Computational Imaging Course

Inverse problems & Computational Imaging

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Objectives

A priori

Bayesian model

Variational Method

Non-local

Regularisation

Level-set

Inverse Problem

PDE

Minimisation

Total Variation

Euler-Lagrange

MRF

Course sequence

11/02	**Inverse imaging & PDE**
18/02	**Inverse imaging & MRF**
03/03	**Flipped Classroom 1-2**
10/03	**Flipped Classroom 3-4**
17/03	**Flipped Classroom 5-6**

Flipped classroom & project:

- **2 groups max for each topic**
- **Topics:** see link
  - #1: Sparsity & Patches, #2 Learning & PDEs
  - #3: Graph cuts, #4 Optimal transport & imaging
  - #4: Texture synthesis, #6 Motion magnification

- **Flipped classroom:**
  - **30' course** (~ 15/20 slides) **prepared jointly by the 2 groups**
    - 4 main aspects to be adressed: considered issue, proposed model/scheme, numerical implementation, experiments
  - **30' for questions/discussions** (students not presenting shall prepare and send in advance two questions per paper)
  - **15' synthesis** (Prof.)

- **Goal of the project:**
  1. Implement and evaluate the proposed framework (Python)
  2. Benchmarking experiments between the two groups (same experimental setup)

- **Targeted skills:**
  1. Understanding and reformulation of comp. Imaging pbs/models
  2. Implement & benchmark algorithms from scientific papers

- **Evaluation:** Graded lab session / Flipped classroom / Questions / Final presentation

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Flipped Classrooms & Projects

- **Evaluated skills:**
  - In-depth understanding and presentation of a state-of-the-art framework from a research paper (flipped classroom)
  - Ability to question a topic/method based on a quick screening of a paper (30’ max per paper) (flipped classroom)
  - Ability to implement an algorithm described in a research paper (project/notebook)
  - Ability to define and perform benchmarking experiments to evaluate and demonstrate the relevance of different algorithms (project/final-presentation)
  - Ability to perform a short presentation of an problem/algorithm and associaed experiments w.r.t. selected key messages (max 10’) (project/final-presentation)

Synthesis : Variational vs. Bayesian

- **Formulation générale :** $\hat{x} = \arg\min_{x} U_1(x,y) + U_2(x)$

Observation term

Regularisation/prior term

Variational methods

x,y «continuous» fonctions from R^2 to R
Gradient descent algorithm using Euler-Lagrange equation
Typical energy terms:

$$U_1(x,y) = \|x-y\|^2,\ \|g(x)-y\|^2$$
$$U_2(x) = \|\nabla x\|^2,\ \|\nabla x\|$$

Pros : theoretical analysis of the existence and unicity of the solution, region-based modeling (level-set), reationship to physical models (fluid dynamics)

Bayesian models/Markov Random Fields

x,y « discrete », matrices R^{NxM}
Statistical criterion (MAP, MPM,…)
Different types of minimisation scheme solution (gradient descent, graph cut, MCMC methods)

$$U_1(x,y) = -\log P(x|y)$$
$$U_2(x) = -\log P(x)$$

Pros : Model parameter estimation, variety of optimisations scheme, existence of the solution

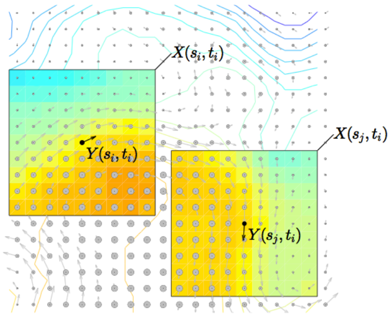
Synthesis : patch, non-local, dictionary & sparsity

$$\hat{x} = \arg\min_{x} U_1(x,y) + U_2(x)$$

- **Problem statement:**

$$U_i(x,y) = \sum_k V_i(x(P_k), y(P_k))$$

k^{th} patch of the image (KxK area)



Non-local model

Key idea: self-similarity in images

$$U_i(x,y) = \sum_{k,l} w(k,l) V_i(x(P_k), y(P_k), x(P_l), y(P_l))$$

Similarity between patches k and l

Interest: using self-similarity in images so that a given image is its own model

Dictionary / Sparsity

$$\forall k,\ x(P_k) = \sum_i \alpha_{i,k} D_i = D \cdot \alpha_k$$

Dictionary of patches

Projection of patch k onto dictionary D

Examples of dictionaries : Fourier, Wavelet, learning (PCA, NNMF, K-SVD,…)

Sparsity prior/constraint on coefficients α_k :

$$\forall k, U_2(x) = U(\alpha), \text{par ex. } \sum_k \|\alpha_k\|$$