Negative-Unlabeled Learning for Diffusion MRI

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Overview of Methods for Diffusion MRI

	Fitting of handcrafted representation (DTI, DKI, NODDI, ...)	Analytic computation of handcrafted metrics [1]	Machine learning							
			Voxel-wise supervised learning (of handcrafted metrics) [2]	Voxel-wise supervised learning (of tissue properties) [2]	Voxel-wise semi-supervised learning [hypothetical method]	Scan-wise supervised learning [3]	Weakly-supervised learning [3]	Multiple-instance learning [hypothetical method]	Novelty detection [4,5,6]	Negative-unlabeled learning [proposed]
Works with few q-space measurements	**No**	✓	✓	✓	✓	✓	✓	✓	✓	✓
Object of direct study	**Handcrafted metrics**	**Handcrafted metrics**	**Handcrafted metrics**	**Tissue properties (for example abnormality)**	**Tissue properties (for example abnormality)**	**Tissue properties (for example abnormality)**	**Tissue properties (for example abnormality)**	**Tissue properties (for example abnormality)**	**Abnormality**	**Abnormality**
Location of labels	**None**	**None**	**Voxel-wise from fitting (which requires none)**	**Voxel-wise**	**Voxel-wise**	**Scan-wise**	**Scan-wise**	**Scan-wise**	**Any (only normal)**	**Any (only normal)**
Location of prediction	**Voxel-wise**	**Voxel-wise**	**Voxel-wise**	**Voxel-wise**	**Voxel-wise**	**Scan-wise**	**Voxel-wise clues for global prediction**	**Voxel-wise**	**Voxel-wise**	**Voxel-wise**
Usage of unlabeled data during training	**No**	**No**	**No**	**No**	✓	**No**	**No**	**No**	**Usually no**	✓
Used knowledge (a) Voxels from one scan belong together	**N/A**	**N/A**	**N/A**	**N/A**	**N/A**	✓	✓	✓		
Used knowledge (b) All voxels from healthy-control scan are healthy	**N/A**	**N/A**	**N/A**	✓	**N/A**	✓		✓	✓	✓
Used knowledge (c) Disease clues may depend on context (other voxels)	**N/A**	**N/A**	**N/A**	**N/A**	**N/A**	✓	✓			

Setting & Approach

- q-Space deep learning [2,3,4,5,6]: Prediction of tissue properties directly from q-space measurements
- Every voxel is a sample
  - Features are q-space measurements
- Only negative (healthy) and unlabeled samples are given
  - i.e. **negative-unlabeled learning** [8]
- No positive (multiple sclerosis) labels are given
  - i.e. **no knowledge about disease is required**
- Goal: distinguish negative and positive samples
- Treating unlabeled samples as positive (which introduces "label noise") is (for certain cost functions) a good method for netagive-unlabeled learning [Zhung&Lee]
  - We use a simpler cost function that yields similar results

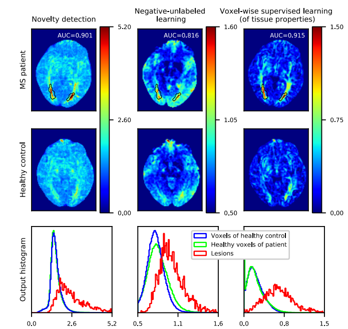
Data

- 94 multiple sclerosis patients, 26 healthy controls
- Six b=0 images, 40 diffusion directions (b_{max}=1200s/mm²)
- SE-EPI, TR=16s, TE=94.5ms, voxel size 1.8mm×1.8mm×2.4mm, matrix 128×128, 57 axial slices, motion/distortion-corrected [9]

Neural Network

- Feature scaling: divide each channel by its mean taken over all scans
- To prevent overfitting of intensity values: divide each scan by its mean and multiply with random scalar between 0.8 and 1.2 in every epoch
- **3D ConvNet**: ReLU, 128,256,512,1 filters 1×1×1, Adam

Results



Discussion & Conclusions

- **Deep learning for diffusion MRI**:
  - **data-driven**: diagnosis directly from raw q-space data
  - **many advantages**: ultra-short scans, optimal usage of information, ...
  - applicable in **various situations**: coarse or missing labels, unknown disease effects, ...
- As expected, supervised q-Space Deep Learning yields best AUC
- Negative-unlabeled learning yields good AUC (0.77) but is surprisingly outperformed by novelty detection (0.89)
- More research is necessary

References

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