BundleWarp, streamline-based nonlinear registration of white matter tracts (Supplement)

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Appendix A Appendix

Appendix A.1 Streamline-based Distances and Cost Functions

Here, we explain streamline-based distances and cost functions that will be used throughout the manuscript. These functions are either used for optimization or for quantitative assessment of the methods.

Appendix A.1.1. Minimum Direct Flip Distance

The minimum average direct-flip distance (MDF) was introduced in QuickBundles paper [2] and is widely used for calculating a distance between two streamlines that have the same number of points. It is defined as follows:
Let S_1 and S_2 be two streamlines with the same number of points.

$$d(S_1, S_2) = \frac{1}{k} \sum_{i=1}^{K} |S_{1i} - S_{2i}|$$

$$d_{direct}(S_1, S_2) = d(S_1, S_2)$$

$$d_{flipped}(S_1, S_2) = d(S_1, S_2^F) = d(S_1^F, S_2)$$

$$MDF(S_1, S_2) = min(d_{direct}(S_1, S_2), d_{flipped}(S_1, S_2))$$

Appendix A.1.2. Bundle-based Minimum Distance

The bundle-based minimum distance (BMD) was introduced and is used as a cost function in the streamline-based linear registration (SLR) method[3]. It is used for calculating the distance between two bundles (two sets of streamlines) in millimeters. The BMD is defined as follows:

Let B_1 and B_2 be bundles where n and m represent total number of streamlines in each bundle respectively. And S_{1i} represents i^{th} streamline in bundle B_1 and S_{2j} represents j^{th} streamline in bundle B_2. A rectangular matrix D is populated with all pairwise MDF streamline distances. Every element of D matrix is calculated by taking the MDF distance of S_{1i} streamline of B_1 bundle with S_{2j} streamline of B_2 bundle, $D_{i,j} = MDF(S_{1i}, S_{2j})$. The most similar streamlines from one bundle to the other are given more weightage by MDF values of the rows and columns of the D matrix.

$$BMD(B_1, B_2) = \frac{1}{2}\left(\frac{1}{n_1}\sum_{i=1}^{n_1} \min_j D(i,j) + \frac{1}{n_2}\sum_{j=1}^{n_2} \min_i D(i,j)\right)^2$$

Appendix A.1.3. Bundle Shape Similarity Score

Bundle shape similarity score (SM) introduced in BUAN method[1] as a quality control measure for assessing the quality of the large number of extracted bundles coming from different subjects and populations. SM internally uses bundle adjacency metric (BA)[2] to calculate bundle shape similarity between two bundles.

Let, B1 and B2 be two bundles, and $\theta > 0$ be a selected adjacency threshold. Where $S1_i$ is a streamline in $B1$ and $S2_i$ is a streamline belonging to $B2$. $S1_i$ is adjacent to $B2$ if $MDF(S1_i, S2_i) \leq \theta$.

Coverage of $B1$ by $B2$ is defined as following:

$coverage(B1, B2) = \frac{\text{number of adjacent streamlines}}{\text{total number of streamlines in B1}}$

SM/BA is defined as follows:

$$SM(B1, B2) = BA(B1, B2) = 0.5(coverage(B1, B2) + coverage(B2, B1))$$

SM ranges between 0 and 1, with 0 being the lowest score (completely different shape) and 1 being the highest score (extremely close in shape).

Appendix A.2 BundleWarp Execution Time

Different types of bundles have different sizes and can be composed of different numbers of streamlines. Moreover, even two bundles of the same type can have a varying number of streamlines. Here, we investigate

BundleWarp execution time based on the number of streamlines in static and moving bundles on a system with 32 GB RAM and one Intel Core i7-7700K CPU with 8 cores.

Fig. A1 shows the execution time of BundleWarp when the static bundle's streamline count is kept fixed at 2010 and the moving bundle's streamline count increases. Here, the x-axis has streamline count in the moving bundle, and the y-axis has BundleWarp execution time in minutes. One of the most common applications of BundleWarp would be to register different subject's bundles to an atlas bundle where the static bundle (atlas bundle) would always be the same, and the moving bundle would change. Most of the time, extracted bundles have a streamline count of less than 4,000. We can see from our experiments in Fig. A1 that BundleWarp is fast, and execution time is most a minute of less than a minute for bundles of typical size (streamlines ¡ 4,000). However, we see that when the moving bundle is very thick and comprised of 8,000 streamlines, BundleWarp execution time doubles to 2 minutes which can still be considered fast for a pure streamline-specific deformable registration.

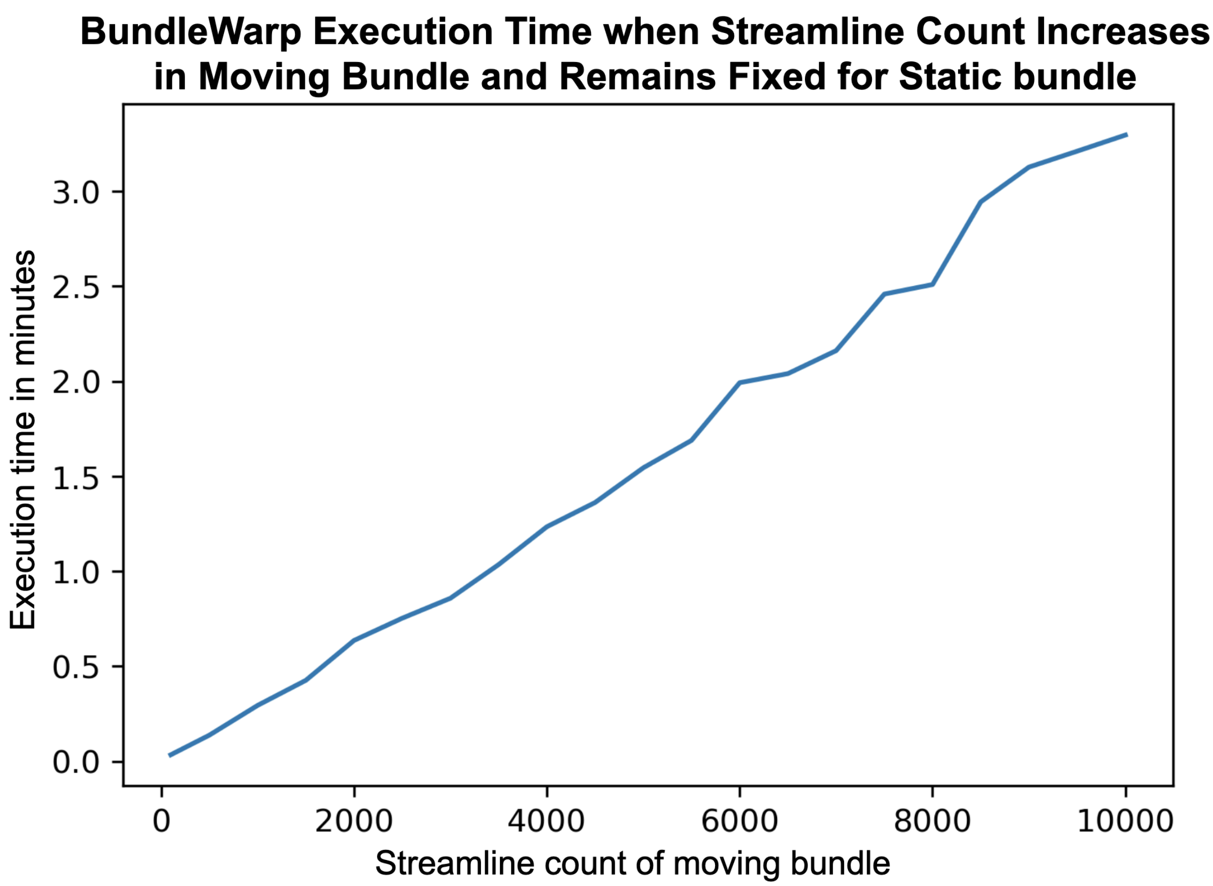

Figure A1. Execution time of BundleWarp in minutes when streamline count increases in moving bundle and remains fixed (2010 streamlines) in static bundle. The x-axis shows the count of streamlines in moving bundle where static bundle always has 2010 streamlines. The y-axis shows BundleWarp execution time for registration of one pair of bundles.

Fig. A2 shows the execution time of BundleWarp when both static and moving bundles' streamline count increases. Here, the x-axis has streamline count in both static and moving bundles, and the y-axis has BundleWarp execution time in minutes. Here, we investigate the BundleWarp execution time when the streamline count increases in both static and moving bundles. We can see that BundleWarp execution time is fast when both bundles have a streamline count of less than 4,000. The execution time increases drastically when the streamline count increases up to 10,000. However, the high execution time would not be the typical case in practice as most bundles do not have 10,000 streamlines and are mostly comprised of less than 4,000 streamlines.

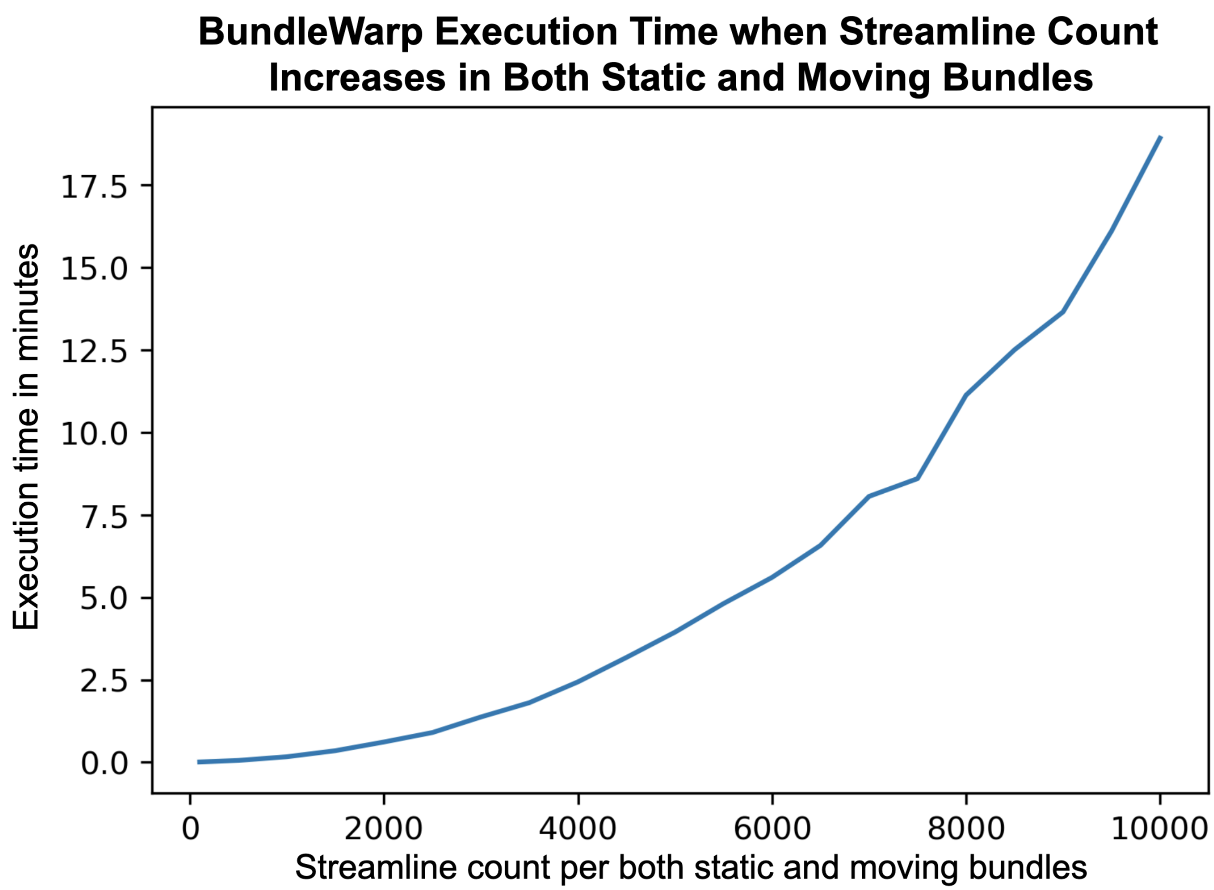

Figure A2. Execution time of BundleWarp in minutes when streamline count increases in both static and moving bundles. The x-axis shows the count of streamlines in each bundle and y-axis shows BundleWarp execution time for registration of one pair of bundles.

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