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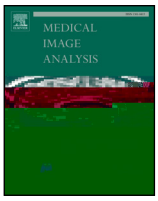

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ABSTRACT

Convolutional neural networks ( ) *white matter* ( )
diffusion magnetic resonance imaging ( ).

(., 201 ., 2011). , - - - - regions of interest ( ) (., 200 ., 201) (, 200 ., 201 ., 2020). - - - , (., 2021). - , (., 200). , , k- , , (., 2011 ., 201 , 201). , convolutional neural networks ( ) - - (., 2020 ., 201 ., 2020).

2021 (, 2021).

(, 201)

2

2. Methods

2.1. Problem formulation and classic fine-tuning

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(., 201)

$\mathcal{M}$ $\mathcal{M}$, . .

, $\mathcal{M}$ $\mathcal{M}$

L $\mathcal{M}$ L $\mathcal{M}$ $\boldsymbol{\theta}$ $\boldsymbol{\theta}$,

, $\mathcal{M}$ $\mathcal{M}$

$\boldsymbol{\theta}$. $\mathbf{X}$ $\mathbf{X}$ -

$\mathbf{F}$ $f(\mathbf{X};\boldsymbol{\theta})$ $\boldsymbol{\theta}$

$$\mathbf{F} = f(\mathbf{X};\boldsymbol{\theta}), \tag{1}$$

$\mathbf{P}$ $\mathbf{P}$

$\mathbf{F}$ L L

2 - (.,
201 ., 201),

$g(\mathbf{F};\boldsymbol{\theta})$ $g(\mathbf{F};\boldsymbol{\theta})$ $\boldsymbol{\theta}$ $\boldsymbol{\theta}$, r -

$\mathbf{P} = g(\mathbf{F};\boldsymbol{\theta}) = g(f(\mathbf{X};\boldsymbol{\theta});\boldsymbol{\theta})$ $\mathbf{P}$

v

$$p^{v}_{\rightarrow,j} = \frac{1}{1+\left(-(b_j+\sum_{i=1}^{M} w_{ij}h^{v}_{,i})\right)}, \quad (\ )$$

w_{ij} b_j . v

$\mathbf{P}^{v}_{\rightarrow} = (p^{v}_{\rightarrow,1},\ldots,p^{v}_{\rightarrow,N})^{\mathsf{T}}$,

$$\mathbf{P}^{v}_{\rightarrow} = \sigma\left(\mathbf{W}\mathbf{H}^{v}+\boldsymbol{b}\right), \quad (\ )$$

$$\mathbf{W} = \begin{bmatrix} w_{11} & \cdots & w_{1M} \\ \vdots & \ddots & \vdots \\ w_{N1} & \cdots & w_{NM} \end{bmatrix}, \quad \boldsymbol{b} = [b_1,\ldots,b_N]^{T}. \quad (\ )$$

$\mathbf{H}^{v} = \widetilde{\mathbf{W}}\,\widetilde{\mathbf{F}}^{v}+\boldsymbol{b}$, $\widetilde{\mathbf{F}}^{v}$ v-
$\widetilde{\mathbf{F}} = f(\mathbf{X};\boldsymbol{\theta})$ $\boldsymbol{\theta}$
, $\widetilde{\mathbf{W}}$ $\boldsymbol{b}$
$\mathbf{W}$ $\boldsymbol{b}$, .
,

$$\mathbf{P}^{v}_{\rightarrow} = \sigma\left(\mathbf{W}\left(\widetilde{\mathbf{W}}\,\widetilde{\mathbf{F}}^{v}+\boldsymbol{b}\ \right)+\boldsymbol{b}\right) = \sigma\left(\mathbf{W}\widetilde{\mathbf{W}}\,\widetilde{\mathbf{F}}^{v}+\mathbf{W}\boldsymbol{b}\ +\boldsymbol{b}\right). \quad (\ )$$

$\mathbf{P}^{v}$. ( ) $\mathbf{P}^{v}_{\rightarrow}$. ( ),
, $\boldsymbol{\theta} = \{\mathbf{W}\ ,\boldsymbol{b}\ \}$
$\boldsymbol{\theta} = \{\mathbf{W}\ ,\boldsymbol{b}\ \}$. , $\mathbf{W}$ $\boldsymbol{b}$
$\boldsymbol{\theta}$, -
$\mathbf{P}^{v}_{\rightarrow}$ -
. , , -
$\mathbf{W}$ $\boldsymbol{b}$
. , $\mathbf{W}$ $\boldsymbol{b}$ $\widetilde{\mathbf{W}}$
$\boldsymbol{b}$, $\mathbf{W}$ $\boldsymbol{b}$

$$\mathbf{W} \leftarrow \widetilde{\mathbf{W}}\widetilde{\mathbf{W}} \quad \boldsymbol{b} \leftarrow \widetilde{\mathbf{W}}\widetilde{\boldsymbol{b}}\ +\widetilde{\boldsymbol{b}}. \quad (\ )$$

, $\boldsymbol{\theta}$ $\boldsymbol{\theta}$, -, ,-
$\mathcal{M}$
.

2.3. A better implementation with warmup

-
$\mathcal{M}$ -
. , -
$\mathbf{W}' = \mathbf{W}\widetilde{\mathbf{W}}$ $\boldsymbol{b}' = \mathbf{W}\boldsymbol{b}\ +\boldsymbol{b}$. , . ( )

$$\mathbf{P}^{v}_{\rightarrow} = \sigma\left(\mathbf{W}'\widetilde{\mathbf{F}}^{v}+\boldsymbol{b}'\right). \quad (\ )$$

$\mathbf{W}'$ $\boldsymbol{b}'$
$\boldsymbol{\theta}$.
-, ,
$\boldsymbol{\theta}$ -( )
-). , $\mathcal{M}$,
$\mathcal{M}$ $\boldsymbol{\theta}$ $\boldsymbol{\theta}$. , $\boldsymbol{\theta}$ $\boldsymbol{\theta}$ (-
) .
$\boldsymbol{\theta}$,
-, $\boldsymbol{\theta}$ $\boldsymbol{\theta}$

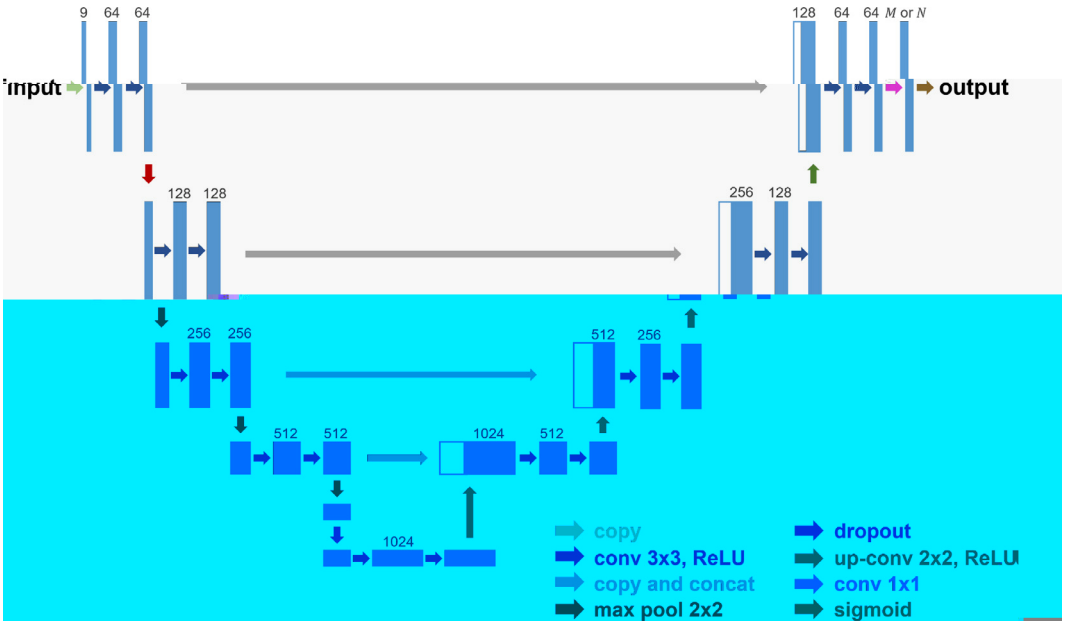

Fig. 1.

M N

$\mathbf{M}$ $\lceil\cdot\rceil$ (10) (11) (12)

(., 201 ., 201).

$\mathbf{M}$, K N $K \times (K-1) \times (2^N - 1)$ K $K = \{100, K \times (K-1) \times (2^N - 1)\}$,

$\mathcal{X}$ $\mathcal{Y}$ $\mathcal{X}$ $\mathcal{Y}$

2.5. Backbone network for WM tract segmentation

(., 201) (., 2021 ., 2021), . 1. 2 - (., 201) .

multi-shell multi-tissue constrained spherical deconvolution (-) (., 201 ., 201) - *constrained spherical deconvolution* ( ) (., 200) - .

2

M N

2.6. Implementation details

- // / - / / (., 201). . (201) -

Table 1

12

1
2

10
11
12

0.001

).

).

3. Results

(., 201)

01 12 . 0 . 0 201

3.1. Data description and experimental settings

3.1.1. The HCP dataset

(., 201)

2 0 (

3.1.2. The private dataset

put28.37749.161 .3d1 Tf 61.1749 614.9611 Tm [( )] TJ 0.0044 6.6]6F677.72 1 Tf 6.7.9701 [( )05591 531.2791 Tm [(segmenting)] T447.98855677.72 1 T

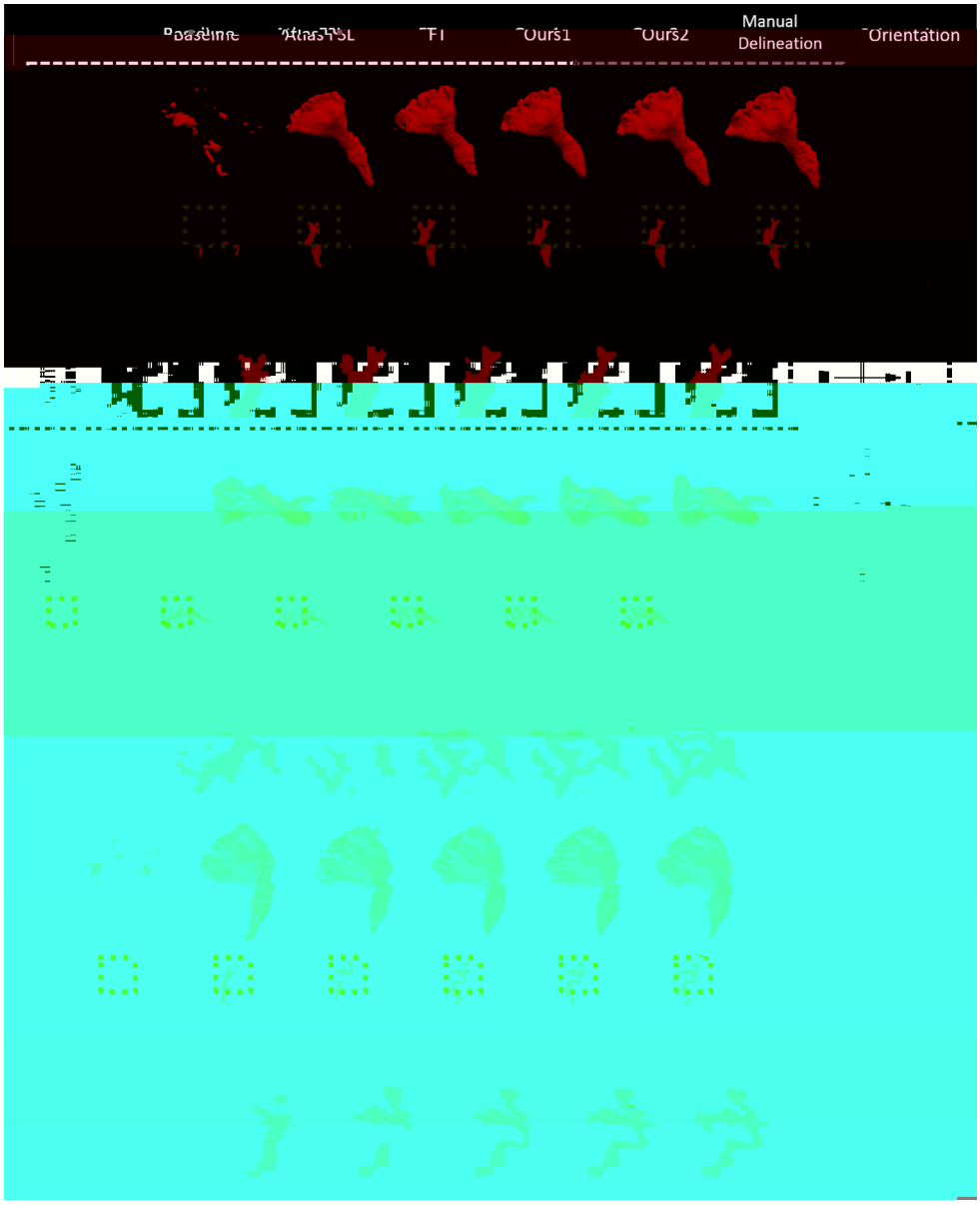

Fig. 2.

2 ( ) 2
( ), (2021), *relative volume difference* ( ) (, 201)

2 (1) *t*- , 1

2 ( ) 2
($p < 0.0$ $p < 0.001$) ($d > 0.$) (d 0.)
2 1, 1 2 ,

3.2.2. Impact of the number of training scans annotated for novel WM tracts

.1.1, / -
1/0 /2, .

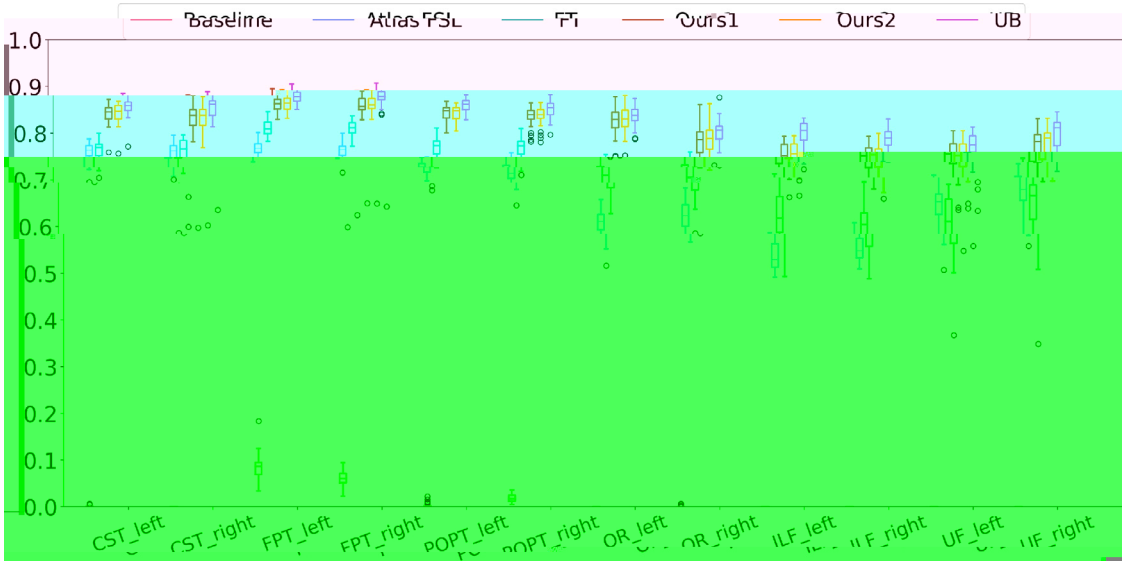

Fig. 3. 12 (1 2)

Table 2

(*d*) (1 2) (***) ($p < .001$) *t*-

1				2			
	d	.	.	.	*d*	2. 2	.	. 1
	p	***	***	***	*p*	***	***	***
	d	2 .2	1. 1	1. 1	*d*	2 .	1. 1	1. 1
	p	***	***	***	*p*	***	***	***
	d	. 0	.	.0	*d*	.1	.1	.2
	p	***	***	***	*p*	***	***	***
	d	2 .	2.	1.2	*d*	2 .0	2.	1.2
	p	***	***	***	*p*	***	***	***
	d	0. 2	.	. 1	*d*	. 2	.2	.
	p	***	***	***	*p*	***	***	***
	d	0.	. 2	2.	*d*	1.12	. 0	2.
	p	***	***	***	*p*	***	***	***
	d	1. 2	.0	. 0	*d*	0.	.	.
	p	***	***	***	*p*	***	***	***
	d	.2	.2	2. 0	*d*	2.	.	2. 0
	p	***	***	***	*p*	***	***	***
	d	.	.2	2.	*d*	.	.	.0
	p	***	***	***	*p*	***	***	***
	d	.0	.	.2	*d*	1.	.2	.2
	p	***	***	***	*p*	***	***	***
	d	1 .	2.0	2. 1	*d*	20. 1	2.0	2. 2
	p	***	***	***	*p*	***	***	***
	d	2 . 2	2.	2.0	*d*	2 .0	2.	2.20
	p	***	***	***	*p*	***	***	***

Table 3

(1 2).

1		2	
0. 1	0. 0	0. 1	0. 0

1 2 - 1 2 - 2 *t*- - 2 - ($p < 0.0$ $p < 0.001$) , ($d > 0.$). 2 1,

Table 4

(d)
2
2
t- . (** p < .01, *** p < .001, . . p ≥ 0.0).

					1	2	
1		0.000	0.	0. 0	**0.777**	**0.784**	0. 2
	d	20.	1. 1	1.	0.1 1	-	-
	p	***	***	***	**	-	-
		0.0 2	0.	0.	**0.811**	**0.812**	0. 0
	d	10. 2	2.00	1.000	0.021	-	-
	p	***	***	***	. .	-	-

Table 5

(d)
2
2 t- .
(* p < .0 , *** p < .001, . . p ≥ 0.0).

					1	2	
1		1.000	0.1 2	0. 2	**0.156**	**0.151**	0.10
	d	1 .	0. 0	1.	0.0	-	-
	p	***	*	***	. .	-	-
		0.	0.1	0.1	**0.129**	**0.131**	0.10
	d	11.2	0. 1	0. 2	0.0	-	-
	p	***	*	*	. .	-	-

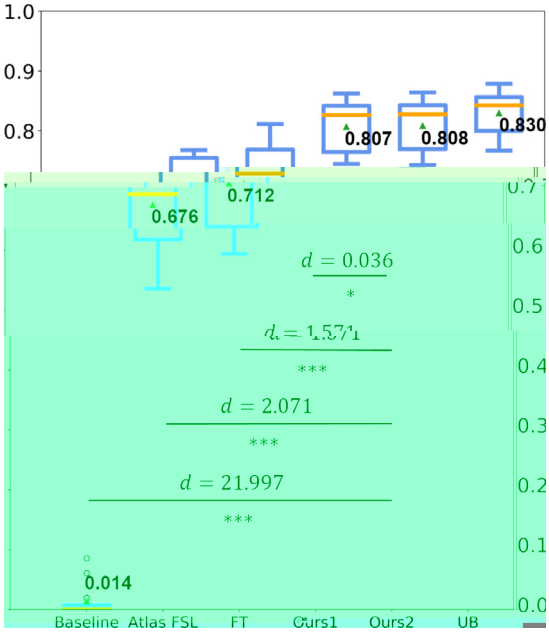

Fig. 4. (d)
2
2
(* p < .0 *** p < .001) t- .

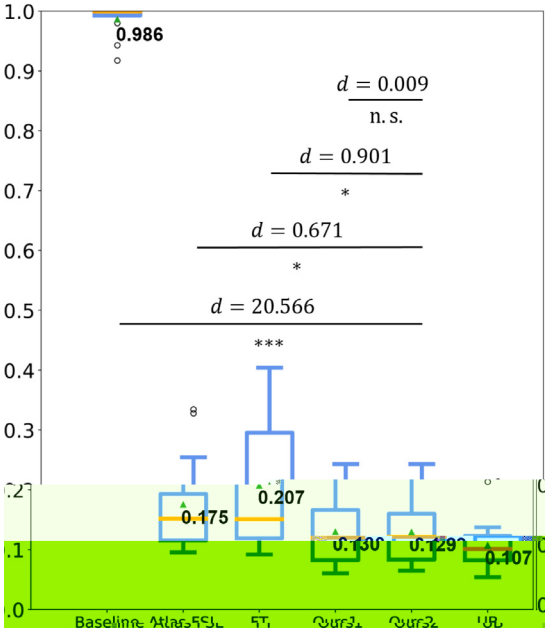

Fig. 5. (d)
2
2 (* p < .0
*** p < .001) t- .
(p ≥ 0.0)

(d < 0.2)

3.2.3. Segmentation performance with different selections of novel WM tracts

.1.1
( ).

12 .2.1,

3.2.4. Impact of data quality

.1.1.
2/1 /

Table 6

( ).

				1	2	
	0.000	0. 1	0. 0	**0.835**	**0.842**	0.
	0.002	0.	0. 0	**0.825**	**0.830**	0.
	0.000	0. 2	0. 0	**0.841**	**0.846**	0.
	0.000	0. 1	0.	**0.834**	**0.835**	0. 0
	0.000	0. 0	0.	**0.823**	**0.823**	0.
	0.000	0. 2	0. 0	**0.783**	**0.780**	0. 01

				1	2	
	0.000	0. 1	0. 02	**0.841**	**0.841**	0.
	0.000	0.				

Table 7

(*d*) – 2 – 2 *t*- .. (* $p < .0$, *** $p < .001$).

					1	2	
1		0.000	0. -	0.0 -	**0.694**	**0.724**	0.
	d	1 .0	1.1	. -	0.	-	-
	p	***	***	***	***	-	-
		0.000	0.	0. -	**0.758**	**0.764**	0. 0
	d	1 .1	1.	2.0	0.102	-	-
	p	***	***	***	***	-	-
		0.000	0. 2	0. -	**0.757**	**0.761**	0.
	d	1 .	1.- -	1.- 2	0.0	-	-
	p	***	***	***	*	-	-

Table 8

(*d*) 2 . . 2 *t*- .. (* $p < .0$, *** $p < .001$, . . $p \geq 0.0$).

					1	2	
1	.	1.000	0.22	1.	**0.258**	**0.213**	0.1 1
	d	1 .- 1	0.1 - 1	1.- 1	0. -	-	-
	p	***	. .	*	***	-	-
	.	1.000	0.2 -	0. 2	**0.159**	**0.157**	0.1 0
	d	1 . -	0.	2. 1	0.0 - 2	-	-
	p	***	***	***	. .	-	-
	.	1.000	0.2 1	0.- 2	**0.183**	**0.176**	0.1
	d	12. 0	0.	1.	0.0	-	-
	p	***	***	***	*	-	-

Table 9

(*d*) 2 + 2 + *t*- .. (* $p < .0$, ** $p < .01$, *** $p < .001$)

				1	2	1 +	2 +
	0.00	0.	0. 2	**0.645**	**0.694**	**0.715**	**0.728**
d	1 .11	2. 1	2.121	1. 2	0.	0.2 1	-
p	***	***	***	***	***	**	-
.	0. 1	0.2 2	0. 0 -	**0.398**	**0.326**	**0.305**	**0.277**
d	10.1	0.- - -	2.11	1.2	0. 0	0.2	-
p	***	*	***	***	***	**	-
	0.00	0. 10	0. -	**0.667**	**0.712**	**0.732**	**0.743**
.	0. 0	0.2 1	0. -	**0.358**	**0.294**	**0.275**	**0.252**
	0.00	0.	0. 1	**0.622**	**0.675**	**0.698**	**0.712**
.	0. 2	0.2 -	0. 2 -	**0.439**	**0.358**	**0.335**	**0.301**

Table 10

				1	2	1 +	2 +
	0.00	0. 02	0. 20	**0.687**	**0.713**	**0.720**	**0.717**
	0.	0.2	0.	**0.344**	**0.286**	**0.284**	**0.280**
	0.000	0.	0.- 2	**0.540**	**0.662**	**0.670**	**0.682**
	0.	0.- 0 -	0. 2	**0.538**	**0.366**	**0.359**	**0.346**

( ),

Declaration of Competing Interest

CRediT authorship contribution statement

Qi Lu: **Wan Liu:** **Zhizheng Zhuo:** **Yuxing Li:** **Yunyun Duan:** **Pinnan Yu:** **Liying Qu:** **Chuyang Ye:** & **Yaou Liu:** &

Acknowledgments

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Appendix A. Segmentation accuracy of the proposed method achieved with and without TractMix for the HCP dataset

1 .2.

Table A:1

12

	1	2	1 +	2 +
	0. 11	0. 12	0. 12	0. 12
	0. 0	0. 0	0. 0	0. 0
	0. 2	0. 2	0. 2	0. 2
	0. 21	0. 21	0. 21	0. 21
	0.	0. 1	0. 1	0.
	0.	0.	0.	0.

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