Unrolling directional total variation regularization algorithm for restoration of vascular structures

Context

With improvements in mathematical techniques and computational power, deep learning has profoundly changed research and applications in AI, specifically in image processing and computer vision. Many scientific endeavours have moved from finding explicit models describing a problem of interest to building large, annotated datasets representing the studied phenomenon. However not everything is resolved: even though deep learning is now broadly used in medical imaging, methods need to be developed to tackle every new domain-specific problem: acquisition and annotation are complex and time consuming, data sharing is difficult due to privacy issues, interpretability and reproducibility are also a concern. To tackle some of these, among these methods, deep unrolling algorithms show promising results in some vision tasks like image restoration, detection or segmentation.

Deep unrolling refers to the technique of taking an iterative optimization method such as proximal gradient descent, alternating directions method multipliers (ADMM) or proximal interior point method, and building a network with a finite number of layers, each layer corresponding to one iteration of the algorithm. A broad range of deep unrolling strategies have been recently proposed for several applications. Some methods keep the data fidelity term explicit and learn both the proximity operator of the regularization term and the optimization algorithm hyperparameters [1]. Consequently, these methods differ from the original optimization algorithm and trade the explicit model interpretability for an implicit model with a potentially higher representation power. A recent method by Bertocchi et. al. [2] proposes an explicit definition of the proximity operator and only learns the optimization algorithm hyperparameters. Contrary to the classical optimization algorithm, these parameters are untied in each iteration thereby increasing the network flexibility to learn the solution space while keeping the advantages of the original algorithm: a high interpretability and stability.

Among tasks that are still challenging despite years of active research [3], [4], the detection of 3D vascular networks is still an open problem, as these structures exhibit a complex geometry (thin structures organized in networks at different scales) and are very sensitive to noise and artifacts. Recently, Merveille et. al. [5] proposed a directional total variation regularization to restore vascular structures that aim at preserving the connectivity of vascular networks. This regularization requires a directional vector field that provides the direction of each vascular structure in the image. However classical curvilinear detectors usually compute rough directions especially for small vessels (see Figure 1), which greatly reduces the power of the directional regularization. The goal of this internship is to combine deep unrolling strategy and directional total variation regularization to restore and detect vascular structures.

Subject

Based on [2], the intern will develop a deep unrolling algorithm for vascular structure restoration using a smooth directional TV regularization. Beyond simply learning optimization algorithm hyperparmeters, the directional vector field would also be learned in order to overcome the usual curvilinear detector limitations. Several optimization algorithms will be compared and an unrolling algorithm to solve the exact directional total variation will also be investigated. These algorithms will be applied

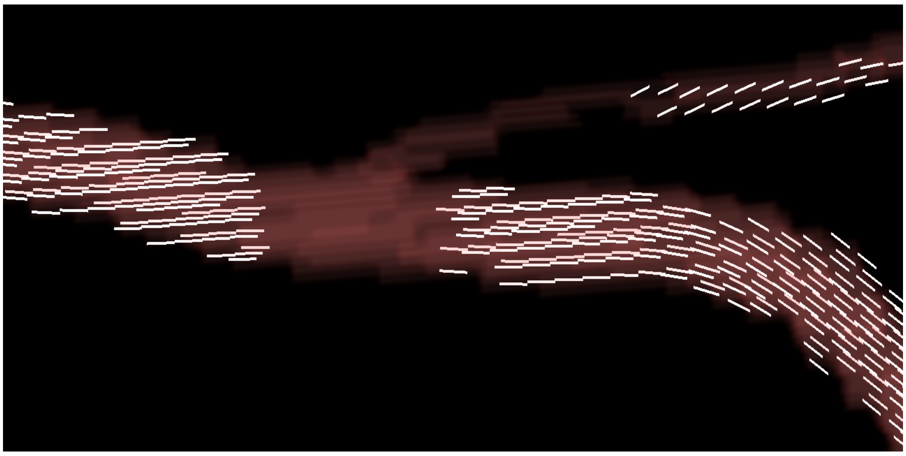

Figure 1: Exemple of directions (in white) computed by a classic curvilinear detector.

to the filtering and segmentation of the hepatic vascular network using public and private annotated dataset.

Profile

Candidates should be motivated by image processing with a particular interest in deep learning and inverse problems. A background in medical imaging and/or an experience with Pytorch are a plus.

Internship information

- 6 month internship starting in January to Mars 2021
- Location: Depending on the intern preference, the internship could be located at the Centre de Vision Numérique in CentraleSupélec or at the Creatis laboratory in INSA Lyon.
- Advisors: Prof. Odyssée Merveille, Prof. Hugues Talbot and Prof. Jean-Christophe Pesquet
- Applications to be sent by mail to odyssee.merveille@creatis.insa-lyon.fr with a detailed CV, covering letter and optionally latest grade transcripts.

References

[1] S. Diamond, V. Sitzmann, F. Heide, and G. Wetzstein, "Unrolled optimization with deep priors," 2017. arXiv: 1705.08041.

[2] C. Bertocchi, E. Chouzenoux, M.-C. Corbineau, J.-C. Pesquet, and M. Prato, "Deep unfolding of a proximal interior point method for image restoration," *Inverse Problems*, vol. 36, no. 3, p. 034 005, 2020.

[3] D. Lesage, E. D. Angelini, I. Bloch, and G. Funka-Lea, "A review of 3D vessel lumen segmentation techniques: Models, features and extraction schemes," *Journal of Medical Image Analysis*, vol. 13, no. 6, pp. 819–845, 2009.

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[5] O. Merveille, B. Naegel, H. Talbot, and N. Passat, "nD variational restoration of curvilinear structures with prior-based directional regularization," *IEEE Transactions on Image Processing*, vol. 28, no. 8, pp. 3848–3859, 2019.