Atlas Encoding by Randomized Forests for Efficient Label Propagation

Darko Zikic, Ben Glocker and Antonio Criminisi

Microsoft Research Cambridge

Microsoft Research

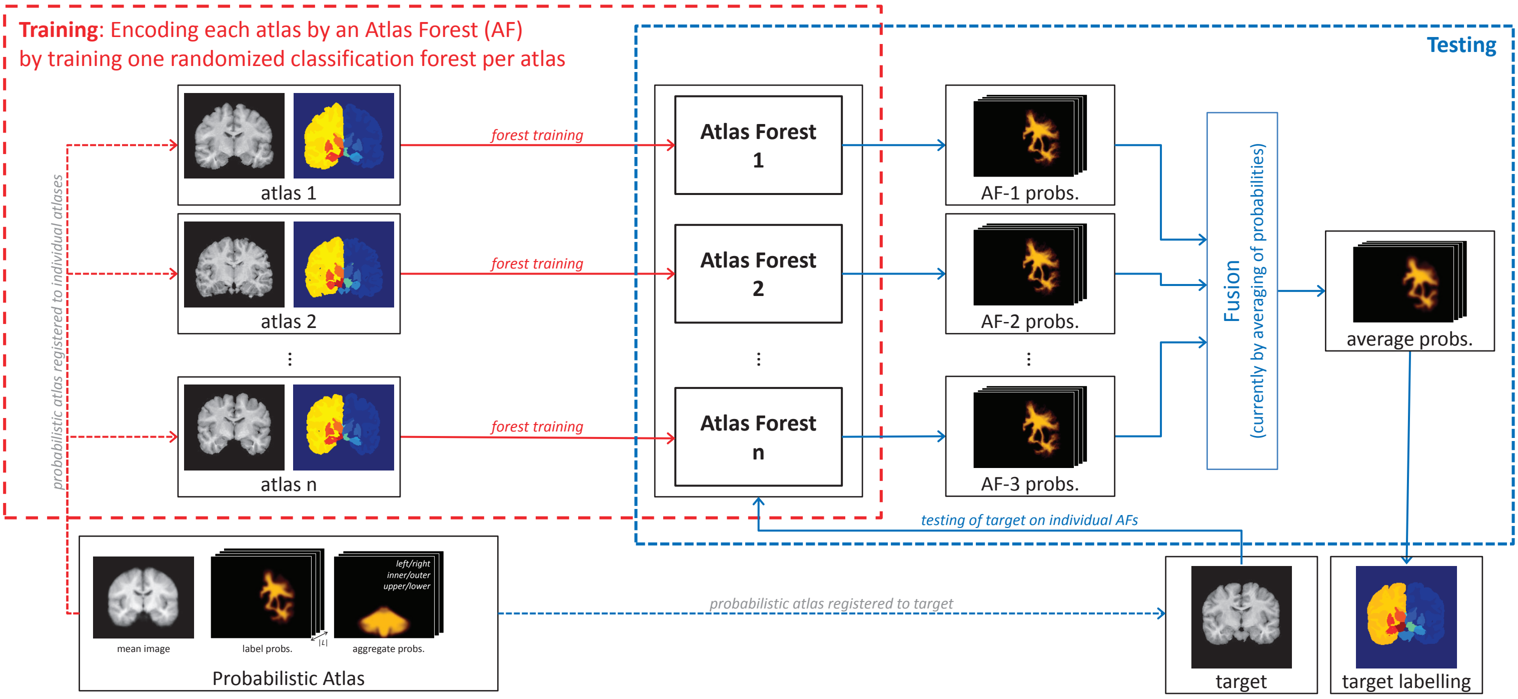
Main Idea: Encode a single atlas by training an atlas-specific randomized forest (Atlas Forest)

for use within a standard multi-atlas label propagation (MALP) framework

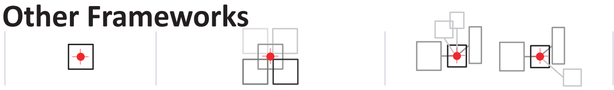
Motivation: Efficient Labelling and Experimentation

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



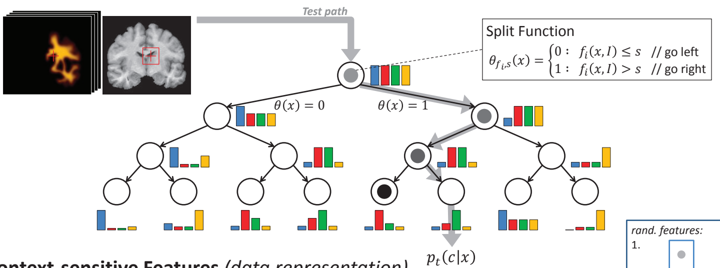
Relation to Other Frameworks

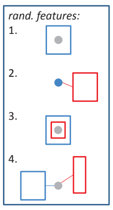


Properties	MALP	Patch-based MALP	Atlas Forests
Atlas Encoding	Local intensity after registration	Collection of patches around point ***x*** after registration (const. patch size)	Context-aware features around ***x*** (variable features: depend on appearance around ***x***)
Correspondence	One-to-one	One-to-many (explicit 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	**Affine**/Deformable	Affine/**Deformable**
Training Required	NO (used in some)	NO (used in some approaches)	YES

More Properties	'Standard' Forest Scheme (training on samples from all atlases)	Atlas Forests
Atlas Selection	Not obvious	Straight forward (pick corresponding AFs)
Addition of New Atlases	Complete retraining for 'proper' use of new data (update of leaf posteriors alone possible)	Training of a single new Atlas Forest
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





- **Context-sensitive Features** *(data representation)*
  - Deterministic features: local intensity of input image and priors at x
  - Randomized, Non-local, parameterized, and intensity-based features $f(x, I)_{\mathrm{p}}$
    1. Local cuboid mean intensity: $\mu(I(C_s(x)))$
    2. Difference of local intensity and offset cuboid intensity mean: $I(x) - \mu(I(C_s(x+u)))$
    3. Difference of local and offset cuboid intensity means: $\mu(I(C_s(x))) - \mu(I(C_r(x+v)))$
    4. Difference of local and offset cuboid intensity means: $\mu(I(C_s(x+u))) - \mu(I(C_r(x+v)))$
- **Training** *(learning intensity-based label prediction from a labelled image)*
  - Determine split function $\theta_{f_i,s}$ at each tree node, by estimating the splitting dimension f_i (from *randomly chosen feature subspace*) and split threshold s for f_i, to optimize Information Gain
- **Testing** *(determining the label for each image point)*
  - For each tree t, apply split tests to reach a leaf, and use the resulting $p_t(c|x)$ in overall prediction $p(c|x) = \frac{1}{n}\sum_{t=1}^{n} p_t(c|x)$

Evaluation: Promising Results with Atlas Forest Encoding

Settings (determined on IBSR)

- trees per atlas forest = 5
- max. depth = 36
- min. samples per leaf = 8
- random features per tree = 10x1000
- axis-aligned split functions
- Registration: non-rigid with FFD + discrete opt. (quite conservative/rigid setting, low image res.)

Pre-processing Steps

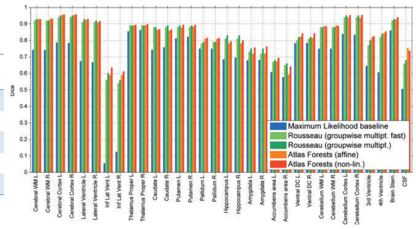
- Skull-stripping, Inhomogeneity correction, Histogram matching

Results on IBSR

(18 atlases, 32 labels)

	[Rousseau] Fast Multi-point	[Rousseau Group-wise MP	Atlas Forests
DSC	82.25%	83.5%	84.60%
Time [min]	22	130	3 (+0.5 for reg.)
AF Variation: no use of probabilistic atlas			77.38%
AF Variation: Affine reg. instead of deformable			82.71%
Standard forest bagging (setup obtained by AFs!)			84.08%

[Rousseau] A Supervised Patch-Based Approach for Human Brain Labeling. Rousseau, Habas, Studholme. *IEEE TMI 2011*

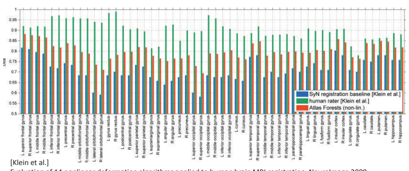


Results on LPBA40

(40 atlases, 54 labels)

	PBL*	SPBL*	SCPBL*	Atlas Forests
DSC	75.06%	76.46%	78.04%	77.46%
Time [min]	10 (per class)	28 (per class)	45 (per class)	8 +0.5 for reg.

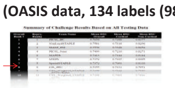
* PBL = Patch Based Labelling, SPBL=Sparse-only PBL, SCPBL=Spatially Consistent PBL
Robust patch-based multi-atlas labelling by joint sparsity regularization.
Wu, G., Wang, Q., Zhang, D., Shen, D.In: MICCAI Workshop STMI. (2012)



[Klein et al.]
Evaluation of 14 nonlinear deformation algorithms applied to human brain MRI registration. NeuroImage 2009

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

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



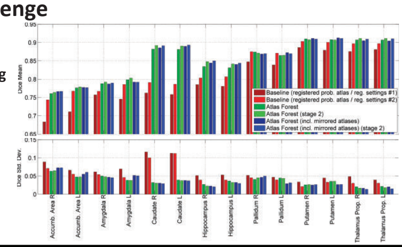
[PICSL-BC]
Wang, H., Avants, B., Yushkevich, P.
A combined joint label fusion and corrective learning approach.
In: MICCAI Workshop on Multi-Atlas Labeling. (2012)

	PICSL-BC (1st at MALC)	Atlas Forests
DSC	76.54%	73.66%
DSC cort	73.88%	71.04%
DSC non-cort	83.77%	80.81%
Time	"computation time for registering each pair of images is about 20 hours" the fusion ``finishes processing one brain image in about three hours"	4 min + 30 sec. for reg.

Results from MICCAI 2013 SATA Challenge

Dinecephalon Segmentation, unregistered data
(OASIS data, 14 labels)
slightly different settings to above, e.g. no skull-stripping

Method	Dice: mean (med)	Hausdorff [mm]
UPENN_SBIA_MAM	0.8686 (0.8772)	3.3043 (3.1006)
PICSL	0.8663 (0.8786)	3.5381 (3.2369)
SBIA_LevelSet	0.8654 (0.8775)	3.4237 (3.1429)
deedsMIND	0.8402 (0.8573)	4.1027 (3.8983)
AtlasForest Stage2	0.8282 (0.8484)	3.7411 (3.5231)
AtlasForest	0.8248 (0.8422)	3.8659 (3.6737)



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