

#### My experience in Juelich as a master student

## Development and Applications of Novel Diffusion MRI Biomarkers in Neurology



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#### **Outline**

- Introduction (DTI, DKI)
- Applications: Gamma distribution function metrics as biomarker of maturation
- Multimodal Study of Brain Tumors

### Introduction



**Diffusion MRI applications:** 

- neurodegenerative pathologies (Alzheimer's and Parkinson's diseases, etc.)
- stroke
- neurosurgical planning
- development and aging
- tumours



### Introduction



#### Water Diffusion is random, microscopic movement due to thermal collisions



## Introduction



#### Diffusion tensor imaging: accounts for diffusion anisotropy



#### Signal attenuation

$$-\mathring{a}^{b_{ij}D_{ij}}$$



**Tensor invariants:** 

#### **Fractional Anisotropy**

#### Mean Diffusivity

$$FA = \sqrt{\frac{3}{2}} \sqrt{\frac{(MD - /_1)^2 + (MD - /_2)^2 + (MD - /_3)^2}{/_1^2 + /_2^2 + /_3^2}}$$

$$MD^{\circ} \frac{{I_1 + I_2 + I_3}}{3} = \overline{I}$$





#### Non- gaussian Diffusion Kurtosis Imaging (DKI)



Water diffusion is <u>anisotropic</u> and <u>restricted</u>

Mean kurtosis:

$$MK \equiv \frac{1}{5} \operatorname{Tr}(\mathbf{K}) = \langle \mathbf{K} \rangle$$

Monoexponential

Non-exponential

## Non- Gaussian method: Gamma Distribution Function Imaging

JÜLICH FORSCHUNGSZENTRUM

F. Grinberg et al., PLOS ONE, 2014



$$S(b) = \hat{0} P(D) \exp(-bD) dD$$

$$P_G(D, \kappa, \theta) = D^{\kappa-1} \frac{\exp(-D/\theta)}{\Gamma(\kappa)\theta^{\kappa}}$$

<u>Free parameters</u> Kappa:  $\kappa = \langle D \rangle^2 / \sigma_G^2$ Theta:  $\theta = \sigma_G^2 / \langle D \rangle$ 



## Application of Gamma Distribution function to children and adults

#### In particular we are interested Following questions...

- 1. Are the GDF parameters efficient in tracking the differences between children and adults?
- Can we extend our knowledge about more subtle microstructural development of specific fibres based on GDF?

## Diffusion kurtosis metrics as biomarkers of microstructural development: A comparative study of a group of children and a group of adults

F. Grinberg et al., Neuroimage, 2017



## **Brain Development and Ageing – Lifelong Changes**



Human brain undergoes life-long changes in many aspects: anatomic, physiological, mental, and also microstructural. Typical trajectories of the changes are often U-shaped or inverted-U-shaped.



#### Two groups for comparison children and adults

Children n=20 (9-12) years



Adults n=21 (38-64) years

## whole-body 3T Siemens MAGNETOM Tim-Trio scanner



## **Averaged histograms**



Whole brain averaged histograms show large shifts between the group of children and the group of adults

![](_page_12_Picture_0.jpeg)

#### **Regional analysis in white matter**

![](_page_12_Figure_2.jpeg)

Regional analysis shows large shifts for various fibers

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## **Regional Analysis**

![](_page_13_Picture_1.jpeg)

#### Differences between the mean values of theta in various region

![](_page_13_Figure_3.jpeg)

Theta values are larger in adults than children in all fibres

![](_page_14_Picture_0.jpeg)

### **Group differences in percentage for Theta parameter**

![](_page_14_Figure_2.jpeg)

![](_page_15_Picture_0.jpeg)

### Fibre ranking based on Cohen's d of Theta

#### Protracted maturation

![](_page_15_Figure_3.jpeg)

7 association fibres 14 Projection fibres 6 Commissural Fibres

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All 4 CFs+2 AFs+1 PFs

2 middle quartile between:1st and 4th quartiles All 1 PFs+2CFs

4<sup>th</sup> quartiles: All 5 AFs+ 2 PFs

Cohen's d (effect size):

![](_page_15_Figure_11.jpeg)

 $\approx 0.2$  - 'small' ≈ 0.5 - 'medium' ≈ 0.8 - 'large' > 1.2 – 'very large' le 16

## Classifiers: Support Vector Machine and k Nearest Neighbour algorithm

![](_page_16_Picture_1.jpeg)

SVM

![](_page_16_Figure_3.jpeg)

kNN

SVM algorithm is based on finding the hyper plane that gives the largest minimum distance to the training examples An object is classified by a majority vote of its neighbors, with the object being assigned to the class most common among its k nearest neighbors

Normalization of feature vector: x

$$X'_{i} = \frac{X_{i} \quad X_{min}}{X_{max} \quad X_{min}}$$

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![](_page_17_Picture_0.jpeg)

## Classification based on DTI and GDF metrics of different regions

#### Accuracies of classification (Alpha=0.01)

	FA	MD	AD	RD	Карра	Theta	DG	sG
SVM	0.89	0.94	0.95	0.76	0.99	0.73	0.87	0.95
kNN	0.87	0.91	0.92	0.78	0.99	0.76	0.92	0.97
k	3	5	3	5	1	1	3	3
γ					γ			
	DTI				GDF			

#### All metrics have shown high accuracies

![](_page_18_Picture_0.jpeg)

## **Summary of first part**

## Gamma distribution function provides promising complementary metrics to a palette of maturation -sensitive MRI tools.

![](_page_19_Picture_0.jpeg)

![](_page_19_Picture_1.jpeg)

#### 24 untreated tumour patient Whole body 3T Siemens MAGNETOM Tim-Trio scanner

![](_page_19_Picture_3.jpeg)

## T1-weighted images

T1-weighted images with contrast enhanced

**T2-weighted image** 

T2FLAIR (Fluid attenuated Inversion Recovery)

![](_page_20_Picture_0.jpeg)

## **Diffusion parameters**

RD

AD

MD

**DTI** metrics

FA

**DKI** metrics

![](_page_20_Figure_4.jpeg)

![](_page_21_Picture_0.jpeg)

## Color-encoded FA and fiber tracking for a tumor human brain in axial plane

![](_page_21_Picture_2.jpeg)

![](_page_21_Picture_3.jpeg)

Diffusion MRI gives a lot of complementary information to tumor assessment

This project is on going process and future work provide more results!

![](_page_22_Picture_0.jpeg)

#### Conclusions

- Novel diffusion models provide information about tissue conditions, which is not attainable with conventional DMRI.
- The results show the efficiency of the gamma parameters, it can show the tumor heterogeneity
- All non-Gaussian models shown to provide valuable information regarding the tissue microstructure and conditions.

![](_page_23_Picture_0.jpeg)

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![](_page_24_Picture_0.jpeg)

# Thank you for your attention !