Report on
Participation in the IronTract Challenge 2019

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Essential details of processing and analysis, and some observations from participating in the IronTract challenge 2019 are presented in this report. Our approach ranked #2 on the training dataset for both the HCP (multi-shell) and overall (DSI) tracks. The ranking on the validation dataset placed our approach at #2 for the overall track, and #3 for the HCP track.

DESIGNER, MSMT_CSD, iFOD2, heuristic length and include filtering

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Essential details

The entire exercise was performed using tools from MRtrix3 (1), FSL (2), ANTS (3), and GNU parallel (4). The data was pre-processed through the DESIGNER (5) preprocessing which includes denoising (6, 7), deringing (8), B1 bias correction, and Rician correction. Constrained spherical deconvolution (9) was then performed using the multi-shell mutitissue response function (MSMT_CSD) (10). The HCP resampled data was used for both the HCP and overall competitions. The seed region was binarized without any additional filtering.

Tractography was performed using the `tckgen` tool in MRtrix3. The main options were iFOD2, different angle thresholds from 10° through 90°, default stepsize of 0.35, and min and max length thresholds. The basic code, with a few additional parameters, for the tractography is shown below.

```
for ang in `seq 10 10 90`
do
    tckgen odf_sfwm.mif tracts.tck -
      ↪ seed_image injectbin.nii.gz -
      ↪ select 1M -minlength 20 -
      ↪ maxlength 50000 -trials 10000
      ↪ -power 0.001 -algorithm iFOD2
      ↪ -seed_unidirectional -angle
      ↪ $ang
 done
```

Six planar include filters, two for each of the x, y, z coordinates, were used to avoid looping tracts. Then, tract density images (TDI) (11) were created using the `tckmap` command. A set of thresholds were applied to each of the TDI image to include portions of the ROC curve for FPR$\in [0, 0.3]$, which turned out to be a key factor for getting a competitive AUC. The TDIs from different angle thresholds were averaged for each of the threshold setting, which formed the final set of maps that were uploaded for scoring.

Observations

The overall experience of participating in this challenge was akin to learning to drive a race car, with all its gears and gadgets to gain an edge in second or third decimal pace in the AUC scores. Most of the settings off the lot, seemed to perform quite competitively. The core tractography algorithms such as iFOD2 are constrained only locally, but to achieve a good score, imposing global constraints, such as using include filters seemed to have helped. It seemed like, if one could pick the settings of any tractography algorithm and execute it to generate an accurate and complete white matter mask, it would match the histological tracing perfectly.It is amazing that the TPR reaches 1 by around FPR of 0.3, implying that the AUC is on average above 0.93, actually. Perhaps because of this, simple default settings were sufficient.

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