Compressed Sensing for Energy–Efficient Wireless Telemonitoring

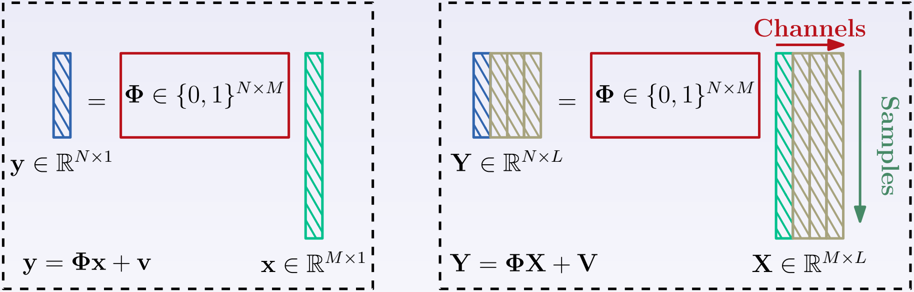
Challenges and Opportunities

Zhilin Zhang[1], Bhaskar D. Rao[2], Tzyy-Ping Jung[3]

[1] Samsung R&D Institute America, [2] ECE Dept, UCSD, [3] Swartz Center for Computational Neuroscience, UCSD

Asilomar, April 25, 2015

Introduction: Low Energy Compression via CS



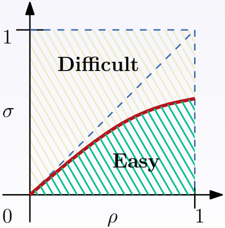
1. Consumes much less energy
2. Recover in the transformed domain where $\mathbf{y} = (\mathbf{\Phi}\mathbf{D})\mathbf{z}$ and $\mathbf{x} = \mathbf{D}\mathbf{z}$
3. Multi-channel Biosignals : MMV Model

The Challenge : Non-Sparsity

insert Fig 3 a, b, c, d here

fig fig fig fig

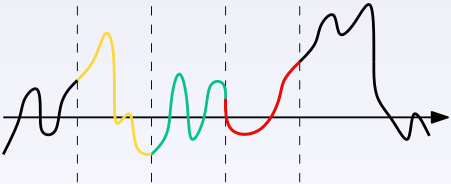
$K = \|x\|_0$, $\rho \triangleq \frac{K}{M}$, $\sigma \triangleq \frac{N}{M}$



1 Biosignals are non-sparse in time or some transformed domains,
2 Non-sparsity comes from artefacts or low sampling rate,
3 Artefact removal raises cost in hardware and energy consumptions,
4 Non-sparse poses challenges for fidelity recovery,

State-of-the-art : BSBL-BO

$$\mathbf{x} = [\underbrace{x_1, \cdots, x_{d_1}}_{\mathbf{x}_1^T}, \cdots, \underbrace{x_1, \cdots, x_{d_g}}_{\mathbf{x}_g^T}]^T$$



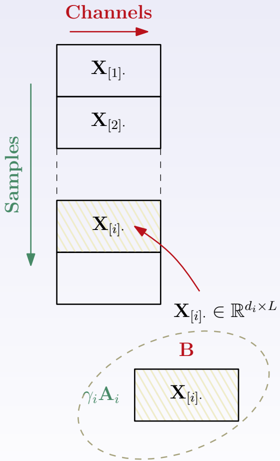
Block Partition

+

Temporal Correlation

1. Block Sparse Bayesian Learning (BSBL) exploits the **temporal correlation** structures,
2. Abandoned **block-sparsity** and assumed all blocks are **non-zero**!
3. Successful and High-Fidelity.

Spatio-Temporal : ST-SBL



1. $\mathbf{X}_{[i]\cdot}$ obeys parameterized Gaussian,

$$p(\mathrm{vec}(\mathbf{X}_{[i]\cdot}); \gamma_i, \mathbf{B}, \mathbf{A}_i) = \mathcal{N}(\mathbf{0}, (\gamma_i \mathbf{A}_i) \otimes \mathbf{B})$$

   Blocks are mutually independent.

2. γ_i determines whether the ith block is a zero block or not; $\mathbf{B} \in \mathbb{R}^{L \times L}$ is a p.s.d captures **spatio correlation**; $\mathbf{A}_i \in \mathbb{R}^{d_i \times d_i}$ is an unknown p.s.d captures **temporal correlation**.

3. The sensor noise $\mathbf{V}$ can be ignored : artifacts and noises are incorporate into $\mathbf{X}$.

ST-SBL : Alternating Optimize of γ_i, $\mathbf{A}_i$ and $\mathbf{B}$

Init: $\mathbf{A}_i = \mathbf{I}_{d_i}$

estimate $\mathbf{B}$

$$\tilde{\mathbf{Y}} \triangleq \mathbf{Y}\mathbf{B}^{-\frac{1}{2}}$$
$$\tilde{\mathbf{X}} \triangleq \mathbf{X}\mathbf{B}^{-\frac{1}{2}}$$

estimate $\mathbf{A}_i$, γ_i

$$\mathbf{A} \triangleq \mathrm{diag}\{\mathbf{A}_i, \cdots, \mathbf{A}_g\}$$
$$\bar{\mathbf{X}} \triangleq \mathbf{A}^{\frac{1}{2}}\mathbf{X}$$
$$\bar{\mathbf{\Phi}} \triangleq \mathbf{\Phi}\mathbf{A}^{\frac{1}{2}}$$

estimate $\mathbf{B}$

1. Estimating $\mathbf{B}$

$$\mathbf{B} = \sum_{i=1}^{g} \gamma_i \mathbf{X}_{[i]\cdot}^T \mathbf{A}_i^{-1} \mathbf{X}_{[i]\cdot}$$

2. Estimating γ_i, $\mathbf{A}_i$

$$\gamma_i = \frac{1}{Ld_i} \sum_{l=1}^{L} \mathrm{Tr}\left[\mathbf{A}_i^{-1}(\mathbf{\Sigma}_{[i]} + \boldsymbol{\mu}_{[i]l}^T \boldsymbol{\mu}_{[i]l})\right]$$

$$\mathbf{A}_i = \frac{1}{L} \sum_{l=1}^{L} \frac{\mathbf{\Sigma}_{[i]} + \boldsymbol{\mu}_{[i]l}^T \boldsymbol{\mu}_{[i]l}}{\gamma_i}$$

3. Updating $\mathbf{X}$

$$\mathbf{X} = \boldsymbol{\mu}\mathbf{B}^{\frac{1}{2}}$$

Applications : Drowsiness Monitoring Based on EEG

illustrate the background of driving drowsy and EEG collecting

fig	fig	fig	fig

- Compression Ratio

$$\mathrm{CR} = \frac{M - N}{M}$$

- Task Driven Analysis (not MSE!)

$$\mathbf{X} \rightarrow \boxed{\mathbf{\Phi}} \rightarrow \mathbf{Y} \rightarrow \boxed{\textbf{ST-SBL}} \rightarrow \hat{\mathbf{X}} \rightarrow \boxed{\textbf{Drowsiness Estimation}} \rightarrow$$