GdR IASIS

Information, Apprentissage, Signal, Image, vISion

Journée Optimisation
Sciences Informatiques, 4 octobre 2024

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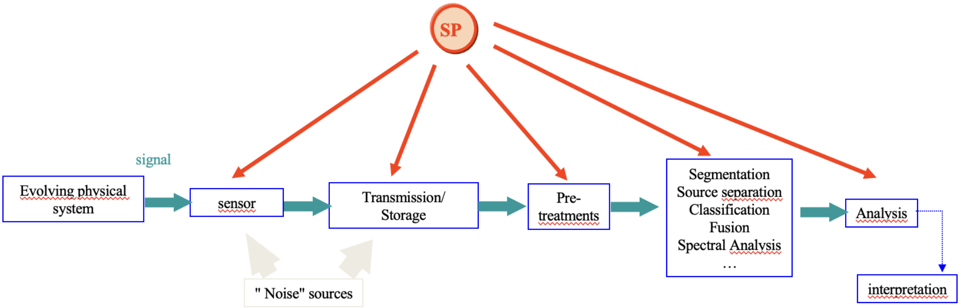

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Eight axes:

1- Machine learning

2- Theory and methods

3- Computational imaging

4- Fusion, multimodality, sensor networks, multicanal processing

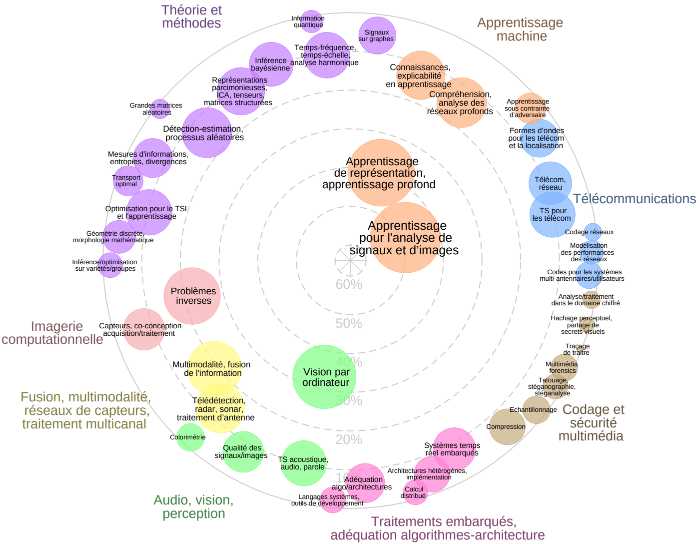
5- Audio, vision, perception

6- Algorithm-architecture adequacy, embedded processing

7- Multimedia coding and security

8- Telecommunications

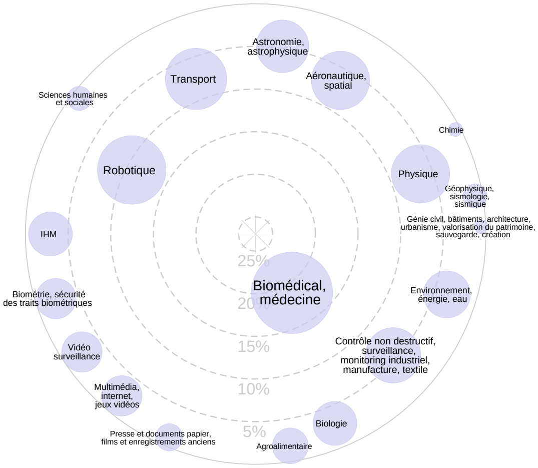
"Thematic" activities of the GdR by keywords



(546 answers at date 24/08/2023, 8 votes per answers among 43+19=62 keywords)

Groupement de recherche
IASIS Information Apprentissage Signal Image viSion

"Applicative" activities of the GdR by keywords



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Theory and Methods: some scientific days

1. Signal processing on graphs
2. Covariance matrices in statistics and learning
3. Multivariate polynomials in statistics and signal processing
4. Simulation and optimization
5. Optimization
6. Classical and quantum information measures (entropy,...)
7. Robust statistics: recent developments
8. Constrained matrix factorization
9. Evaluation of optimization algorithms and Monte Carlo algorithms (benchmarks)
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2. Non-conventional optical imaging
3. Co-design (hybrid sensors and algorithms for innovative systems)
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- **Blind source separation**
- ...

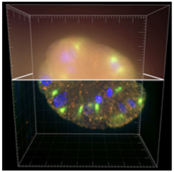
Opimization in GdR IASIS

Not only users but contributors

Typical problems: Inverse problems

Estimate variable u from **noisy incomplete observed data** g

- Restoration/Deconvolution/super-resolution



g : observation

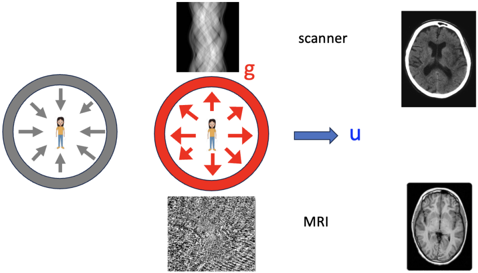
u : image we want to retrieve

Biological Imaging, Satellite Imaging, Astrophysical Imaging

Typical problems: Inverse problems

Estimate variable u from **noisy incomplete observed data** g

- Image reconstruction (ex: medical imaging)



Typical problems: Inverse problems

Estimate variable u from **noisy incomplete observed data** g through the physical observation system

$$\mathrm{g} = A\mathrm{u} + \mathrm{n}$$

$\mathrm{g} \in \mathbb{R}^m$ observed noisy degraded data,
$\mathrm{u} \in \mathbb{R}^n$ reconstructed/restored super-resolved image,
A observation matrix (in $\mathbb{R}^m \times \mathbb{R}^n$)
n multidimensional random variable, additive white Gaussian noise.

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Regularized least square solution

$$\hat{\mathrm{u}} = \underset{\mathrm{u} \in \mathbb{R}^N}{\arg\min} \left\{ \frac{1}{2} \|A\mathrm{u} - \mathrm{g}\|_2^2 + R(\mathrm{u}) \right\}$$

Typical problems

$$\hat{\mathrm{u}} = \arg\min_{\mathrm{u}\in\mathbb{R}^N} \left\{ \|A\mathrm{u} - d\|_2^2 + R(\mathrm{u}) \right\}$$

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- $R(\mathrm{u}) = \|\mathrm{u}\|_2^2, \|\mathrm{u}\|_p^p, \|\mathrm{u}\|_1, \|\mathrm{u}\|_0, \|D\mathrm{u}\|_2^2, \|D\mathrm{u}\|_p^p, \|D\mathrm{u}\|_1, \ldots$
- Non differentiability of $\|.\|_1$, non convexity of $\|.\|_p^p, 0 < p < 1$, non continuity of $\|.\|_0$ (NP-hard problem),...

Typical problems

$$\hat{u} = \arg\min_{u \in \mathbb{R}^N} \left\{ \|Au - d\|_2^2 + R(u) \right\}$$

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- **Algorithms** from gradient descent type, proximal, primal-dual, alternating directions method of multipliers, Branch-and-bound,...

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- **Stochastic interpretation**: Maximum a posteriori using Bayes rule

$$\hat{u} = \arg\max_{u \in \mathbb{R}^N} P(g \mid u).P(u)$$

- Stochastic optimization algorithms, SGD, SA, sampling from multidimensional density,...

Parameter estimation

$$J(\mathrm{u}, \theta) = \frac{1}{2}\|A(\theta_1)\mathrm{u} - \mathrm{g}\|_2^2 + R(\mathrm{u}, \theta_2)$$

- **Deterministic approaches**
  - Regularizing parameter estimation: Cross-validation, L-curve, homotopy, bi-level method, NN learning,
  - Joint estimation with constraints on parameters, e.g. physical constraints on θ_1,
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- **Stochastic approaches**
  - Stein Unbiased Risk Estimator (SURE),
  - Maximum Likelihood (ML) estimator with problem of sampling on n-dimensional Gibbs distribution,
  - Expectation-minimization (EM) algorithm for ML estimator with latent variables,
  - ...

Discrete/Continuous Sparse Optimization

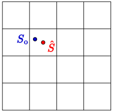

Figure: Discrete case

- the reconstructed peaks are necessarily on the fine grid;
- (non-)convex combinatorial optimization;
- a lot of algorithms;
- large literature.

$$\arg\min_{u \in \mathbb{R}^N} \frac{1}{2} \|g - Au\|_2^2 + \lambda \|u\|_{0 \text{ or } 1}$$

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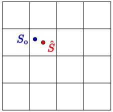

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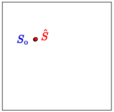

Figure: Off-the-grid case

- not limited by the grid;
- functional convexity on an **infinite dimensional** space;
- measure space with non Hilbertian structure, non reflexive Banach space;
- more recent field of research.

$$\underset{m \in \mathcal{M}(\mathcal{X})}{\arg\min} \frac{1}{2} \|g - \mathcal{A}m\|_2^2 + \lambda \|m\|_{TV}$$

Optimization is everywhere in Learning, Signal, Image and Vision!

Thank you for your attention

Parameter estimation: deterministic approach

$$J(\mathrm{u}, \theta) = \frac{1}{2}\|A(\theta_1)\mathrm{u} - \mathrm{g}\|_2^2 + R(\mathrm{u}, \theta_2)$$

- Regularizing parameter estimation: Cross-validation, L-curve, homotopy, bi-level method, NN learning, ...

$$\hat{\theta} = \underset{\theta \in \Theta}{\arg\min}\ \mathcal{L}(\hat{\mathrm{u}}(\theta))$$

$$\hat{\mathrm{u}}(\theta) = \underset{\mathrm{u} \in \mathbb{R}^N}{\arg\min}\ \left\{\frac{1}{2}\|A(\theta_1)\mathrm{u} - \mathrm{g}\|_2^2 + R(\mathrm{u}, \theta_2)\right\}$$

Parameter estimation: stochastic approach

$$J(\mathrm{u}, \theta) = \|A(\theta_1)\mathrm{u} - \mathrm{g}\|_2^2 + R(\mathrm{u}, \theta_2)$$

- Stein Unbiased Risk Estimator (SURE)
- Maximum Likelihood (ML) estimator with problem of **sampling** on n-dimensional Gibbs distribution
- **Expectation-minimization** (EM) algorithm for ML estimator with latent variables:

E-step: compute $E_{\mathrm{u}|\mathrm{g},\theta^k}[\log P(\mathrm{g}, \mathrm{u}|\theta)] = Q(\theta, \theta^k)$

M-step: $\theta^{k+1} = \arg\max_{\theta \in \Theta} Q(\theta, \theta^k)$