# A Novel Average Curves Tractography Technique - Validation Using a Physical Phantom

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## Introduction

Probabilistic tractography methods have been developed as an alternative to deterministic algorithms due to their ability to handle the uncertainty of fibre orientations. However, deterministic tractography have several advantages over probabilistic tractography for some applications such as neurosurgery. Visualization of the deterministic streamline trajectories is similar to the expected white matter fibre tracts, whereas the output of probabilistic methods may be harder to interpret and it can be difficult to identify the most probable path. Connectivity maps from probabilistic methods can also leak into unexpected regions of white matter. In this study, we present a deterministic version of probabilistic tractography, which results in a single well defined trajectory for every major connection from a seed point using an average curves approach. The output of this approach represents the most probable of all possible paths. We evaluated the results of the algorithm applied to images of a physical phantom, which contained regions of crossing, branching and fanning. The results are very consistent with the true fibre path for the phantom.

## Methods

**Average Curves:** A curve is represented numerically as a sequence of points in space. We consider a representative curve from a given collection of curves in space as the average curve of the collection. The representative curve needs to be as close as possible to all the curves in the collection which can be achieved by ensuring that the average curve minimises the difference from all the other curves.

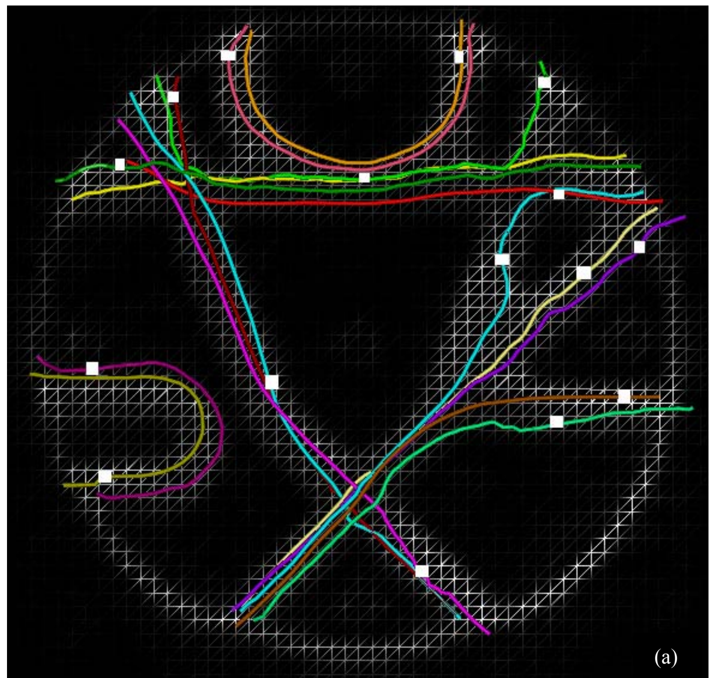
The classical distance between point-sets is the Hausdorff measure. The asymmetric *Hausdorff distance* from set *A* to set *B* is $H'(A,B) = \max_{a \in A}(|b(a) - a|)$. and $b(a) = \arg\min_{b \in B}(|b - a|)$ . The *Average minimum distance* from A to B is $G'(A,B) = \underset{a \in A}{Mean}(|b(a) - a|)$

The *mean curve* is calculated using an arc-length re-parameterisation method, which re-parameterises the curves by placing a high number of points on each curve at equal arc length steps. Each of the points is then averaged over a number of curve-instances to produce the vertices of the average curve. The *median curve* is selected from the collection as the curve which differs least from all other curves. We used the distance criteria above to identify the best curve from the set of likely curves for each criterion. The procedure repeats with the selected curves until the number of curves no longer reduces and the result(s) are chosen as the median curve(s).

Probabilistic tracts generated from a single seed point can branch into two or more main paths. We therefore used a distance based clustering method which tests several distance metrics to separate the sets of branched curves. Initially, we generate a number of tracts from a seed point based on a probabilistic algorithm; we then divide the curves into those forward and backward from the seed point, then each of the two set curves were separated further using the clustering algorithm to find all branch sets. Curves that are short compared to the average chord-length of curves of each branch are deleted from the sets. Finally the average curves methods were applied for each set of branched curves from the seed point and the resultant curves were concatenated.

We applied this technique to data from a physical phantom, described below, using wild-bootstrap probabilistic tracking [1] from 16 pre-defined seed positions with 1000 iterations. Branches which contained small number of curves (<5%) were not considered for the average curves generation.

**Physical Phantom:** DTI data was acquired from a physical phantom [2] using a 3T MRI system with 3x3x3 $mm^3$ voxel resolution, b value=1500 $s/mm^2$ and 65 directions (1 unweighted and 64 diffusion directions).



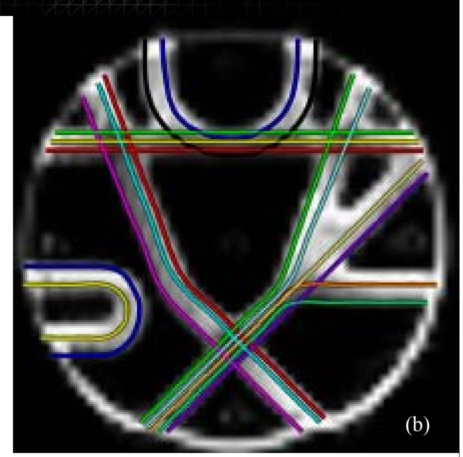




**Figure**: (a) Wireframe FA Image from the phantom overlaid with mean curves (coloured) and seed points (white). (b) Ground truth.

## Results

The average curves approach was applied to all possible branch curves from 16 seed points of the phantom data. From these potential curves, Figure (a) shows mean curves of the most probable branch for each seed point and Figure (b) shows the ground-truth fibres overlaid on a FA map. We used different colours for the average curves and ground truth images for some fibres to provide a clearer view. Most of the average curves fibres correctly matched the ground truth well.

## Discussion

In this study, we evaluated a novel deterministic method of probabilistic tractography on a physical phantom, which was created with the aim of benchmarking different tractography techniques. Our method is capable of tracking fibres through regions of crossing, branching and fanning. One limitation of our study is that we use some semi-automated parameters to identify the short curves and separate the curves from generated curves.

It is often difficult to evaluate the merit of different fibre tracking techniques for reconstructing fibres and the best approach can depend on the application. Deterministic methods are simple and fast and therefore may be used interactively. However, with such approaches, a single mistake can send the subsequent trajectory off track. Probabilistic methods consider this uncertainty in fibre orientation when calculating estimates of fibre tracts. It can be extremely difficult to find the most probable path from the output of probabilistic methods. The average curves approaches that we propose here provide not only an estimate of the representation of probabilistic curves by deterministic way but also take into account an additional measure of uncertainty by considering all possible connections.

## References

1. Jones DK. 2008. IEEE Transactions on Medical Imaging 27: 1268-1274.
2. Poupon et al. 2008. Magnetic Resonance in Medicine 60(6): 1276–83.