Learning Conditional Deformable Templates with Convolutional Networks

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Learning framework to **estimate deformable templates** together with alignment network. Enables *conditional* template generating functions based on desired attributes.

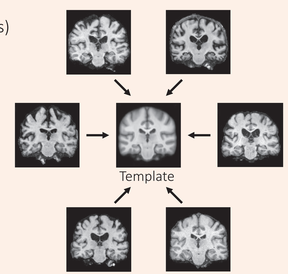
Code: **voxelmorph.mit.edu**

Motivation

Deformable templates (atlases)
- Fundamental in many tasks (e.g., neuroimaging analysis)
- Enable analysis, representative visualization

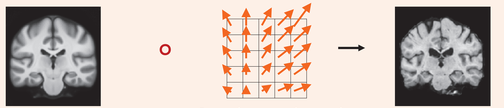
Traditional approaches
- Jointly optimize template and deformation
  - **long runtimes,** rarely done in practice
- Unconditional
  - require several templates for diverse data
- Practitioners use (limited) existing templates

- **Our Method**
  - Jointly learn registration network and atlas
  - Atlases can be conditioned on desired attributes



Method

Probabilistic generative model for deformable template

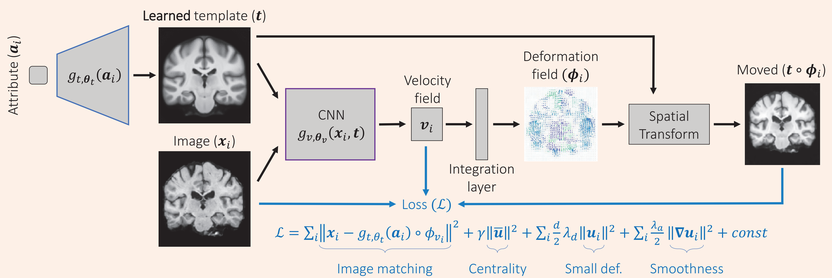


Deformable template $t = f_\theta(a)$
conditional: fcn. of attrib. a
unconditional: param per pixel

Smoothness and central deformation prior
$p(v) \propto \exp(-\lambda\|\nabla u_v\|^2)\prod_j \mathcal{N}(0,\Lambda^{-1})$

Image likelihood
$x \sim \mathcal{N}(t \circ \phi_z, \sigma^2 I)$

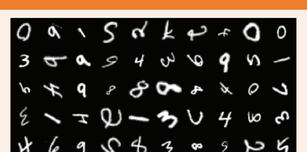
Goal
joint network $g(x,a)$ estimates **template** t and **deformation (velocity)** v simultaneously



$$\mathcal{L} = \sum_i \underbrace{\|x_i - g_{t,\theta_t}(a_i) \circ \phi_{v_i}\|^2}_{\text{Image matching}} + \underbrace{\gamma\|\bar{u}\|^2}_{\text{Centrality}} + \sum_i \underbrace{\frac{d}{2}\lambda_d\|u_i\|^2}_{\text{Small def.}} + \sum_i \underbrace{\frac{\lambda_s}{2}\|\nabla u_i\|^2}_{\text{Smoothness}} + const$$

Experiments: MNIST

Data: MNIST, with different *scaling* and *rotation*
Results:
- Central atlases (low total MSE)
- Sharp, representative
- **Low deformations to data**
- Smooth fields (Jacobians of 1)
- Fast runtime

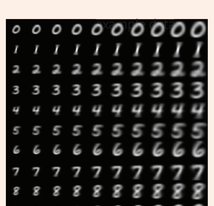


Example data

Main Atlases

Class rotation and scale templates

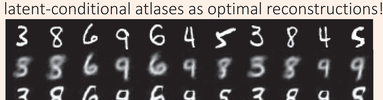
Class and scale templates



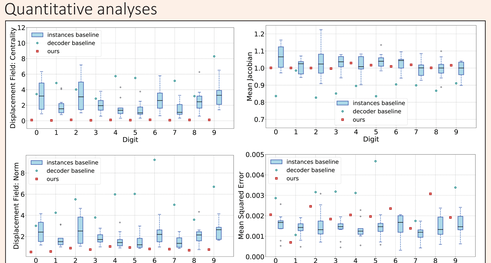
Decoder-only templates

Latent attribute: what if we learn attributes from inputs?
Network learns latent-conditional atlases as optimal reconstructions!

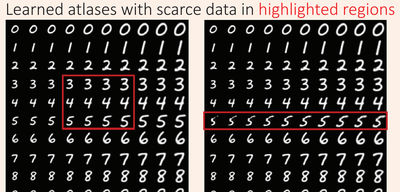
Input digit
Tiny-AE recon
Our recon looks like an atlas



Quantitative analyses



Learned atlases with scarce data in highlighted regions



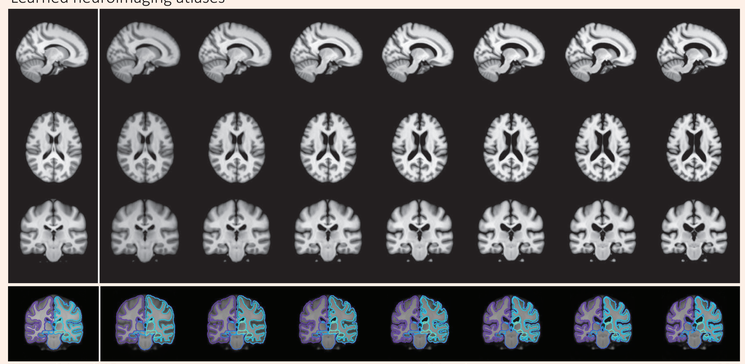
Conditioning attributes eliminate variability!

Conditional

Unconditional

Experiment: Neuroimaging

Learned neuroimaging atlases



Unconditional 15 ← age-conditional → 90

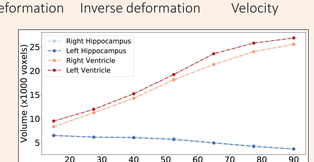
Example atlas registration

Atlas Scan Warped atlas Warped scan

Deformation Inverse deformation Velocity

Data: ADNI and ABIDE MRIs, attributes: age and sex

Results:
- **Central** atlases (low total MSE)
- Low deformations to brain MRIs
- Smooth fields (Jacobians of 1)
- **Improved segmentation results**
  Atlas-based segmentation Dice:
  - 80 ($\pm$1) using our atlas & model
  - 73 ($\pm$2) using classical atlas



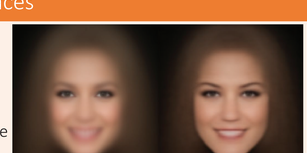
- Conditional templates recover known age patterns
  - growth of ventricles
  - shrinkage of hippocampus

Experiment: Faces

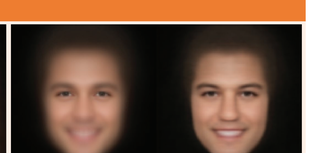
Data
CelebAMask-HQ
affine-aligned

Attributes
smiling, gender, age

Results
sharper averages



Average Atlas



Average Atlas