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LERCO

METHODOLOGICAL APPROACH

Automatic segmentation of knee
cartilage from qMRI T2 images

2024



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INTRODUCTION

The new methodological approach was developed within the LERCO project, research program 4 under the leadership of Daniel Jandačka, Ph.D. as part of the activity HA1 - Stage 6: Application of project results.

Daniel Jandačka, Ph.D. and Jaroslav Uchýtil, Ph.D. participated in the work for the LERCO team, research program 4.

Approved

Date:

Approved: prof. Mgr. Daniel Jandačka, Ph.D., leader RP4

doc. Mgr. Steriani Elavsky, Ph.D., excellent researcher



AUTHOR LIST

Nourhan Ibrahim, nourhan.ibrahim@student oulu.fi, 1

Dominik Vilimek, dominik.vilimek@vsb.cz, 2

Jaroslav Uchytíl, jaroslav.uchytil@osu.cz, 3

Victor Casula, victor.casula@oulu.fi, 1

Daniel Jandacka, daniel.jandacka@osu.cz, 3

Miika Nieminen, miika.nieminen@oulu.fi, 1,4

Egor Panfilov, egor.panfilov@oulu.fi, 1

1 - Research Unit of Health Sciences and Technology, University of Oulu, Finland

2 - Department of Cybernetics and Biomedical Engineering, VSB Technical University of Ostrava,
Czech Republic

3 - Department of Human Movement Studies, University of Ostrava, Czech Republic

4 - Department of Diagnostic Radiology, Oulu University Hospital, Finland



DESCRIPTION OF THE METHOD

Title

- Automatic segmentation of knee cartilage from qMRI T2 images: comprehensive study in Czech 4HAIE cohort
- Automatic segmentation of knee cartilage from qMRI T2 images: added value of Transformer model and T2 maps
- Automatic segmentation of knee cartilage from qMRI T2 images: added value of Swin UNETR model and T2 maps

Purpose (the aim of the study)

Quantitative MRI (qMRI), particularly T2 mapping, is a promising imaging technique to assess early structural changes in articular cartilage caused by knee osteoarthritis (KOA). Large-scale and reliable manual segmentation of knee cartilage is burdensome. This work aims to develop an automatic deep learning method for cartilage segmentation from qMRI T2 scans. Additionally, we study the impact of using images at different echo times and complementary value of T2 maps on the performance of segmentation model.

Methods

The data from the 4HAIE cohort was used, which comprised active runners and inactive controls aged 18-65 from Czech Republic (Jandacka et al., 2020). Sagittal T2 mapping scans were obtained from the right knees, separately for medial and lateral knee compartments (TR 1690ms, TE_s 12/24/36/48/60ms, pixel spacing 0.625mm, slice thickness 3mm). Femoral and tibial cartilage tissues were manually annotated (one slice per scan) by two trained readers using in-house software. T2 maps were derived by exponential fitting using all 5 echoes. A subset of 1250 subjects was selected and randomly split into 1997 scans for method development and 500 for testing subject-wise (2



scans per knee – lateral and medial compartments). The images were standardized via z-score normalization over all echo times, and similarly for T2 maps. The models were trained in 5-fold scenario over 30 epochs using Adam optimizer and cross-entropy loss to segment femoral (FC) and tibial (TC) cartilage tissues. First, we compared two deep learning architectures – conventional U-Net and state-of-art Swin UNETR. Different features sizes in Swin UNETR – 24, 48, or 60 – were analyzed. Second, we explored three configurations of training data: using images from first echo, first and second echo, or all echo times; and observed the performance on the complete test set, as well as the data at individual echo times. Third, we analyzed how the best configuration performs when trained on images, T2 maps, or 2-channel input (i.e. images in tandem with T2 maps). Model performance was evaluated using Dice score (DSC), average symmetric surface distance (ASSD), and Hausdorff distance (HD), as well as agreement in average T2 values.

Results

Trained on all echo times, Swin UNETR with features size of 48 yielded higher DSCs (0.825(0.082) for FC and 0.851(0.064) for TC) than with 24 and similar to 60, which was also comparable to U-Net (0.824(0.088) for FC and 0.853(0.069) for TC). When trained on a single or two echoes, performance of the models degraded on unseen echoes, with degradation being more pronounced in U-Net than in Swin UNETR (Figure 1). The model trained on T2 maps showed comparable DSCs, ASSDs, HDs, and T2 agreement to the model trained on all echoes, both in femoral and tibial cartilage scores (Table 1). T2 model was consistently more accurate in all metrics compared to image-based models trained on a single or two echoes. Using T2 maps in addition to MRI scans showed only marginal improvement in segmentation metrics, yet it led to higher agreement with manual annotators (Table 1).

Conclusions

In this study, we developed a deep learning method for automatic knee cartilage segmentation from qMRI T2 data and analyzed its performance in multiple scenarios. We observed that training on all echoes provided superior generalization than using only a subset of echoes, and we quantified this effect. We additionally proposed using T2 maps with and without MRI images as segmentation model input. Lastly, we showed that T2 maps can be successfully used instead of the



scans, thus improving data efficiency at training time and without notable change in performance. Since T2 maps are quantitative by design, we believe that T2 maps can be recommended as a representation format in the future T2 segmentation studies to achieve higher cross-dataset generalization.

Figure 1:

Average Dice scores of the U-Net and Swin UNETR architectures in different data configurations when evaluated on different echo times. The error bars show standard errors.

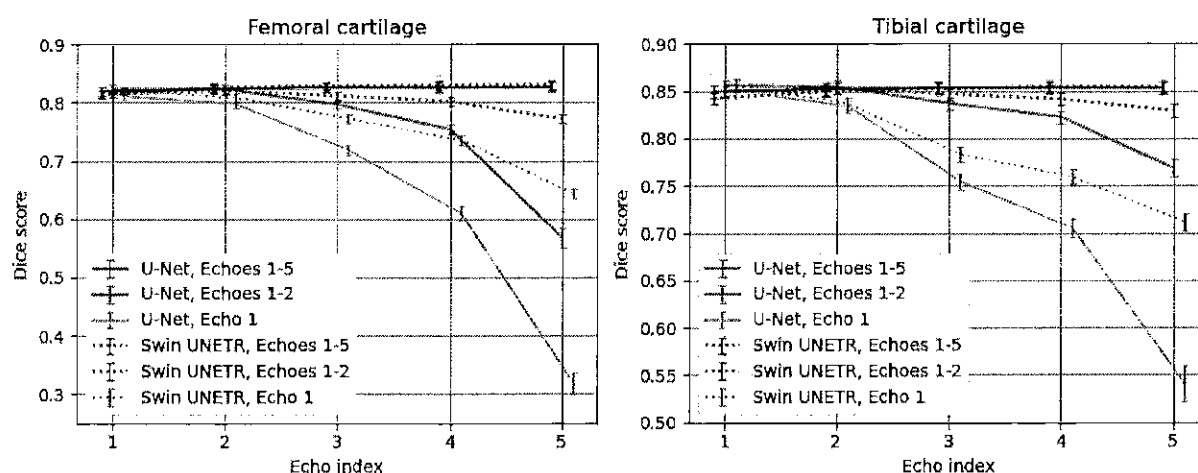


Table 1:

Performance of the Swin UNETR model in different data configurations. Evaluation is done on the images obtained at all echo times

Data configuration	Dice Score		Average Symmetric Surface Distance		Hausdorff Distance		Agreement in average T2 (mean diff. [limits of agreement])	
	Femoral	Tibial	Femoral	Tibial	Femoral	Tibial	Femoral	Tibial
Image (Echo 1)	0.756(0.109)	0.789(0.101)	0.393(0.501)	0.370(0.261)	4.159(4.282)	2.070(2.890)	0.08 [-8.59, 8.74]	-0.10 [-5.02, 4.83]
Image (Echoes 1 & 2)	0.804(0.081)	0.844(0.071)	0.272(0.193)	0.294(0.280)	3.108(2.920)	1.976(4.354)	0.17 [-6.96, 7.31]	-0.18 [-4.32, 3.97]
Image (Echo 1-5)	0.825(0.082)	0.851(0.064)	0.236(0.131)	0.276(0.233)	2.571(2.245)	1.782(3.206)	0.00 [-6.92, 6.92]	-0.17 [-4.48, 4.13]
T2 map	0.833(0.076)	0.855(0.071)	0.246(0.314)	0.281(0.544)	2.735(3.501)	1.722(1.536)	-0.13 [-6.29, 6.04]	-0.10 [-4.57, 4.36]
Image (Echo 1-5) and T2	0.824(0.062)	0.860(0.063)	0.241(0.260)	0.267(0.398)	2.664(2.840)	1.704(1.480)	0.37 [-5.79, 6.52]	-0.05 [-4.06, 3.97]