A plug-and-play framework for curvilinear structure segmentation based on a learned reconnecting regularization

S. Carneiro Esteves, Antoine Vacavant and Odyssée Merveille

Context

Cardiovascular diseases : leading cause of death in the world according to the World Health Organization

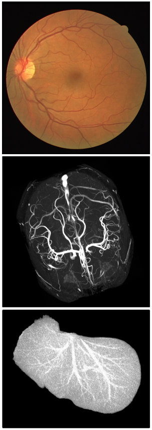
→ Visualization of vascular structures *via* angiographic images

MRI-TOF of the brain

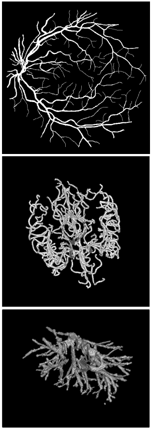
Vascular Network Analysis Importance

- Improvement in diagnosis and management of diseases
- Providing tools for visualization and treatment

Context



Angiographic images



Manual segmentation

Need for precise localization of the vascular network

Segmentation of the vascular structure from angiographic images

Structures difficult to segment

Automatic segmentation methods

Automatic segmentation methods

Approach	
Classical	
Supervised Deep learning	

Automatic segmentation methods

Approach	**Global Quality**
Classical	-
Supervised Deep learning	+

Automatic segmentation methods

Approach	Global Quality	Capacity to Generalize
Classical	-	+
Supervised Deep learning	+	-

Hybrid methods

- Bridging Classical and Deep Learning approaches
- Taking advantages of both approaches

Hybrid methods based on the variational approach

Variational approach definition

$$u^\star = \underset{u}{\text{Argmin}}\, D(u, f) + \lambda R(u)$$

with,

- $u^\star \in \mathbb{R}^n$ the solution image
- $f \in \mathbb{R}^n$ the initial image
- $D, R \in \Gamma_0(\mathbb{R}^n)^2$
- λ the regularization coefficient

$g \in \Gamma_0(\mathbb{R}^n)$ the set of lower semi-continuous , convex et proper functions on $\mathbb{R}^n$.

Hybrid methods based on the variational approach

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- λ the regularization coefficient

Constraints difficult to model

Hybrid methods

- Replacing R with a learned model
- Plug the model into the minimization resolution

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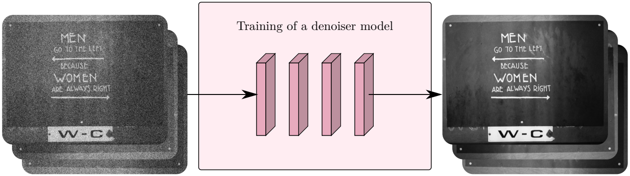
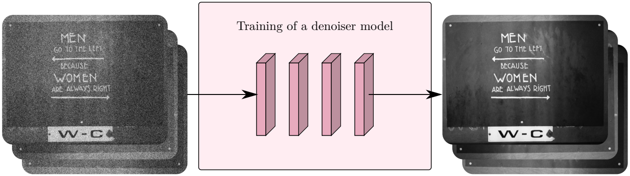
Plug-and-play approach

(1)

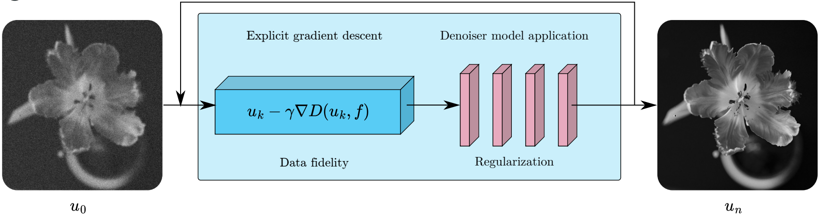


Plug-and-play approach

1



2



No annotation required for main task

Meinhardt *et al.* "Learning Proximal Operators: Using Denoising Networks for Regularizing Inverse Imaging Problems", ICCV 2017

Plug-and-play approach

- Tested on different applications
  Demosaicking, inpainting, deblurring, ...
- With different resolution algorithms
  HQS[2], *ADMM*[3], *PDHG*[1] , ...
- Strategies to ensure method convergence [4]

[1] Meinhardt *et al.* "Learning Proximal Operators: Using Denoising Networks for Regularizing Inverse Imaging Problems", ICCV 2017

[2] Zhang *et al.* "Learning deep CNN denoiser prior for image restorations", CVPR 2017

[3] Le Pendu *et al.* "Preconditioned plug-and-play admm with locally adjustable denoiser for image restoration", SIAM 2023

[4] Pesquet *et al.* "Learning maximally monotone operators for image recovery.", SIAM 2021

Variational segmentation: Chan model[1]

Definition

$$u^\star = \underset{u}{\operatorname{argmin}}\, D(u, f) + \lambda R(u)$$

With :

- $f \in [0,1]^n$
- $u^\star \in [0,1]^n$

c_1 and c_2 foreground and the background constants

[1] Chan *et al.* "Algorithms for finding global minimizers of image segmentation and denoising models", SIAM, 2006.

Variational segmentation: Chan model[1]

Definition

$$u^\star = \underset{u \in [0,1]^n}{\operatorname{argmin}} \langle c, u \rangle_F + \lambda TV(u)$$

With :

- $f \in [0,1]^n$
- $u^\star \in [0,1]^n$
- $c = (c_1 - f_j)^2 - (c_2 - f_j)^2$
- $TV(u) = \|\nabla u\|_{2,1}$

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Problem reformulation

$$u^\star = \underset{u}{\operatorname{argmin}} \langle c, u\rangle_F + \lambda TV(u) + \iota_{[0,1]^n}(u) \qquad \iota_{[0,1]^n}(u) = \begin{cases} 0 & \text{if } x \in [0,1] \\ +\infty & \text{otherwise} \end{cases}$$

c_1 and c_2 foreground and the background constants

[1] Chan *et al.* "Algorithms for finding global minimizers of image segmentation and denoising models", SIAM, 2006.

Primal-Dual method

$$u^\star = \underset{u}{\operatorname{argmin}}\, D(u,f) + g(Lu) + k(u)$$

- $D(u) = \langle u, c_f \rangle_F$
- $k(u) = \iota_{[0,1]^n}$
- $g(.) = \lambda \|.\|_{2,1}$
- $L = \nabla$

Resolution:

$$u_{i+1} = \operatorname{prox}_{\tau k}(u_i - \tau(\nabla D(u_i) + L^T v_i))$$
$$v_{i+1} = \operatorname{prox}_{\sigma g^\star}(v_i + \sigma L(2u_{i+1} - u_i))$$

τ, σ the gradient descent step sizes

Condat L. " A primal-dual splitting method for convex optimization involving lipschitzian, proximable and linear composite terms", Journal of Opt. Theory and Applications, 2013.

Variational segmentation of vascular structures

→ TV[1] tend to make thin structures disappeared

[1] Rudin *et al.* "Nonlinear total variation based noise removal algorithms", Physica D: Nonlinear Phenomena, 1992

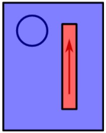
[2] Merveille *et al.* "*n*D variational restoration of curvilinear structures with prior-based directional regularization", IEEE TIP, 2019

Variational segmentation of vascular structures

→ TV[1] tend to make thin structures disappeared

nD directional TV[2]

$$R(u) = \| \nabla_m u \|_{2,1},$$
$$\nabla_m u = \bar{\mathcal{V}}(f)\nabla_{\mathrm{d}} u + (1 - \bar{\mathcal{V}}(f))\nabla u,$$



- $\bar{\mathcal{V}}$ a prior on the presence of tubular structures
- ∇_{d} the directional gradient

Estimation of structures direction thanks to the prior in order to integrate it in the gradient computation

[1] Rudin *et al.* "Nonlinear total variation based noise removal algorithms", Physica D: Nonlinear Phenomena, 1992

[2] Merveille *et al.* "nD variational restoration of curvilinear structures with prior-based directional regularization", IEEE TIP, 2019

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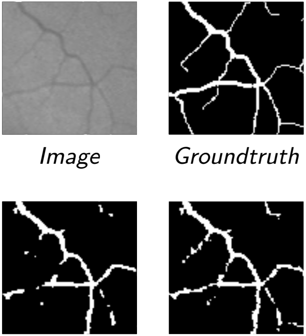

Image *Groundtruth*

TV *nD TV*

[1] Rudin *et al.* "Nonlinear total variation based noise removal algorithms", Physica D: Nonlinear Phenomena, 1992

[2] Merveille *et al.* "*n*D variational restoration of curvilinear structures with prior-based directional regularization", IEEE TIP, 2019

Variational segmentation of vascular structures

$\rightarrow$ TV[1] tend to make thin structures disappeared

nD directional TV[2]

$$R(u) = || \nabla_m u ||_{2,1},$$

$$\nabla_m u = \bar{\mathcal{V}}(f) \nabla_{\mathrm{d}} u + (1 - \bar{\mathcal{V}}(f)) \nabla u,$$

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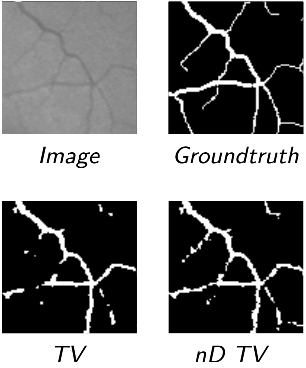


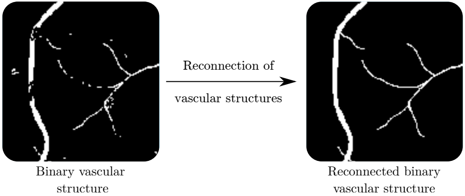
Connectivity is not preserved

[1] Rudin *et al.* "Nonlinear total variation based noise removal algorithms", Physica D: Nonlinear Phenomena, 1992

[2] Merveille *et al.* "*n*D variational restoration of curvilinear structures with prior-based directional regularization", IEEE TIP, 2019

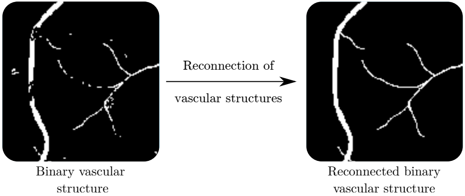
Idea

1. **Learn** a model that reconnects vascular structures



Idea

1. **Learn** a model that reconnects vascular structures



2. **Plug it** into a variational segmentation resolution as a regularization term

Proposed method

What do I need to learn to reconnect vascular structures ?

- An annotated dataset
- An architecture to train

Proposed method

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Proposed method

What do I need to learn to reconnect vascular structures ?

- **An annotated dataset**
- An architecture to train

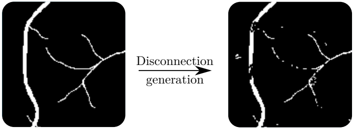
Dataset creation

- Easy to disconnect
- Independant toward the modality

$\rightarrow$ **Use of binary structures**

Proposed method

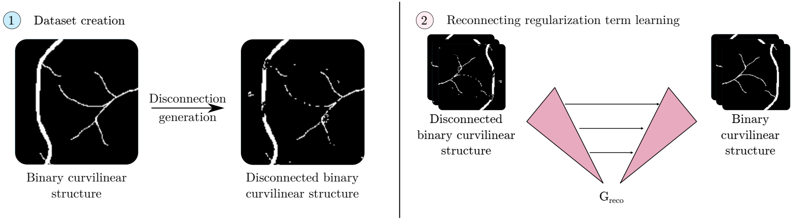
1 Dataset creation



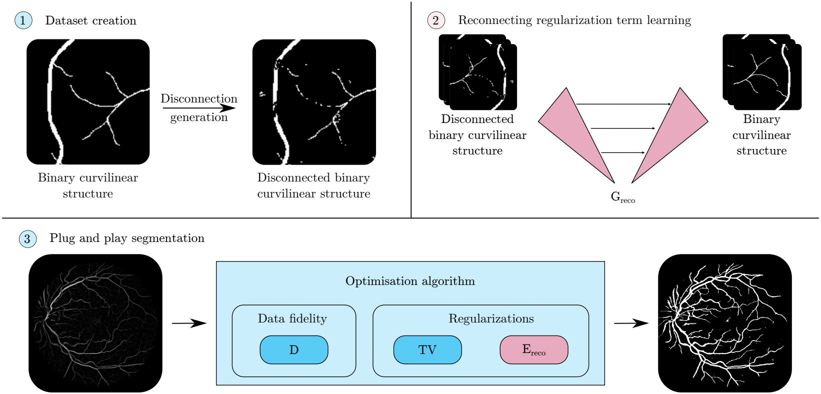
Binary curvilinear structure

Disconnected binary curvilinear structure

Proposed method



Proposed method



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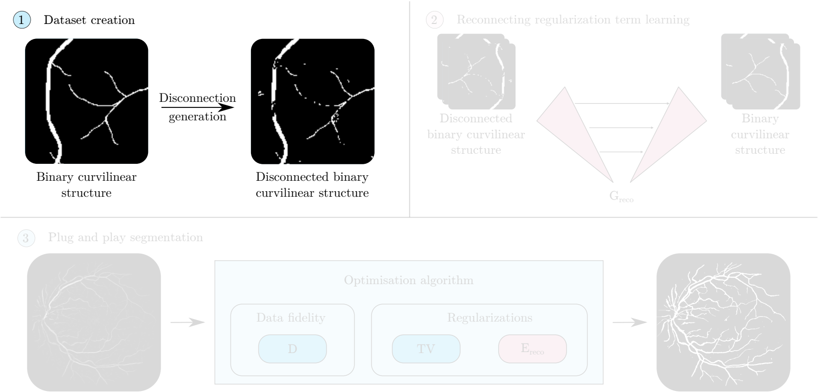

1. Dataset creation

Observations

Segmentations

Groundtruth

1. Dataset creation

Observations

Segmentations

Groundtruth

Hypothesis

- The thinner the vessel, the more likely it is to become disconnected
- The thinner the vessel, the bigger the disconnection
- Artefact presence

1. Dataset creation

Inputs of the algorithm

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- A binary vascular structure:
  - A manual annotation
  - A synthetic vascular tree

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- A binary vascular structure:
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- The number of disconnections to create

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- A binary vascular structure:
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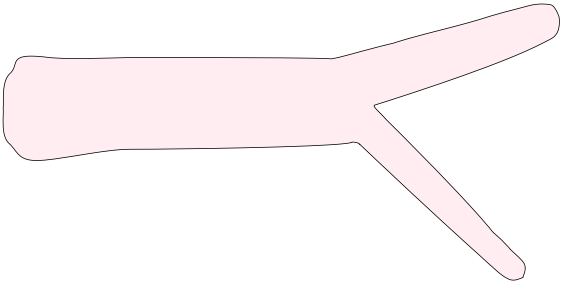
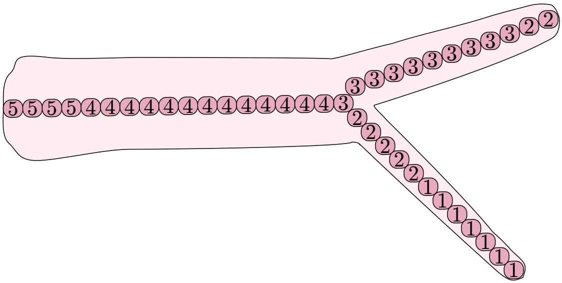
  - A synthetic vascular tree
- The number of disconnections to create
- The mean size s of disconnections

1. Dataset creation



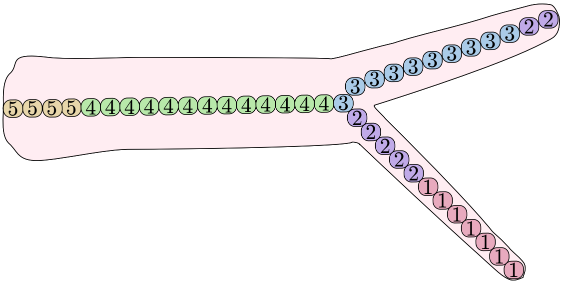
Binary vascular structure

1. Dataset creation



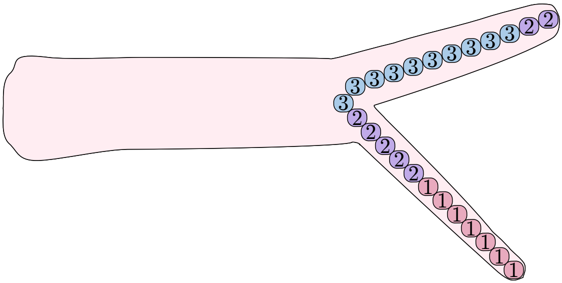
Extraction of the structure radius on the centerlines

1. Dataset creation



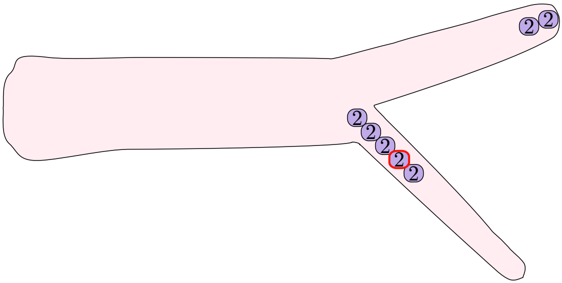
Classification of each centerline pixel in m classes in function of their radius

1. Dataset creation



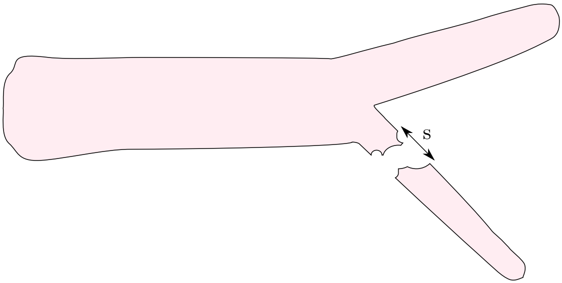
Selection of 3 classes with the thinnest structures

1. Dataset creation



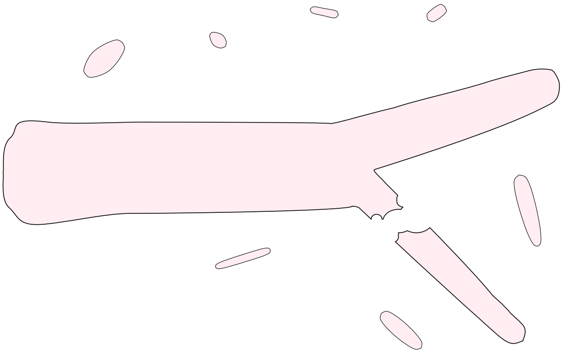
Draw a class and then a pixel from the centerline to select the center of a disconnection

1. Dataset creation



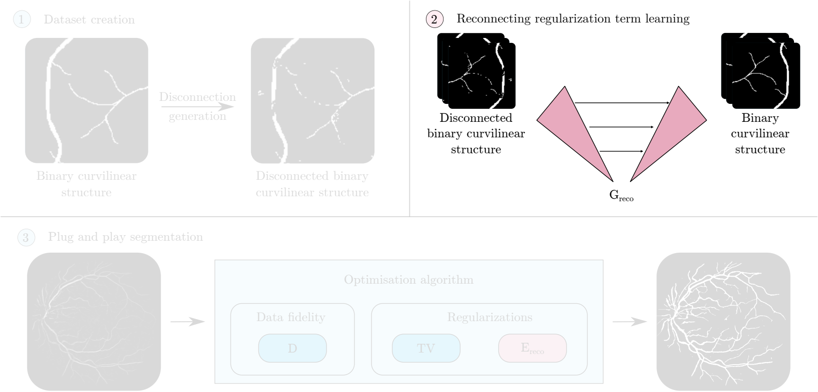
Disconnect the structure at the selected pixel

1. Dataset creation



Add fragments

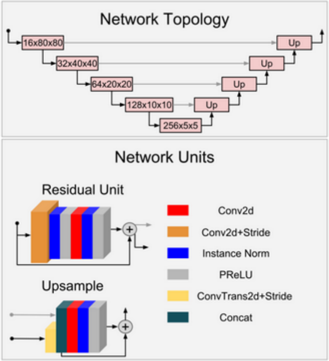
Proposed method



2. Reconnecting regularization term learning

Model architecture: Residual U-Net[1]

- Reconnection of binary vascular structures similar to segmentation task
- U-Net architecture : the gold standard for biomedical image segmentation



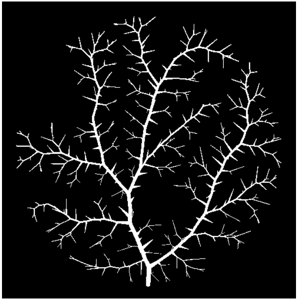
Residual U-Net architecture

[1] Kerfoot *et al.* " Left-ventricle quantification using residual u-net", International Workshop on Statistical Atlases and Computational Models of the Heart, 2018

2. Reconnecting regularization term learning

Loss function:

- Unbalanced classes (background, structure)

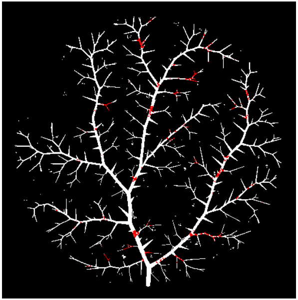


Example of a connected vascular structure

2. Reconnecting regularization term learning

Loss function:

- Unbalanced classes (background, structure)
- Fragments : small part of the vascular structure (6% of the structure in 2D)



Example of a structure with the disconnections highlighted

2. Reconnecting regularization term learning

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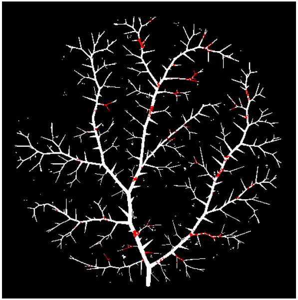


Example of a structure with the disconnections highlighted

Dice loss not adapted

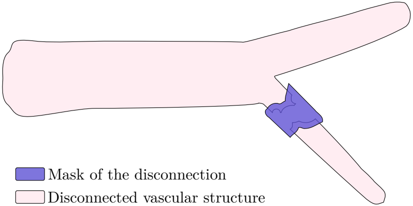
2. Reconnecting regularization term learning

Proposed Dice loss :

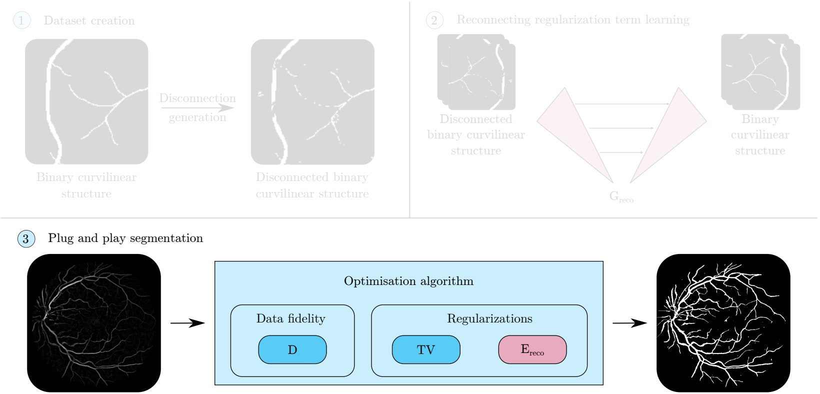
$$\mathcal{L}(x, y) = \mathcal{D}(x, y) + \mathcal{D}(x, y; M),$$

avec :

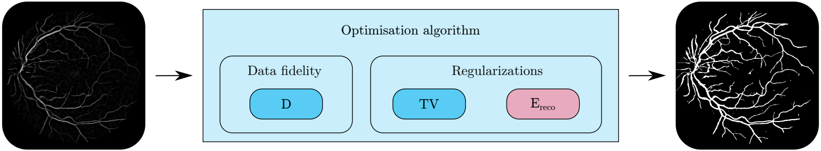
- $x \in [0, 1]^n$ a disconnected image composed of n pixels
- $y \in \{0, 1\}^n$ its annotation,
- $M \in \{0, 1\}^n$ the mask containing the missing fragments and their neighbors.



Proposed method



3. Plug and play segmentation



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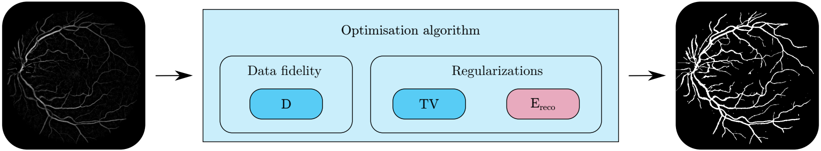
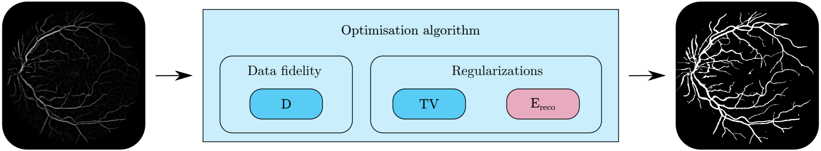


Our model

$$G_{reco} : \{0,1\}^n \to [0,1]^n$$

Applicable to binary or near-binary images

3. Plug and play segmentation



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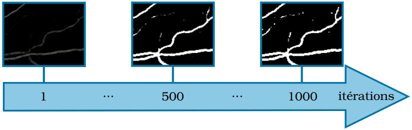
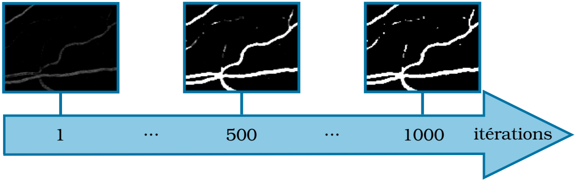
Variational optimisation scheme



u_i evolution through iterations

3. Plug and play segmentation

Variational optimisation scheme



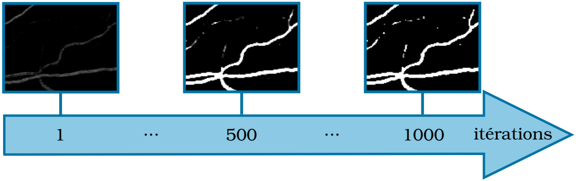
u_i evolution through iterations

$$\underset{u}{\mathrm{Argmin}} \langle c, u \rangle_F + \lambda TV(u) + \iota_{[0,1]^n}(u) \quad \text{as a first step}$$

$$\underset{u}{\mathrm{Argmin}} \langle c, u \rangle_F + \lambda TV(u) + E_{\mathrm{reco}}(u) \quad \text{when } u \text{ is near binary}$$

3. Plug and play segmentation

Variational optimisation scheme



u_i evolution through iterations

$$\underset{u}{\text{Argmin}} \langle c, u\rangle_F + \lambda TV(u) + \iota_{[0,1]^n}(u) \quad \text{if } i < \alpha$$

$$\underset{u}{\text{Argmin}} \langle c, u\rangle_F + \lambda TV(u) + E_{\text{reco}}(u) \quad \text{if } i \geq \alpha$$

3. Plug and play segmentation

Primal-dual algorithm:

$$u_{i+1} = \text{prox}_{\tau k}(u_i - \tau(\nabla D(u_i) + L^T v_i))$$
$$v_{i+1} = \text{prox}_{\sigma g^\star}(v_i + \sigma L(2u_{i+1} - u_i))$$

Proposed algorithm :

$$u_{i+1} = \Phi(u_i - \tau(\nabla D(u_i) + L^T v_i))$$
$$v_{i+1} = \text{prox}_{\sigma g^\star}(v_i + \sigma L(2u_{i+1} - u_i)),$$
$$\Phi(x) = \begin{cases} \text{prox}_{\iota_{[0,1]^n}}(x) \text{ if } i < \alpha \\ \text{G}_{\text{reco}}(P(x)) \text{ otherwise} \end{cases}$$

- $D(u) = \langle u, c_f \rangle_F$
- $g(.) = \lambda \|.\|_{2,1}$
- $L = \nabla$
- $P(.)$ the projection in the image set
- α the iteration from which G_{reco} is plugged

1. Context

2. Proposed method

3. Experiences

4. Conclusion and perspectives

Experiences

Compared methods

- Chan Model with the TV[1]
- Chan Model with the *n*D directional TV[2]
- Our proposed method combining the Chan model with G_{reco}

→ Optimization of the regularization coefficient for each model

[1] Chan et al. "Algorithms for finding global minimizers of image segmentation and denoising models", SIAM, 2006
[2] Merveille et al. "nD variational restoration of curvilinear structures with prior-based directional regularization", IEEE TIP, 2019

Datasets

Evaluation Dataset

DRIVE [1] : 20 retinophotographies and their annotations

[1] Staal *et al.* "Ridge-based vessel segmentation in color images of the retina", Trans. on Medical Imaging, 2004

[2] Kerautret *et al.* "OpenCCO: An Implementation of Constrained Constructive Optimization for Generating 2D and 3D Vascular Trees". Image Processing On Line, 2023

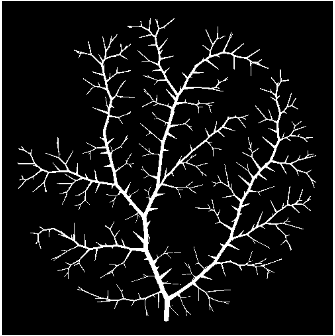
Datasets

Evaluation Dataset

DRIVE [1] : 20 retinophotographies and their annotations

Training Dataset

OpenCCO[2] : 80 synthetic vascular trees



[1] Staal *et al.* "Ridge-based vessel segmentation in color images of the retina", Trans. on Medical Imaging, 2004

[2] Kerautret *et al.* "OpenCCO: An Implementation of Constrained Constructive Optimization for Generating 2D and 3D Vascular Trees". Image Processing On Line, 2023

Quantitative evaluation of vascular segmentations

Matthews correlation coefficient (MCC)

$$\mathrm{MCC} = \frac{VP \times VN - FP \times FN}{\sqrt{(VP + FP)(VP + FN)(VN + FP)(VN + FN)}}$$

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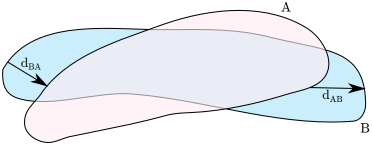

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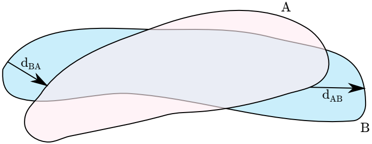
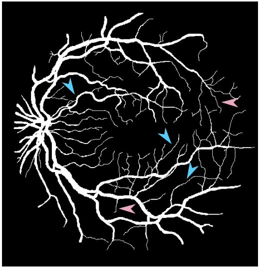


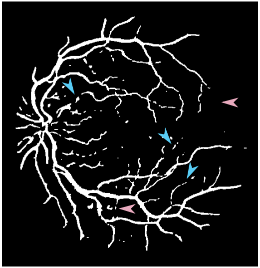
Number of connected components β_0

$$\epsilon_{\beta_0} = \left| \frac{\beta_0 - \beta_{0\,\mathrm{GT}}}{\beta_{0\,\mathrm{GT}}} \right|$$

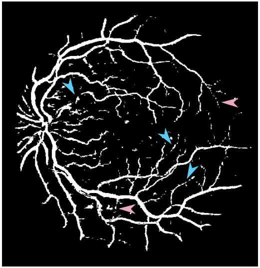
Analysis



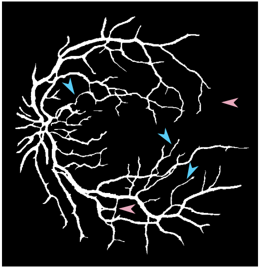
Groundtruth



TV



Directional TV

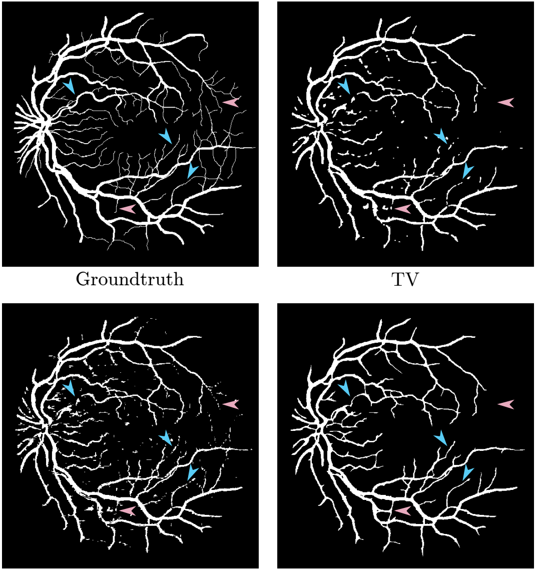


Proposed method

	MCC ↑	ASSD ↓	ϵ_{β_0} ↓
TV	0.732 ± 0.026	2.017 ± 0.452	22.668 ±15.203
*n*D TV	0.733 ± 0.026	1.896 ± 0.497	23.458 ± 17.921
$G_{\text{reco, CCO}}$	**0.742** ± 0.023	2.386 ± 0.0.627	**2.325** ± 2.274

- Better structure detection
- A better-connected structure

Analysis



Groundtruth TV

Directional TV Proposed method

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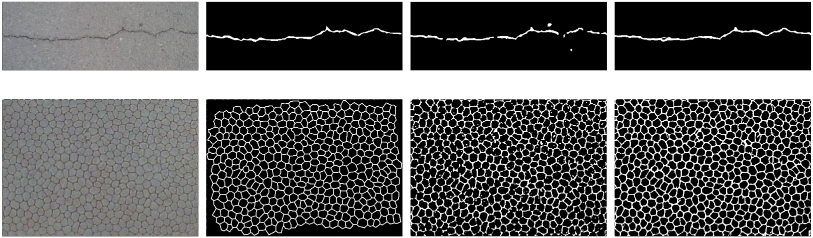
- Better structure detection
- A better-connected structure
- Disappearance of certain vascular fragments.

Generalization

Plug and play segmentation with G_{reco} trained on OpenCCO on two datasets containing curvilinear structures :

- Road cracks
- Cells from the corneas of pigs' eyes



(a) Original image (b) Groundtruth (c) TV (d) Our method

1. Context

2. Proposed method

3. Experiences

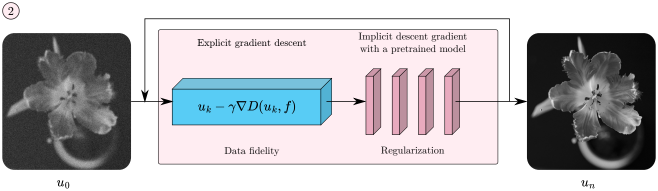
4. Conclusion and perspectives

Conclusion

- Development of a plug-and-play segmentation method
  - Unsupervised and generalizable
  - Connectivity preservation

Limits and perspectives

- No convergence assurance
  Idea : Learn a maximally monotone operator[1]
- Injecting the reconnector model from an iteration α
  Idea : adopt a Deep Equilibrium approach[2]



Deep Equilibrium approach

[1] Pesquet *et al.* "Learning maximally monotone operators for image recovery.", SIAM 2021

[2] Gilton *et al.* "Deep equilibrium architectures for inverse problems in imaging", IEEE Trans. on Computational Imaging, 2021

Thank you !