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Poster

Juggling Increases Interhemispheric Brain Connectivity: A Visual and Quantitative dMRI Study

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Abstract

We use visualization to help analyze a diffusion magnetic resonance imaging study that has investigated the effects of learning how to juggle on nerve fiber microstructure in the human brain. Building on a standard voxel-wise statistical analysis, we perform a more elaborate visual analysis of the affected fiber bundles. Based on the visualization, we hypothesize that brain image data allows us to distinguish learners from controls with better-than-random accuracy; we test this hypothesis with a machine learning technique. We believe that our results exemplify the value of more tightly integrating statistical with visual analysis and machine learning in brain imaging studies, in order to complement the group-wise view of traditional analysis with insights about specific individuals.

1. Introduction

It has been found recently that learning-induced neuroplasticity in adult white matter can be observed using diffusion MRI [SKBJB09]. It is a goal of our study to visualize which fiber bundles are affected by learning how to juggle.

2. Experimental Setup

30 healthy volunteers (age 24.3 ± 3.8 years) with no previous experience in juggling have been selected for this study and gave informed consent. Over a period of two months, one of the co-authors (PG) taught half of the participants how to juggle, to a point where they were able to perform a continuous three-ball cascade for at least 45 seconds. The remaining 15 participants served as a control group.

Diffusion MRI was acquired before and after the training period, as well as two months after training had ended. The control group was also scanned three times, at the same time intervals. The measurement protocol comprised eight reference images at $b = 0\,\mathrm{s/mm}^2$, as well as diffusion-weighted images at $b = 1000\,\mathrm{s/mm}^2$ in 64 distinct directions.

3. Visualization Pipeline

3.1. Data Preprocessing and Statistical Analysis

Preprocessing and statistical analysis used a combination of FSL (www.fmrib.ox.ac.uk/fsl), Teem (teem.sf.net), and in-house software. Eddy-current artifacts and head motion were reduced using affine registration, diffusion tensors and corresponding Fractional Anisotropy (FA) maps were estimated.

All three scans of each subject were affinely transformed to a space mid-way between scans one and two. The resulting per-subject averages were non-linearly registered to a predefined FA template, and the aligned subjects were averaged to create a study-specific template. To reduce the impact of misregistration, a Tract-Based Spatial Statistics skeleton was created [SJJB*06], thresholded at $\mathrm{FA} = 0.25$, and used as a common anatomical reference, onto which FA values from each individual scan were projected.

A general linear model was applied to test for differences between the first scan ("before learning") and the second and third scans, which were treated as the same condition ("after learning"). Statistical analysis was done by non-parametric permutation-based testing with Threshold-Free Cluster Enhancement [SN09], as recommended by FSL. At significance level $p < 0.05$, we obtained a cluster of 225 voxels within the corpus callosum that exhibited increased FA in the group that had learned how to juggle. No other significant changes were detected in either group.

3.2. Tractography-based Visualization

In order to visually identify the fiber bundles affected by the FA increase in the group of learners, we inverted the non-

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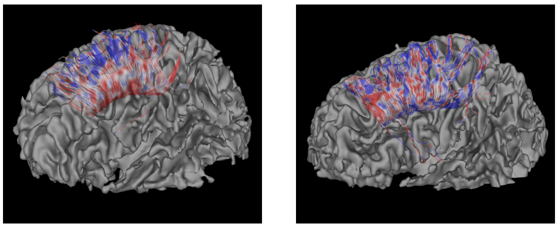

(a) A juggling subject *(b) A control subject*

Figure 1: *Visualization allows us to identify the affected fibers, and to inspect FA changes in individual subjects.*

linear and affine transformations that had been applied during image registration, and projected the cluster identified by statistical analysis back into the coordinate systems of each original scan. Since streamline tractographies of several subjects were visually found to be very similar among rescans, we only considered tractography results from the first scan for further analysis. Anatomical context was provided by semi-transparently overlaying an isosurface at FA $= 0.2$. Figure 1 shows two representative examples of the resulting visualizations.

In all subjects, visual inspection of the reconstructed fiber tracts revealed that they include connections between the sensory and motorcortex in both hemispheres. This suggests that learning how to juggle, a task that requires complex visuo-motor control and interaction between the left and right hands, increases the structural connectivity between the corresponding regions in the two brain hemispheres.

Even though no significant changes had been detected in the control group, we projected the same cluster also to their scans, to allow for a visual comparison. A blue-to-red color map indicates local FA decrease (blue) or increase (red) in each individual subject. Since visualization happens in each subject's mid-way space, it does not suffer from the limitations of non-linear registration inherent in standard statistical analysis. We found that the effects of juggling on FA in individual subjects are on a similar order as noise-based fluctuations, making statistical group analysis obligatory to separate significant systematic effects from random noise. Despite this, visualization did confirm a slight overall FA increase specific to the group of jugglers.

3.3. Individual Classification

Visual inspection led us to hypothesize that overall FA changes in the affected tract might allow us to detect, with better-than-random accuracy, whether or not a given subject had learned how to juggle.

To test this hypothesis, we trained a simple Bayes classifier [Alp10] to distinguish between learners and controls. Testing was done in a leave-one-out fashion, such that each subject in turn is left out of the training data, and then classified. As features, we used a normalized histogram of FA changes (40 bins, range $=[-0.1, 0.1]$) over all voxels crossed by the streamlines that had been shown in the visualization.

Classification achieved an accuracy of 70%. At confidence level $p < 0.05$, a two-sided binomial test rejects the null hypothesis that this result has been achieved by randomly assigning each subject to one of the groups ($p = 0.04$)

4. Related Work

Previous work has used diffusion imaging to study the effect of juggling on white matter architecture [SKBJB09], but did not include any tractography or machine learning results. Moreover, the previous work has not reported a significant FA increase in the corpus callosum. A potential reason for this might lie in the fact that its authors encountered image artifacts due to mechanical vibrations for diffusion directions with a strong x-component, which were addressed by decreasing the impact of such directions in the tensor fit. The region identified in our study includes many voxels in which diffusion takes place primarily in x-direction, and which can be expected to be particularly affected by this. No such correction was required in our data.

5. Conclusions

To the best of our knowledge, we present the first experimental evidence that juggling increases interhemispheric brain connectivity, and that observing this effect with dMRI can be used to distinguish learners from controls with better-than-random accuracy.

Our analysis has combined standard statistical tests with visualization and machine learning. This provides more detailed information about individuals and within-group variability, it visualizes the affected fiber tracts as a whole, and reduces the impact of imperfections in non-linear registration. Therefore, we expect that the proposed integrative approach will also benefit future studies.

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