Eurographics Workshop on Visual Computing for Biology and Medicine (2020)
B. Kozlíková, M. Krone, and N. N. Smit (Editors)

Supplementary Material: Interactive Classification of Multi-Shell Diffusion MRI

Agajan Torayev and Thomas Schultz

University of Bonn, Germany

Abstract

In this supplement, we report results that are less central to evaluating our proposed method for interactive classification of multi-shell diffusion MRI data, but still relevant. In particular, we report results from domain-specific features as an additional baseline, and we separately report precision and recall values corresponding to the F1 scores in the main manuscript.

1. Results from Domain-Specific Features

For different purposes, such as accelerating measurements or human interpretation, domain-specific representations have been established for data from multi-shell diffusion MRI. It is natural to consider these as feature representations for classification tasks, since they have been carefully designed to considerably reduce the dimensionality while preserving important information.

1.1. SHORE Features

For accelerating diffusion MRI measurements with compressive sensing, several domain-specific basis functions have been developed that permit a more concise representation of the diffusion MR signal. They include the Spherical Polar Fourier (SPF) basis [ATB09], SPF dual (SPFdual) basis [MCGD11], Solid Harmonic (SoH) basis [DDLB*11], and SHORE (simple harmonic oscillator based reconstruction and estimation) [OKS*09].

For our experiments, we selected SHORE because Merlet et al. [MD13] found it to be superior to others for compressed sensing recovery. We fitted SHORE basis functions to our data using the Python package DIPY [GBA*14], and used the corresponding coefficients as a feature representation.

The dimensionality of the resulting feature vector can be varied by tuning the radial order parameter of the SHORE basis: Setting it to 2, 4, and 6 gives 7, 22, and 50-dimensional feature vectors, respectively. Table S1 shows that, on both sets, results with a radial order of 4 led to the highest average F1 score. Comparing results to Table 1 in the main manuscript indicates that SHORE-4 allows us to maintain the same classification accuracy as when using the raw data, while speeding up random forest training. However, it does not match the quality of PCA- or CNN-based features.

1.2. Kurtosis Features

The diffusional kurtosis model [JHR*05] is frequently fitted to multi-shell diffusion MRI data in order to generate human interpretable maps, such as axial, radial, or mean kurtosis. Its parameters are the coefficients of a second-order diffusion tensor, as well as a fourth-order kurtosis tensor that accounts for non-Gaussian diffusion. Taken together, they contain 21 coefficients, which we used as a feature vector for our classification task. Results in Table S1 suggest that the diffusional kurtosis imaging (DKI) model is not superior to SHORE-4 for tract classification.

2. Comparison of Precision and Recall

Table 1 in the main manuscript uses the F1 score to compare results from classification with our proposed dual-branch CNN-based features to results obtained with the raw signal or PCA coefficients.

F1 combines the achieved precision and recall. To allow for a more detailed comparison, Table S2 reports the corresponding precision values, Table S3 the corresponding recall. Our features dominate alternatives in almost all cases, with respect to both precision and recall, often by a substantial margin. The only exception are the *corticospinal tract* and the *corpus callosum* in Set 1, for which PCA-based features achieved a slightly higher recall, at the cost of substantially decreased precision.

		Pre-Processing	CG	CST	FX	CC	Avg.	RF training	RF testing
Set 1	**SHORE-2**	162.0 s	0.2732	0.3867	0.1742	0.6141	0.3620	1.84 s	6.75 s
	SHORE-4	338.0 s	0.2489	0.4587	0.3098	0.6348	0.4131	2.60 s	6.77 s
	SHORE-6	537 s	0.1747	0.4295	0.2639	0.6078	0.3690	4.16 s	6.90 s
	DKI	3131 s	0.2271	0.4189	0.2197	0.5856	0.3628	2.63 s	6.67 s

		IFO-l	IFO-r	ILF-l	ILF-r	SLF-l	SLF-r	Avg.	RF training	RF testing
Set 2	**SHORE-2**	0.1909	0.2287	0.1839	0.1324	0.1193	0.1964	0.1753	2.03 s	10.58 s
	SHORE-4	0.1807	0.2137	0.2050	0.1801	0.1389	0.2130	0.1886	2.83 s	10.43 s
	SHORE-6	0.1324	0.1628	0.1733	0.1453	0.0864	0.1477	0.1413	4.18 s	10.55 s
	DKI	0.1814	0.2161	0.1953	0.1468	0.1260	0.2053	0.1785	2.75 s	10.63 s

Table S1: *The classification accuracy with domain-specific features matches the one when using the raw data, at a reduced computational cost for training (compare to Table 1 in the main manuscript). However, it does not match the quality of PCA- or CNN-based features.*

		CG	CST	FX	CC	Avg.
Set 1	**Raw Signal**	0.3995	0.3959	0.5150	0.5962	0.4766
	PCA (k=11)	0.4094	0.3774	0.5356	0.5832	0.4764
	MultiScaleAE2d	**0.6363**	**0.7025**	**0.5410**	**0.7096**	**0.6473**

		IFO-l	IFO-r	ILF-l	ILF-r	SLF-l	SLF-r	Avg.
Set 2	**Raw Signal**	0.4368	0.4794	0.2802	0.4985	0.6061	0.3432	0.4407
	PCA (k=11)	0.3422	0.4285	0.3125	0.2501	0.4654	0.3522	0.3585
	MultiScaleAE2d	**0.5485**	**0.6498**	**0.4636**	**0.6335**	**0.6069**	**0.5582**	**0.5768**

Table S2: *Precision of classifiers trained with different features. Values correspond to F1 scores in Table 1 of the main manuscript.*

		CG	CST	FX	CC	Avg.
Set 1	**Raw Signal**	0.1392	0.6133	0.2029	0.8099	0.4413
	PCA (k=11)	0.3431	**0.6536**	0.2477	**0.8361**	0.5201
	MultiScaleAE2d	**0.4963**	0.6330	**0.3178**	0.8174	**0.5661**

		IFO-l	IFO-r	ILF-l	ILF-r	SLF-l	SLF-r	Avg.
Set 2	**Raw Signal**	0.1137	0.1514	0.2308	0.0907	0.1168	0.2173	0.1534
	PCA (k=11)	0.1658	0.3029	0.2541	0.1351	0.2782	0.2953	0.2386
	MultiScaleAE2d	**0.4241**	**0.3929**	**0.5460**	**0.3200**	**0.5745**	**0.7187**	**0.4960**

Table S3: *Recall of classifiers trained with different features. Values correspond to F1 scores in Table 1 of the main manuscript.*

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