A semi-automatic approach for the extraction of white matter fiber bundles across subjects

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Introduction - Analysis of Diffusion Tensor Imaging (DTI) data in multi-subject imaging studies is usually performed by analyzing quantitative diffusivity measures (e.g. Apparent Diffusion Coefficient (ADC), Fractional Anisotropy (FA), Eigenvalues, etc.) with Voxel Based Morphometry [1] or Tract Based Spatial Statistics [2]. In recent years, various new techniques for quantitative tractography-based analysis of white matter fiber bundles have evolved [3, 4]. For this kind of analyses, fiber tracts have to be reconstructed in advance. Quantitative analysis is then performed for selected fiber bundles of interest. Henceforth, the correct delineation of fiber bundles is eminently important for tractography-based group analysis, which is why Wakana [4] defined guidelines for the extraction of major white matter tracts. However, extraction of fiber bundles for multiple subjects is still time consuming and prone to errors. Obtaining consistent and reproducible results for multiple subjects is thus challenging. We propose a new semi-automatic approach to extract white matter fiber bundles for multiple subjects. Prototype fiber bundles are not defined individually, but in a common template space. To compensate individual, inadequate results, reliability maps for the fiber bundles are computed and employed to classify the fiber tracts of each data set. The whole process can be performed fully automatically, except for the (manual) definition of the fiber bundles.

Semi-automatic extraction of white matter fiber bundles

To perform the semi-automatic extraction of fiber bundles for multiple subjects, standard DTI processing and fiber tracking is performed first. Then, non-linear coregistration is employed to create a unique template and transform the individual data sets (including FA, ADC, fiber tracts, etc.) into the common template space. All further processing is carried out in this template space. Prototype fiber bundles of interest are defined once (e.g. by placing ROIs as proposed by Wakana [4]) and are used to extract the individual bundles for all data sets. Bundles are then voxelized and the density in occupied voxels is assessed. For each fiber bundle, reliability maps are computed that provide information about the reliability of the association between voxels and fiber bundles. The more data sets contribute to one voxel the higher the confidence that the voxel belongs to the fiber bundle. Finally, the reliability maps are employed to classify the fiber tracts of each data set and obtain the individual fiber bundles for each data set.

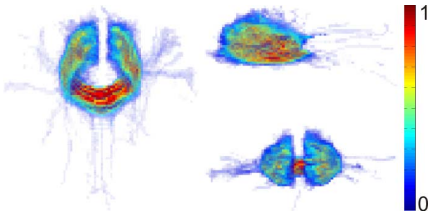

Fig. 1 – 3D representation of the reliability map for one fiber bundle (Fmin). Blue indicates reduced and red high reliability for a voxel.

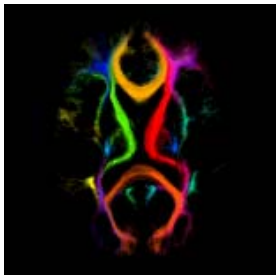

Fig. 2 – Color-coded reliability map for all fiber bundles (one exemplary slice is shown).

Materials and Methods - In order to demonstrate the feasibility of the proposed technique, DTI data sets of 15 healthy volunteers were acquired on a clinical 3 T whole body MR-Scanner (Magnetom Tim Trio, Siemens Healthcare, Erlangen, Germany), using a conventional twice refocused Echo Planar Imaging (EPI) sequence [5]. A 12 channel phased array matrix head coil was employed and the following parameters were used: T_E=113 ms, T_R=7900 ms, α = 90°, iPAT=2, matrix of 96×96, 55 slices with a thickness of 2.5 mm, resulting in a voxel size of 2.5×2.5×2.5 mm³. Five b_0 images without diffusion weighting as well as 70 diffusion weighted images sampled with different gradient directions at b=1000 s/mm² were acquired. In-plane interpolation was performed on the MR-Scanner, resulting in a voxel size of 1.25×1.25×2.5 mm³. The Diffusion Toolkit [6] was utilized to perform whole brain fiber tractography. Tracts having a length less than 30 mm were subsequently removed from the data set. By using the FA maps, non-linear co-registration was performed for all data sets with the ANTs framework [7] and a common template was extracted. ROIs were placed into the template according to the guidelines provided by Wakana et al [4]. Based on these ROIs, 18 fiber bundles (FB1) were obtained for each data set (e.g. forceps major (Fmaj), forceps minor (Fmin), cortico-spinal tracts (CST), inferior fronto-occipital fasciculus (IFO), uncinate fasciculus (UNC), temporal part of the superior longitudinal fasciculus (SLFt), etc). For all bundles, reliability maps were computed and utilized to classify fiber tracts and to extract individual, corrected fiber bundles (FB2) for each data set.

Results - The 3D representation of the reliability maps for one exemplary fiber bundle (forceps minor) is shown in Fig. 1. Blue indicates reduced and red increased reliability for a voxel. For certain areas the reliability is reduced due to the fact that only a minority of data set contributes to these voxels. The color-coded reliability map for all fiber bundles in one exemplary slice is shown in Fig. 2. Different fiber bundles are visualized with different colors. The reliability in each voxel is indicated by the color intensity. Exemplary fiber bundles (Fmaj, Fmin, IFO_{Right}, UNC_{Right}, CST_{Right}, $SLFt_{Right}$) for 3 data sets are presented in Fig. 3. Bundles without correction (FB1) are shown on top and bundles that were extracted by performing reliability-based classification (FB2) are shown at the bottom. For all FB2 bundles, the visual inspection revealed significant improvement of fiber bundle delineation and better correspondence to the expected course of the fiber bundles. FB1 fiber bundles that contained additional wrong tracts (e.g., due to the placement of ROIs) were successfully corrected.

Discussion & Conclusion – We presented a new method for semi-automatic, consistent extraction of fiber bundles from multiple data sets. For each fiber bundle, reliability maps were computed to assess the contribution of each voxel to the particular bundle. The reliability maps were then used to classify the fiber tracts of each data set. By using multiple tractography data sets, we were able to correct erroneous or wrongly labeled tracts that usually occur in individual data sets. Resulting fiber bundles are more consistent across subjects compared to bundles that are extracted with conventional ROI based methods.

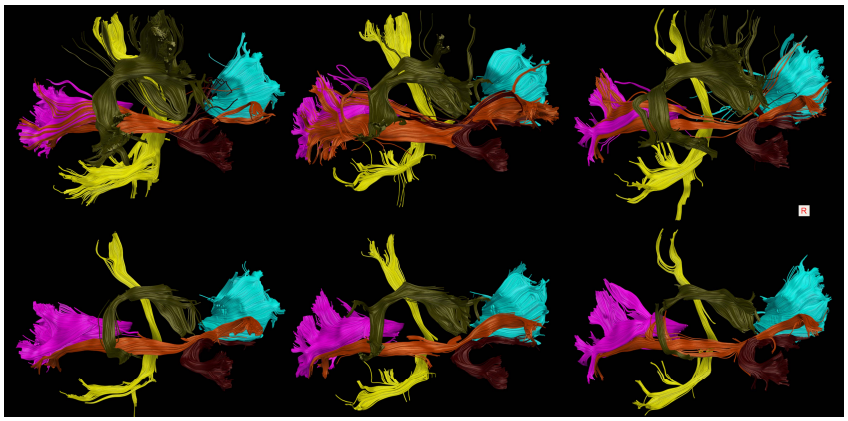

Fig. 3 – For 3 data sets exemplary fiber bundles are presented (Fmaj (magenta), Fmin (cyan), IFO_R (light brown), UNC_R (dark brown), CST_R (yellow), $SLFt_R$ (olive)). Bundles without correction are shown in the top row and bundles that were extracted by performing reliability-based classification are shown in the bottom row.

We further believe that this approach might be suitable for fast generation of white matter atlases. For this it appears beneficial to employ automated extraction methods instead of applying manual ROI drawing procedures. For example, cluster analysis can be used to extract fiber bundles fully automatically [8].
Reliability maps might also be able to improve the quantitative tractography-based analysis itself by identifying voxels that are not contributing with respect to the analyzed fiber bundle. Such voxels can then be excluded from the analysis or handled in a different way.

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References - [1] Ashburner et al, 2000, Neuroimage 11, 805-821 [2]Smith et al, 2006, Neuroimage 31, 1487-1505 [3] Berman et al, 2005, Neuroimage 27, 862–871 [4] Wakana et al, 2007, Neuroimage 36, 630–644 [5] Heid, 2000, Proc Intl Soc Mag Reson Med, 8 [6] Wang et al, 2007, Proc Intl Soc Mag Reson Med 15, #3720 [7] Klein et al, 2009, Neuroimage 46, 786-802 [8] Ros et al, 2011, Proc Intl Soc Mag Reson Med 19, #3965