ANTs, BET, or...neither? An exploration of brain masking and machine learning tools applied to magnetic resonance elastography

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BACKGROUND

- Magnetic resonance elastography (MRE) is a developing technology within the field of magnetic resonance imaging that measures the mechanical (stiffness) properties of human tissue, similar in concept to the "palpation of internal organs" [1]
- MRE is clinically used to measure cirrhosis in the liver [2], but an effort exists to expand MRE to other parts of the human body, including the brain
- Advanced Normalization Tools (ANTs) [3] and Brain Extraction Tool (BET) [4] are tools to extract the brain from an MRI, but no specific tools exist for MRE





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- Masking is necessary to eliminate regions with incorrect phase information to create accurate elastograms after phase unwrapping using nonlinear inversion (NLI) [5]

METHODS

- TorchIO is a PyTorch library applying deep learning techniques to 3D medical imaging [6]
- Elastographs were used from 77 subjects with manual masks from previous studies
- An ANTs mask, BET mask, or no mask was added to the elastograph, either as an overlay or cut, to explore the potential of improving accuracy
- Elastographs from a different site were used as model testing data



TorchIO						
Mask Cut + TorchIO	0.004	-0.018	0.050	0.007	0.948	

Comparison of performance of top masking algorithms using Dice scores compared to manual masking gold standard. Diagonal values in blue are the mean Dice score for each method. Lower diagonal is the subtraction of the mean Dice score of the row minus the mean Dice score of the column. Green indicates that the row performed better than the column on mean Dice score. The upper diagonal is the -log10(p) for the paired t-test between the two methods. Yellow indicates that the p-value is significant, gray indicates non-significant, p<0.01 (i.e. -log10(p) greater than 2.

DISCUSSION

- The trivial result of using basic thresholding showed very good Dice scores
- For TorchIO, utilizing a mask overlay generally showed better accuracy compared to "cutting out" the image
- Qualitatively, the model seemed to do well superiorly but had trouble with inferior brain structures, such as the cerebellum and brainstem
- Our results show promise of creating an accurate and robust masking tool by utilizing more datasets with varying dimensions of data



This flowchart illustrates the three main paths taken, detailing the preprocessing and processing pipelines. The top path represents using only TorchIO for processing, inputting the image into a U-Net and outputting the resulting mask. The middle path represents using ANTs for preprocessing the image, either overlaying the generated ANTs mask over the input image or "cutting out" the input image with the ANTs mask. The bottom path represents using BET for preprocessing.

RESULTS

- Dice scores were calculated to compare output and manual masks, comparing overlay versus cut preprocessing, data normalization, and number of training epochs
- The results were compared to basic thresholding through the ANTs library, which sets the lower limit to the average image intensity and upper limit to the maximum image intensity
- Using ANTs for masking and thresholding produced the best results \bullet
- Elastograms resulting from mechanical inversion also support that more accurate masks produce more reliable stiffness measures

This visual is an example of the manual masks versus the mask generated by the machine learning model. The top row shows example masks that the model was trained on. Qualitatively, the model's mask looks relatively similar to the manual mask. The bottom row shows example masks that the model was tested on using external data. Qualitatively, while some of the model's masks look similar, there are some errors as seen in the mask's holes and highlights in the eye (which are not a part of the brain).



We hope that with the continued development of our tool, we can enable automated tools for MRE and expand its use in the brain. The ability to automatically mask out distorted regions is a step forward to enabling new neuroimaging applications. Continued development of our tool may also lead to increased availability and reliability of tools that can provide reliable across-site elastographs.

REFERENCES

- [1] L. V. Hiscox et al., 'Magnetic resonance elastography (MRE) of the human brain: technique, findings and clinical applications', Physics in Medicine & Biology, vol. 61, no. 24, p. R401, Nov. 2016.
- [2] R. Loomba et al., 'Magnetic resonance elastography predicts advanced fibrosis in patients with nonalcoholic fatty liver disease: a prospective study', Hepatology, vol. 60, no. 6, pp. 1920–1928, Oct. 2014.
- [3] B. B. Avants, N. J. Tustison, M. Stauffer, G. Song, B. Wu, and J. C. Gee, 'The Insight ToolKit image registration framework', Frontiers in Neuroinformatics, vol. 8, 2014.
- [4] S. M. Smith, 'Fast robust automated brain extraction', *Human Brain Mapping*, vol. 17, no. 3, pp. 143–155, 2002.

[5] E. E. W. Van Houten, J. B. Weaver, M. I. Miga, F. E. Kennedy, and K. D. Paulsen, 'Elasticity reconstruction from experimental MR displacement data: initial experience with an overlapping subzone finite element inversion process', Medical *Physics*, vol. 27, no. 1, pp. 101–107, 2000. [6] F. Pérez-García, R. Sparks, and S. Ourselin, 'TorchIO: A Python library for efficient loading, preprocessing, augmentation and patch-based sampling of medical images in deep learning', Computer Methods and Programs in Biomedicine, vol. 208, p. 106236, 2021.

MAGNETIC RESONANCE ELASTOGRAPHY IS A NEWLY DEVELOPED **NEUROIMAGING MODALITY TO UNDERSTAND AND DIAGNOSE DISEASES IN THE** BRAIN. A TOOL POWERED BY MACHINE LEARNING IS NEEDED TO EFFICIENTLY AND RELIABLY EXTRACT THE BRAIN TO FORM A BRAIN ELASTOGRAPH.

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