Main Idea: Encode a single atlas by training an atlas-specific randomized forest (Atlas Forest) for use within a standard multi-atlas label propagation (MALP) framework.

Motivation: Efficient Labelling and Experimentation
1. only 1 registration per target (no reg. of all atlases to target)
2. computationally efficient encoding scheme while keeping advantages of MALP, e.g. ability for atlas selection

Training: Encoding each atlas by an Atlas Forest (AF) by training one randomized classification forest per atlas

Evaluation: Promising Results with Atlas Forest Encoding

Results on ISBR (18 atlases, 32 labels)

Results on LPBA40 (40 atlases, 54 labels)

Results from MICCAI 2012 Multi-Atlas Labeling Challenge (MALC)

Results from MICCAI 2013 SATA Challenge

Relation to Other Frameworks

Properties

MALP

Patch-based MALP

Atlas Forests

Atlas Encoding

Local intensity after registration

Collection of patches around a point after registration (const. patch size)

Context-aware features around a point (variable features: depend on appearance around a point)

Correspondence

One-to-one

One-to-many (explict localization)

One-to-many (implicit localization)

Registrations per Target

N (all atlases to target)

N (all atlases to target)

1 (probabilistic atlas to target)

Registration Type

Deformable

Atlas-Deformable

Affine/Deformable

Training Required

NO (used in some approaches)

YES

“Standard” Forest Scheme

(training on samples from all atlases)

Atlas Forests

Atlas Selection

Not obvious

Complete remaining for “proper” use of new data (potential of local posterior scan position)

Efficient Experimentation

New training for every training/testing split of data

Each AF is trained only once for any data split

Efficient Training

More data per tree: more resources needed, requires (potentially non-trivial) bagging

Fast training, possible without bagging

Randomized Classification Forest

Split Function

P_{f}(x) = \begin{cases} 0 & \text{if } f(x; \mathbf{\theta}) \leq t \text{ or left} \\ 1 & \text{if } f(x; \mathbf{\theta}) > t \text{ or right} \end{cases}

Context-sensitive Features (data representation)

Deterministic features: local intensity of input image and priors at x

Randomized, non-local, parameterized, and intensity-based features f(x; \mathbf{\theta})

1. Local cubical mean intensity: \mu_{c}(f(x; \mathbf{\theta}))
2. Difference of local intensity and offset cuboid intensity mean: f(x; \mathbf{\theta}) - \mu_{c}(f(x; \mathbf{\theta}))
3. Difference of local and offset cuboid intensity mean: \mu_{c}(f(x; \mathbf{\theta})) - \mu_{c}(f(x; \mathbf{\theta}))
4. Difference of local and offset cuboid intensity mean: \mu_{c}(f(x; \mathbf{\theta})) - \mu_{c}(f(x; \mathbf{\theta}))

Training (learning intensity-based label prediction from a labelled image)

Determine split function f_{\theta} at each tree node, by estimating the splitting dimension f_{j} from (randomly chosen feature subspace) and split threshold s for f_{j} to optimize Information Gain

Testing (determining the label for each image point)

For each tree \mathbf{\theta}, apply split tests to reach a leaf, and use the resulting p_{\mathbf{\theta}}(c|x) in overall prediction p(c|x) = \sum_{\mathbf{\theta}} p_{\mathbf{\theta}}(c|x)

Results on Data from MICCAI 2012 Multi-Atlas Labeling Challenge (MALC)

OASIS data, 134 labels (98 cortical, 36 non-cortical)

Results from MICCAI 2013 SATA Challenge

Dinexaphon Segmentation, unregistered data (OASIS data, 14 labels)

slightly different settings to above, e.g. no skull-stripping