Volumetric Image Visualization

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Objects in a 3D image may be located and delineated by

- interactive methods,
- automatic methods, and
- differential methods that can correct errors from the previous approaches in an interactive fashion.

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In this lecture, we will learn how 3D objects can be segmented by optimum connectivity and some prior information.

Pattern classifiers, such as deep neural networks, may be able to create a membership map where object voxels have higher values than most background voxels.



However, simple user interaction allows to separate the respiratory system as one optimum-path tree rooted at a seed voxel *A*.

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In this method, an image Î = (D_I, I) is a 6-neighborhood graph and the cost of a path from a seed set S = {A, B} to other voxels C ∈ D_I is the maximum gradient value along it.

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- The paths propagate in a non-decreasing order of cost, the seeds compete among themselves, and each seed s ∈ S conquers its most closely connected voxels, generating one optimum-path tree rooted at s.

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- Each object is formally defined as one optimum-path forest rooted at its internal seeds.
- The method is also called a watershed transform from markers, as implemented by the Image Foresting Transform (IFT) algorithm [4].

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The optimum-path forest can also be updated in a differential way (in sublinear time) from additional seeds [5].



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Seeds for each lung and traquea segmentation can also be found automatically in a few seconds, based on a sequence of IFT-based image operators [1].



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An object shape model can be built from normal examples (images and masks in a common coordinate system) and a texture model can identify anomalous regions in test images.



A multi-object statistical atlas adaptive for anomalous MR-image segmentation [2].

Automatic seed estimation by object shape models

The model estimates seeds, they compete among themselves, and the objects are optimum-path forests rooted at their internal seeds.





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MR-image segmentation of the left and right brain hemispheres, and the cerebellum without pons, medulla, and spinal cord.

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MR-image segmentation of the left and right brain hemispheres, and the cerebellum without pons, medulla, and spinal cord.

Finally, the segmentation result from any method can be converted into an optimum-path forest rooted at computed seeds [7, 8] for fast interactive corrections in a differential way [5, 12].



CT-image segmentation of foot bones.

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- Automatic methods usually rely on a shape and/or texture (e.g., a neural network) object model pre-trained from a number of interactively segmented examples.
- Differential interactive methods have the challenge of
 - correcting errors without destroying parts already accepted as correct,
 - minimize the user effort and time to complete segmentation, and
 - update/learn an active object model from each new user input.

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The object model should be active in its learning process, specific for each image, and generalized for new images only when the number of examples is high enough [9].

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We will see now the next practical task.

- A.M. Sousa, S.B. Martins, F. Reis, E. Bagatin, K. Irion, and A.X. Falcão. ALTIS: A Fast and Automatic Lung and Trachea CT-Image Segmentation Method. *Medical Physics*, doi 10.1002/mp.13773, 46(11), pp. 4970–4982, Nov 2019
- S.B. Martins, J. Bragantini, C. Yasuda, and A.X. Falcão. An Adaptive Probabilistic Atlas for Anomalous Brain Segmentation in MR Images. *Medical Physics*, doi: 10.1002/mp.13771, 46(11), pp. 4940–4950, Nov 2019.
- [3] K.C. Ciesielski, A.X. Falcão, and P.A.V. Miranda. Path-value functions for which Dijkstra's algorithm returns optimal mapping. *Journal of Mathematical Imaging and Vision*, 10.1007/s10851-018-0793-1, vol. 60, pp. 1025-1036, 2018.
- [4] A. X. Falcão, J. Stolfi and R. de Alencar Lotufo. The image foresting transform: theory, algorithms, and applications. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 10.1109/TPAMI.2004.1261076, 26(1), pp. 19-29, 2004.

- [5] A.X. Falcão and F.P.G. Bergo . Interactive Volume Segmentation with Differential Image Foresting Transforms. *IEEE Trans. on Medical Imaging*, 10.1109/TMI.2004.829335, 23(9), pp. 1100–1108, 2004.
- [6] T.V. Spina, J. Stegmaier, A.X. Falcão, E. Meyerowitz, and A. Cunha. SEGMENT3D: A Web-based Application for Collaborative Segmentation of 3D Images Used in the Shoot Apical Meristem. *IEEE Intl. Symp. on Biomedical Imaging (ISBI)*. 10.1109/ISBI.2018.8363600, pp. 391-395, 2018.
- [7] A.C.M. Tavares, P.A.V. Miranda, T.V. Spina, and A.X. Falcão. A Supervoxel-based Solution to Resume Segmentation for Interactive Correction by Differential Image-Foresting Transforms. 13th International Symposium on Mathematical Morphology and its Application to Signal and Image Processing, LNCS 10225, 10.1007/978-3-319-57240-6_9, pp. 107–118, 2017.

- [8] P.A.V. Miranda, A.X. Falcão, G. Ruppert and F. Cappabianco. How to Fix any 3D Segmentation Interactively via Image Foresting Transform and its use in MRI Brain Segmentation. 8th IEEE Intl. Symp. on Biomedical Imaging: From Nano to Macro (ISBI), 10.1109/ISBI.2011.5872811, pp. 2031–2035, 2011.
- [9] T.V. Spina, S.B. Martins, and A.X. Falcão. Interactive Medical Image Segmentation by Statistical Seed Models. XXIX SIBGRAPI - Conference on Graphics, Patterns and Images, doi: 10.1109/SIBGRAPI.2016.045, pp. 273–280, 2016.
- [10] P. Rauber, A.X. Falcão, T.V. Spina, and P.J. de Rezende. Interactive Segmentation by Image Foresting Transform on Superpixel Graphs. Proc. of the XXVI SIBGRAPI - Conference on Graphics, Patterns and Images, 10.1109/SIBGRAPI.2013.27, pp. 131–138, 2013.

[11] P. A. V. Miranda and L. A. C. Mansilla. Oriented Image Foresting Transform Segmentation by Seed Competition, *IEEE Transactions on Image Processing*, 10.1109/TIP.2013.2288867, 23(1), pp. 389-398, 2014.

[12] M.A.T. Condori, F.M. Cappabianco, A.X. Falcão, and P.A.V. de Miranda. An Extension of the Differential Image Foresting Transform and its Application to Superpixel Generation. *Journal of Visual Communication and Image Representation*, doi 10.1016/j.jvcir.2019.102748, 2020, to appear.

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