Automatic Classification of Brain Tractography Data

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Target Audience
This research is intended for clinicians and researchers interested in the use of diffusion MRI for the mapping of brain white matter tracts.

Purpose
Diffusion MRI tractography is a method that produces images of the molecular diffusion processes in tissue. These images can be used in pre-neurosurgical planning to map brain connections that are considered critical to motor, visual, and language function. Usually, brain tractography data is classified and segmented manually by a trained technician, who "cleans" the tracks based on prior assumptions of anatomical connectivity and learned shape characteristics. This is a very time consuming process that requires a significant amount of training and can be highly variable. As an alternative, this study explores the use of an automatic classification method, which uses a training set to ultimately output a set of classified de-noised tracts from a set of streamlines. Other studies have worked on automatic supervised classification methods for DTI streamlines[1]. However, these studies are based on a much smaller sample size of registered tracts and do not address the variability of the ground truth classifications that are used as a basis of comparison. Manually segmented tracts vary due to both differences in probabilistic tractography and differences in human operators. Algorithms that depend on registration may also suffer from poor performance when registration is affected by features such as a tumor mass. This study aims to better understand and optimize algorithms for automatic classification of tractography data, by using a larger dataset to investigate the impact of tractography variability and registration on algorithm performance.

Methods
***Data Set*:** As a proof of principle, this study used probabilistic qBall fiber tracking[2] to trace a set of fiber populations from the left and right External Capsule to classify streamlines as either Inferior Fronto-Occipital Fasciculus (IFOF), Uncinate Fasciculus, or noise. Two different experts in neuroradiology independently performed tractography on the brains of 16 different healthy subjects to produce around 2500 streamlines for each subject. The experts then established a ground truth by manually classifying these tracks as IFOF, Uncinate, or noise, using the software TrackVis. In total, the training set consisted of around 75000 streamlines and the test set consisted of around 5000 streamlines.
***Classifier*:** The data was classified with a linear support vector machine classifier that uses stochastic gradient descent while learning and a log loss function. The sklearn.linear_model.SGDClassifier python package was used to implement this model.
Feature Vectors: The feature vector extracted for each streamline includes the unregistered x, y, and z coordinate values of 50 equidistant points interpolated along the length of the streamline, the contour length, and the end-to-end length.
Evaluation Metric: The classifier algorithm was evaluated using the metric of the percent volume overlap with the same tract cleaned by a human operator. This percent overlap was computed only for voxels with more than 5 streamlines and compared with the inter-human operator percent overlap. A paired t-test was then performed to show how likely it is that the percent volume overlap for algorithm vs. human operator comes from the same statistical population as the percent volume overlap for human operator vs. human operator.

Results
IFOF: For the IFOF, the tracts classified by the algorithm and the tracts classified by humans were almost indistinguishable for the left side (p-value = .9021) and were very similar for the right side (p-value= 0.57). The IFOF represents a well-defined tract with low variability. The algorithm segmented the IFOF well and the variability across subjects was similar for both the algorithm and the human operators, suggesting that this variability is dominated by probabilistic tractography effects.
Uncinate: In contrast, the variability across subjects was higher for the Uncinate tracts. The Uncinate tracts classified by the algorithm and the Uncinate tracts classified by the humans were quite different due to false positive streamlines identified by the algorithm. In addition, the variability across subjects was similar for the left side, but quite different on the right side. It is difficult to make any conclusions about how much of this variability is due to differences in tractography and how much is due to differences in the classification method.
Conclusion: This study shows how a registration free automatic classification method compares to a manual classification method with variance due to human operators. While this algorithm sometimes outputs false positives when identifying tract streamlines, it should be noted that the sensitivity of the algorithm is much more important than the specificity. Humans can easily further refine an output with false positives in a semi-automatic classification method. In the future, this algorithm will be used to quantify the improvement due to registration and quantify the variance that is due to probabilistic tractography.

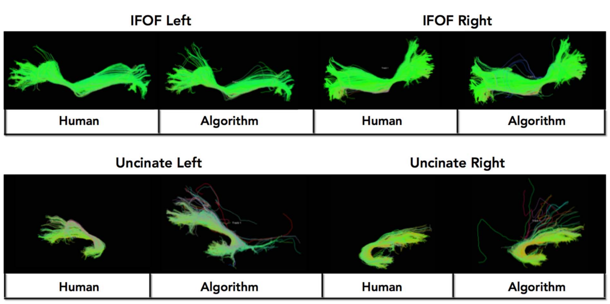

Figure 1: Representations of the tracts as classified by the algorithm and representations of the tracts as classified by a trained technician

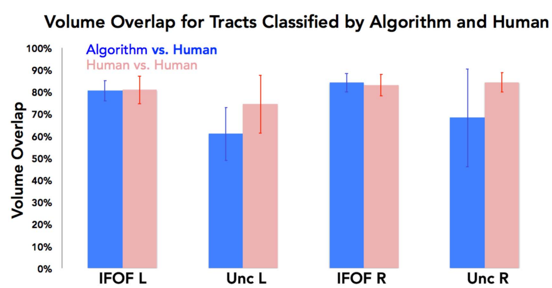

Figure 2: Comparison of the percent volume overlap for tracts classified by human operator vs. tracts classified by the algorithm and the percent volume overlap for tracts classified by two different human operators.

Tract	IFOF Left	Uncinate Left	IFOF Right	Uncinate Right
P-Value	.90	.06	.57	.02

Figure 3: P-Values representing the probability that the percent volume overlap for tracts classified by a human and by the algorithm comes from the same population as the percent volume overlap for tracts classified by two different human operators.

References
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2. Tuch, David S. "Q-ball imaging." *Magnetic Resonance in Medicine* 52.6 (2004): 1358-1372.