




1 LabelProp: A semi-automatic segmentation tool for 2 3D medical images

3 **Nathan Decaux** ^{1,2}, **Pierre-Henri Conze** ^{1,2}, **Juliette Ropars** ^{1,3}, **Xinyan**
4 **He**², **Frances T. Sheehan**⁴, **Christelle Pons** ^{1,3,5}, **Douraid Ben Salem** ^{1,3},
5 **Sylvain Brochard** ^{1,3}, and **François Rousseau** ^{1,2}

6 **1** LaTIM UMR 1101, Inserm, Brest, France **2** IMT Atlantique, Brest, France **3** University Hospital of
7 Brest, Brest, France **4** Rehabilitation Medicine, NIH, Bethesda, USA **5** Fondation ILDYS, Brest, France

DOI: [10.xxxxxx/draft](https://doi.org/10.xxxxxx/draft)

Software

- [Review](#) 
- [Repository](#) 
- [Archive](#) 

Editor: Johanna Bayer 

Reviewers:

- [@WangKehan573](#)
- [@animikhaich](#)

Submitted: 16 January 2024

Published: unpublished

License

Authors of papers retain copyright
and release the work under a
Creative Commons Attribution 4.0
International License ([CC BY 4.0](#))

8 Summary

9 LabelProp is a tool that provides a semi-automated method to segment 3D medical images
10 with multiple labels. It is a convenient implementation of our peer-reviewed method designed to
11 assist medical professionals in segmenting musculoskeletal structures on scans based on a small
12 number of annotated slices ([Decaux et al., 2023](#)). LabelProp leverages deep learning techniques,
13 but does not require a training set or pretrained weights to function. It is available as a PyPi
14 package and offers both a command-line interface (CLI) and an API. Additionally, LabelProp
15 provides two plugins, namely 'napari-labelprop' and 'napari-labelprop-remote', which facilitate
16 training and inference on a single scan within the multi-dimensional viewer Napari. It is available
17 on GitHub with pretrained weights (<https://github.com/nathandecaux/napari-labelprop>)

18 Statement of need

19 Segmenting musculoskeletal structures from MR images is crucial for clinical research, diagnosis,
20 and treatment planning. However, challenges arise from the limited availability of annotated
21 datasets, particularly in rare diseases or pediatric cohorts ([Conze et al., 2020](#)). While manual
22 segmentation ensures accuracy, it is labor-intensive and prone to observer variability ([Vădineanu](#)
23 [et al., 2022](#)). Existing semi-automatic methods based on point and scribbles require minimal
24 interactions but often lack reproducibility ([Chanti et al., 2021](#); [Lee & Jeong, 2020](#) ; [Sakinis et](#)
25 [al., 2019](#); [Zhang et al., 2021](#)).

26 LabelProp addresses these challenges with a novel deep registration-based label propagation
27 method. This approach efficiently adapts to various musculoskeletal structures, leveraging
28 image intensity and muscle shape for improved segmentation accuracy.

29 A key innovation of LabelProp is its minimal reliance on manual annotations. Demonstrating
30 the capability for accurate 3D segmentation from as few as three annotated slices per MR
31 volume ([Decaux et al., 2023](#)), it significantly reduces the workload for medical professionals
32 and is particularly beneficial where extensive annotated data is scarce. This feature aligns with
33 the method of slice-to-slice registration ([Ogier et al., 2017](#)), but is further enhanced by deep
34 learning techniques.

35 Similar to Voxelmorph, the underlying model in this approach learns to generate deformations
36 without supervision ([Balakrishnan et al., 2019](#)). However, it specifically focuses on aligning
37 adjacent 2D slices and can be trained directly on the scan that needs to be segmented or on a
38 complete dataset for optimal results. When training the model with at least two annotations
39 for a scan, a constraint is added to ensure that the generated deformations are consistent from
40 both an image and segmentation perspective. Additionally, weak annotations in the form of

scribbles can be provided during training on intermediate slices to provide additional guidance for propagation. Examples of manual annotations and “scribbles” are shown in Fig. 1.

During the inference phase, each annotation is propagated to its nearest neighboring annotation, resulting in two predictions for each intermediate slice from different source annotations. The label fusion process involves weighting each prediction based on their distance to the source annotation or an estimate of the registration accuracy. Importantly, the propagation method is label-agnostic, allowing for the simultaneous segmentation of multiple structures, regardless of whether they are manually annotated on the same slice or not.

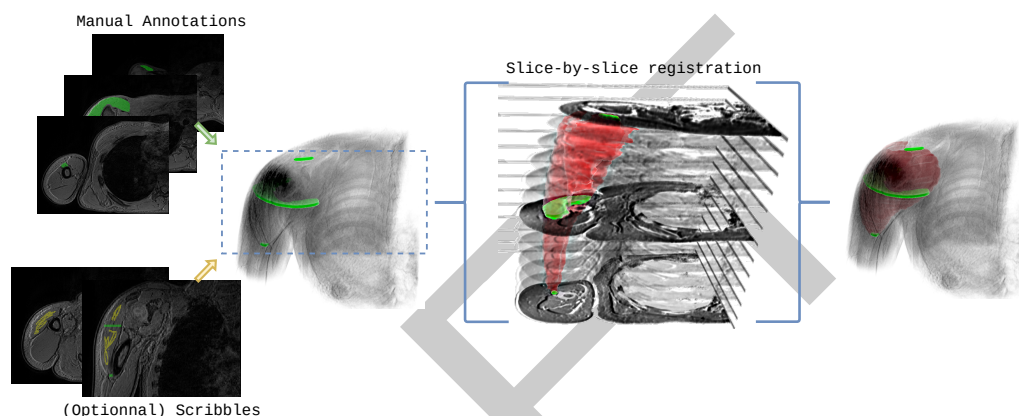


Figure 1: Example of propagation from 3 manual annotations of the deltoid muscle in a MRI, in axial plane. Optionnal scribbles (yellow) can be provided, without plane constraints, for further guidance.

Software Details

LabelProp is composed of three main components: labelprop, napari-labelprop, and napari-labelprop-remote. The labelprop algorithm is accompanied by a command-line interface (CLI) and a REST API. The CLI enables unsupervised pretraining or training with sparse annotations on a dataset, and inference on a single volume. The API provides access to training with annotations and inference on a single subject via HTTP requests. It is used in the napari-labelprop-remote plugin, but can be adapted to other extendable viewer/segmentation tools such as 3D slicer or MITK. The napari-labelprop plugin brings the labelprop algorithm into the interactive Napari platform, allowing users to conduct both the training and inference stages of label propagation directly within the Napari environment. The napari-labelprop-remote plugin extends the functionality of napari-labelprop, allowing users to perform training and inference on a remote server through the labelprop API. These tools provide a versatile and user-friendly toolkit for 3D bioimage segmentation, offering the flexibility to work locally or remotely, and leveraging deep learning to efficiently generate 3D segmentations from slice annotations.

Acknowledgements

This work was partially funded by ANR (AI4Child project, grant ANR-19-CHIA-0015) and Innoveo from CHRU de Brest.

References

- Balakrishnan, G., Zhao, A., Sabuncu, M. R., Guttag, J., & Dalca, A. V. (2019). VoxelMorph: A learning framework for deformable medical image registration. *IEEE Transactions on Medical Imaging*, 38(8), 1788–1800. <https://doi.org/gfx7zs>

- 70 Chanti, D. A., Duque, V. G., Crouzier, M., Nordez, A., Lacourpaille, L., & Mateus, D. (2021).
71 IFSS-Net: Interactive Few-Shot Siamese Network for Faster Muscle Segmentation and
72 Propagation in Volumetric Ultrasound. *IEEE Transactions on Medical Imaging*, 40(10),
73 2615–2628. <https://doi.org/gh4vsp>
- 74 Conze, P.-H., Brochard, S., Burdin, V., Sheehan, F. T., & Pons, C. (2020). Healthy versus
75 pathological learning transferability in shoulder muscle MRI segmentation using deep
76 convolutional encoder-decoders. *Computerized Medical Imaging and Graphics*, 83, 101733.
77 <https://doi.org/gpjrzf>
- 78 Decaux, N., Conze, P.-H., Ropars, J., He, X., Sheehan, F. T., Pons, C., Ben Salem, D.,
79 Brochard, S., & Rousseau, F. (2023). Semi-automatic muscle segmentation in MR
80 images using deep registration-based label propagation. *Pattern Recognition*, 140, 109529.
81 <https://doi.org/10.1016/j.patcog.2023.109529>
- 82 Lee, H., & Jeong, W.-K. (2020). Scribble2Label: Scribble-Supervised Cell Segmentation via
83 Self-Generating Pseudo-Labels with Consistency. *arXiv:2006.12890 [Cs]*. <http://arxiv.org/abs/2006.12890>
84
- 85 Ogier, A., Sdika, M., Foure, A., Le Troter, A., & Bendahan, D. (2017). Individual mus-
86 cle segmentation in MR images: A 3D propagation through 2D non-linear registration
87 approaches. *International Conference of the IEEE Engineering in Medicine and Biology*
88 *Society*, 317–320.
- 89 Sakinis, T., Milletari, F., Roth, H., Korfiatis, P., Kostandy, P., Philbrick, K., Akkus, Z., Xu,
90 Z., Xu, D., & Erickson, B. J. (2019). Interactive segmentation of medical images through
91 fully convolutional neural networks. *arXiv Preprint arXiv:1903.08205*.
- 92 Vădineanu, Ș., Pelt, D. M., Dzyubachyk, O., & Batenburg, K. J. (2022). An Analysis of the
93 Impact of Annotation Errors on the Accuracy of Deep Learning for Cell Segmentation.
94 *Proceedings of The 5th International Conference on Medical Imaging with Deep Learning*,
95 1251–1267. <https://proceedings.mlr.press/v172/vadineanu22a.html>
- 96 Zhang, J., Shi, Y., Sun, J., Wang, L., Zhou, L., Gao, Y., & Shen, D. (2021). Interactive
97 medical image segmentation via a point-based interaction. *Artificial Intelligence in Medicine*,
98 111, 101998. <https://doi.org/gqg5d6>