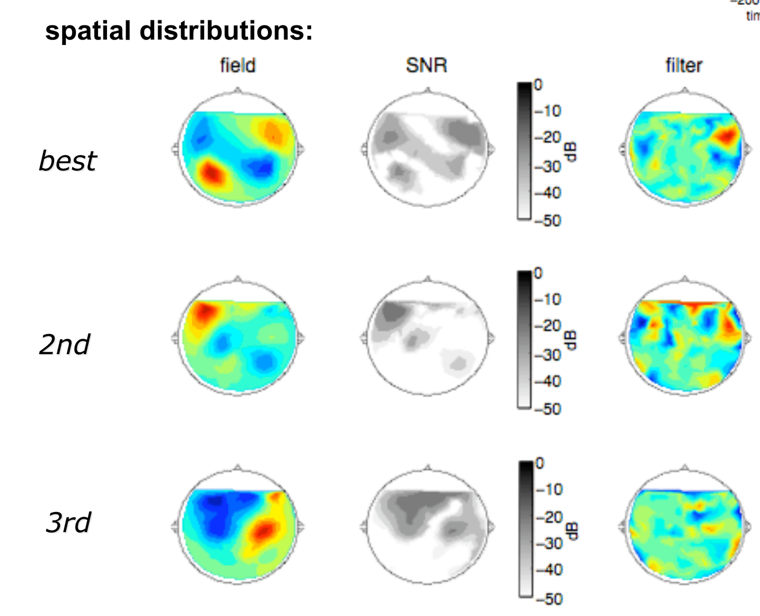
**20 best components:**




**best component:**




**spatial distributions:**





de Cheveigné, A. and Simon, J. Z. (2008). "Denoising based on spatial filtering." *Journal of Neuroscience Methods* 171: 331-339.