# Incorporating intuitive prior in image reconstruction

#### Barbara Gris

*bgris.maths@gmail.com* LJLL, UPMC, Paris

Joint work with Stanley Durrleman (ICM, France), Alain Trouvé (ENS Paris-Saclay, France), Ozan Öktem (KTH, Sweden)

Introduction

## INTRODUCTION





L Introduction

?



#### <u>Goal</u>: reconstruct image $I \in X$ from data $g \in Y$

<u>Goal</u>: reconstruct image  $I \in X$  from data  $g \in Y$ Strategy: minimize

$$I\mapsto D\Big(T(I),g\Big)$$

with  $T: X \mapsto Y$  (known forward operator)

<u>Goal</u>: reconstruct image  $I \in X$  from data  $g \in Y$ Strategy: minimize

$$I\mapsto D\Big(T(I),g\Big)+R(I)$$

with  $T : X \mapsto Y$  (known forward operator) and  $R : X \mapsto \mathbb{R}^+$  a regularizing function.







Goal: reconstruct image  $I \in X$  from data  $g \in Y$ Strategy: minimize

$$I \mapsto D(T(I),g) + R(I)$$

with  $T: X \mapsto Y$  (known forward operator) and  $R: X \mapsto \mathbb{R}^+$  a regularizing function. Possible choice:  $R(I) = C(I_0, I)$ 

<u>Goal</u>: reconstruct image  $I \in X$  from data  $g \in Y$ Strategy: minimize

$$I\mapsto D\Big(T(I),g\Big)+R(I)$$

with  $T : X \mapsto Y$  (known forward operator) and  $R : X \mapsto \mathbb{R}^+$  a regularizing function. <u>Possible choice</u>:  $R(I) = C(I_0, I)$ 

 $\rightarrow C = L^2$ -distance





<u>Goal</u>: reconstruct image  $I \in X$  from data  $g \in Y$ Strategy: minimize

$$I\mapsto D(T(I),g)+R(I)$$

with  $T : X \mapsto Y$  (known forward operator) and  $R : X \mapsto \mathbb{R}^+$  a regularizing function.

<u>Possible choice</u>:  $R(I) = C(I_0, I)$ 

 $\longrightarrow C = L^2$ -distance

 $\longrightarrow C$  comes from a deformation cost

<u>Goal</u>: reconstruct image  $I \in X$  from data  $g \in Y$ Strategy: minimize

$$I\mapsto D(T(I),g)+R(I)$$

with  $T : X \mapsto Y$  (known forward operator) and  $R : X \mapsto \mathbb{R}^+$  a regularizing function.

<u>Possible choice</u>:  $R(I) = C(I_0, I)$ 

 $\longrightarrow C = L^2$ -distance

 $\longrightarrow C$  comes from a deformation cost

$$\varphi \mapsto D\Big(T(\varphi \cdot I_0), g\Big) + R(\varphi)$$

### Definition (Large deformation) For $v \in L^1([0, 1], V)$ , we set $\varphi^v$ the flow of v:

$$\begin{cases} \dot{\varphi}^{\mathbf{v}}(t) = \mathbf{v}(t) \circ \varphi^{\mathbf{v}}(t) \\ \varphi^{\mathbf{v}}(0) = \mathbf{Id} \end{cases}$$

## Definition (Large deformation) For $v \in L^1([0, 1], V)$ , we set $\varphi^v$ the flow of v:

$$\begin{cases} \dot{\varphi}^{\mathbf{v}}(t) = \mathbf{v}(t) \circ \varphi^{\mathbf{v}}(t) \\ \varphi^{\mathbf{v}}(0) = \mathbf{Id} \end{cases}$$

 $\longrightarrow$  Large deformation:  $\varphi_{t=1}^{v}$ .

## Definition (Large deformation) For $v \in L^1([0, 1], V)$ , we set $\varphi^v$ the flow of v:

$$\begin{cases} \dot{\varphi}^{\mathsf{v}}(t) = \mathsf{v}(t) \circ \varphi^{\mathsf{v}}(t) \\ \varphi^{\mathsf{v}}(0) = \mathsf{Id} \end{cases}$$

- $\longrightarrow$  Large deformation:  $\varphi_{t=1}^{\nu}$ .
- $\longrightarrow$  Action on images:  $\varphi \cdot I = I \circ \varphi^{-1}$ .

Introduction



Diffeomorphometry and geodesic positioning systems for human anatomy, Miller et al, Technology 2014.

Introduction



$$v \in L^2([0,1], V) \mapsto D\Big(T(\varphi_{t_1}^v \cdot I_0), g\Big) + \int_0^1 c(v_t) \mathrm{d}t$$

Diffeomorphometry and geodesic positioning systems for human anatomy, Miller et al, Technology 2014.

- Introduction



$$oldsymbol{v} \in L^2([0,1],V) \mapsto D\Big(T(arphi_{t_1}^v \cdot I_0),g\Big) + \int_0^1 c(v_t) \mathrm{d}t$$
 $c(v) = |v|_V^2$ 

[ J. Hinkle, M. Szegedi, B. Wang, B. Salter, S. Joshi. 4D CT image reconstruction with diffeomorphic motion model.] [ C. Chen, O. Öktem. Indirect Image Registration with large diffeomorphic deformations.]

Diffeomorphometry and geodesic positioning systems for human anatomy, Miller et al, Technology 2014.

- Introduction



Diffeomorphometry and geodesic positioning systems for human anatomy, Miller et al, Technology 2014.

[J. Hinkle, M. Szegedi, B. Wang, B. Salter, S. Joshi. 4D CT image reconstruction with diffeomorphic motion model.] [C. Chen, O. Öktem. Indirect Image Registration with large

[C. Chen, O. Oktem. Indirect Image Registration with large diffeomorphic deformations.]

[Sylvain Arguillere. Géométrie sous-riemannienne en dimension infinie et applications à l'analyse mathématique des formes. PhD thesis, Paris 6, 2014.]

[Alain Trouvé. Diffeomorphisms groups and pattern matching in image analysis. International Journal of Computer Vision, 28(3):213–221, 1998.]

































#### Incorporating a structure in large deformations:

- Sparse LDDMM (Deformetrica) [S. Durrleman, M. Prastawa, G. Gerig, and S. Joshi. Optimal data-driven sparse parameterization of diffeomorphisms for population analysis. In Information Processing in Medical Imaging, pages 123-134. Springer, 2011]
- Higher order momentum [S. Sommer M. Nielsen, F. Lauze, and X. Pennec. Higher-order momentum distributions and locally affine Iddmm registration. SIAM Journal on Imaging Sciences, 2013]
- GRID [U. Grenander, A. Srivastava, S. Saini. A pattern-theoric characerization of biological growth. IEEE, 2007]
- Poly-affine [V. Arsigny, X. Pennec, N. Ayache, 2005. Polyrigid and Polyaffine Transformations: A Novel Geometrical Tool to Deal with Non-rigid Deformations – Application to the Registration of Histological Slices. Medical Image Analysis 9, 507–523]
- Diffeons [L. Younes. Constrained diffeomorphic shape evolution. Foundations of Computational Mathematics, 2012.]

- 1. Defining easily complex generators
- 2. Evolution of generators during integration of the flow
- 3. Ensuring mathematical properties





- 1. Defining easily complex generators
- 2. Evolution of generators during integration of the flow
- 3. Ensuring mathematical properties

- Structured vector field

#### STRUCTURED VECTOR FIELDS USING A DEFORMATION PRIOR

-Structured vector field

Deformation module: definition and first examples



Structured vector field

Deformation module: definition and first examples


Structured vector field



Structured vector field



Structured vector field



- Structured vector field



Structured vector field



Structured vector field



Structured vector field



Structured vector field



Structured vector field



Structured vector field



Structured vector field



Structured vector field



Structured vector field



Structured vector field



Structured vector field



Structured vector field



Structured vector field



Structured vector field



Structured vector field

Deformation module: definition and first examples

#### Incorporate structure in vector fields

-Structured vector field

- Incorporate structure in vector fields
- Easy combination of structures

Modular large deformations

From a deformation module to a deformation model

# STRUCTURED LARGE DEFORMATION

- Modular large deformations



- Modular large deformations

From a deformation module to a deformation model

## Definition (Finite energy controlled paths on $\mathcal{O}$ ) We denote by $\Omega$ the set of mesurable curves $t \mapsto (q_t, h_t) \in \mathcal{O} \times H$ such that :

• 
$$\dot{q}_t = \xi_{q_t}(v_t)$$
 where  $v_t = \zeta_{q_t}(h_t) \in \zeta_{q_t}(H)$ 

- Modular large deformations



Modular large deformations

- From a deformation module to a deformation model

### Definition (Finite energy controlled paths on O)

We denote  $\Omega$  the set of mesurable curves  $t \mapsto (q_t, h_t) \in \mathcal{O} \times H$  such that :

• 
$$\dot{q}_t = \xi_{q_t}(v_t)$$
 where  $v_t = \zeta_{q_t}(h_t) \in \zeta_{q_t}(H)$ 

• Energy 
$$E(q, h) \doteq \int_0^1 c_{q_t}(h_t) dt < \infty$$

Modular large deformations

From a deformation module to a deformation model

### Definition (Finite energy controlled paths on $\mathcal{O}$ )

We denote  $\Omega$  the set of mesurable curves  $t \mapsto (q_t, h_t) \in \mathcal{O} \times H$  such that :

• 
$$\dot{q}_t = \xi_{q_t}(v_t)$$
 where  $v_t = \zeta_{q_t}(h_t) \in \zeta_{q_t}(H)$ 

• Energy 
$$E(q, h) \doteq \int_0^1 c_{q_t}(h_t) dt < \infty$$

 $\longrightarrow \varphi_{t=1}^{\zeta_q(h)}$  is a modular large deformation.

$$\longrightarrow \varphi_{t=1}^{\zeta_q(h)} \cdot q_0 = q_1.$$

 $\longrightarrow \varphi^{\zeta_q(h)}$  is defined by  $(q_{t=0}, h) \in \mathcal{O} \times L^2([0, 1], H)$ .

Modular large deformations



Modular large deformations



Modular large deformations



Modular large deformations



Modular large deformations



Modular large deformations



Modular large deformations



Modular large deformations



Modular large deformations



Modular large deformations


Modular large deformations



Modular large deformations



Modular large deformations



Modular large deformations



Modular large deformations



Modular large deformations



Modular large deformations



Modular large deformations



Modular large deformations



Modular large deformations



Modular large deformations



Modular large deformations



Modular large deformations



Modular large deformations



Modular large deformations



Modular large deformations



Modular large deformations



Modular large deformations



Modular large deformations



Modular large deformations



Sub-Riemannian structure on  $\mathcal{O}$ 



Sub-Riemannian structure on  $\mathcal{O}$ 

# SUB-RIEMMANNIAN STRUCTURE ON ${\mathcal O}$

-Sub-Riemannian structure on  $\mathcal{O}$ 

### Proposition

Wet set  $\rho$  :  $(q, h) \in \mathcal{O} \times H \mapsto (q, \xi_q \circ \zeta_q(h)) \in T\mathcal{O}$ . Then  $(\mathcal{O} \times H, c, \rho)$  defines a sub-Riemannian structure on  $\mathcal{O}$  and

$$Dist(a,b)^2 = \inf\{\int_0^1 c_q(h) \mid h \in L^2([0,1],H), \dot{q} = \rho_q(h), \\ q_{t=0} = a, q_{t=1} = b\}$$

### Theorem

If  $Dist(a, b) < \infty$  the energy *E*, there exists  $(q, h) \in \Omega$  such that  $q_{t=0} = a, q_{t=1} = b$  and  $Dist(a, b) = \sqrt{\int_0^1 c_q(h)}$ .

[B. G., S. Durrleman, A. Trouvé, A sub-Riemannian modular framework for diffeomorphism based analysis of shape ensembles, SIAM Journal of Imaging Sciences, 10.1137/16M1076733 (2018).]

[S. Arguillère. Géométrie sous-riemannienne en dimension infinie et applications à l'analyse mathématique des formes, PhD thesis, Paris 6, 2014]

[A. Agrachev, D. Barilari, U. Boscain. Introduction to Riemannian and Sub-Riemannian geometry, 2014.]

-Sub-Riemannian structure on  $\mathcal{O}$ 

Relaxed problem

### Proposition

Let  $M = (\mathcal{O}, H, \zeta, \xi, c)$  be a deformation modules satisfying the UEC and  $\mu : \mathcal{O} \mapsto \mathbb{R}^+ C^1$ . Let  $a \in \mathcal{O}$  and

$$J_a:h\in L^2([0,1],H)\mapsto \int_0^1 c_{q_t}(h_t)\mathrm{d}t+\mu(q_{t=1},b)$$

with  $q_{t=0} = a$  and (q, h) horizontal. Minimizers of  $J_a$  can be parametrized by an element  $\eta \in T_a^*\mathcal{O}$ .

- Applications

- Image reconstruction

# APPLICATIONS IMAGE RECONSTRUCTION

### Applications

Image reconstruction

?



### - Applications





- Applications

Image reconstruction

## Goal:

• Using  $I_0$  as a prior to reconstruct from data g

- Applications

Image reconstruction

## <u>Goal</u>:

• Using  $I_0$  as a prior to reconstruct from data g

• Define a deformation module  $M = (\mathcal{O}, H, \zeta, \xi, c)$ 

- Applications

- Image reconstruction

## <u>Goal</u>:

- ▶ Using *I*<sub>0</sub> as a prior to reconstruct from data *g*
- Define a deformation module  $M = (\mathcal{O}, H, \zeta, \xi, c)$

Strategy: using geodesics parametrized by  $(a, \eta) \in T_a^* \mathcal{O}$  to transform  $I_0$ .

$$J_{I_0,g}(\boldsymbol{a},\eta) = \boldsymbol{C}(\boldsymbol{a},\eta) + \frac{1}{\lambda} \boldsymbol{D}\Big(\boldsymbol{T}(\varphi_{t=1}^{\zeta_q(h)} \cdot \boldsymbol{I}_0), \boldsymbol{g}\Big)$$

with (q, h) the geodesic parametrized by  $(a, \eta)$ .  $\rightarrow$  A well-defined regularization method (existence, stability and convergence).

[B.G., Incorporation of a deformation prior in image reconstruction (2018)]

- Applications





### - Applications





- Applications





- Applications





### - Applications





### - Applications




# - Applications





# - Applications





# - Applications





# - Applications





# - Applications





# - Applications





# - Applications





# - Applications





# - Applications





# - Applications





- Applications





- Applications





- Applications





- Applications





- Applications





- Applications





- Applications





- Applications





- Applications





- Applications





- Applications

Image reconstruction



[J. Adler et al. ODL - a Python framework for rapid prototyping in inverse problems. In preparation, KTH, Royal Institute of Technology. Code and documentation available

online: https://github.com/odlgroup/odl.

- Applications





- Conclusion

- Incorporate known prior in image reconstruction
- Reconstruction in low dimension

- Conclusion

- Incorporate known prior in image reconstruction
- Reconstruction in low dimension

Questions ?