How to Write a Good Research Paper

Vincent Lepetit

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Papers Communicate Ideas

The greatest ideas are worthless if you keep them to yourself!

Publish or Perish

- As a PhD student, you need to publish at good conferences and in good journals

- Number of publications is important, but also their impact

Publication Culture

- Physics, biology, .. : focus on journal publications;

- Computer Science: mostly conferences.

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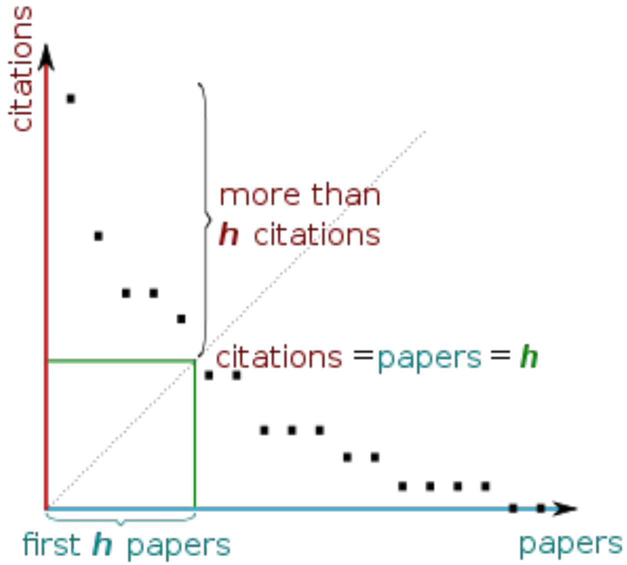
H-Index

Attempts to measure both the productivity and impact.

H-index = n iff published n papers each cited at least n times, but not $n+1$ papers each cited $n+1$ times

[see Google Scholar]



Far from perfect, but used to evaluate applications

To be 1) accepted, and 2) have an impact, a paper needs to be:

- Important, timely, original, technically-reliable,
- Well-presented,
- Convincing.

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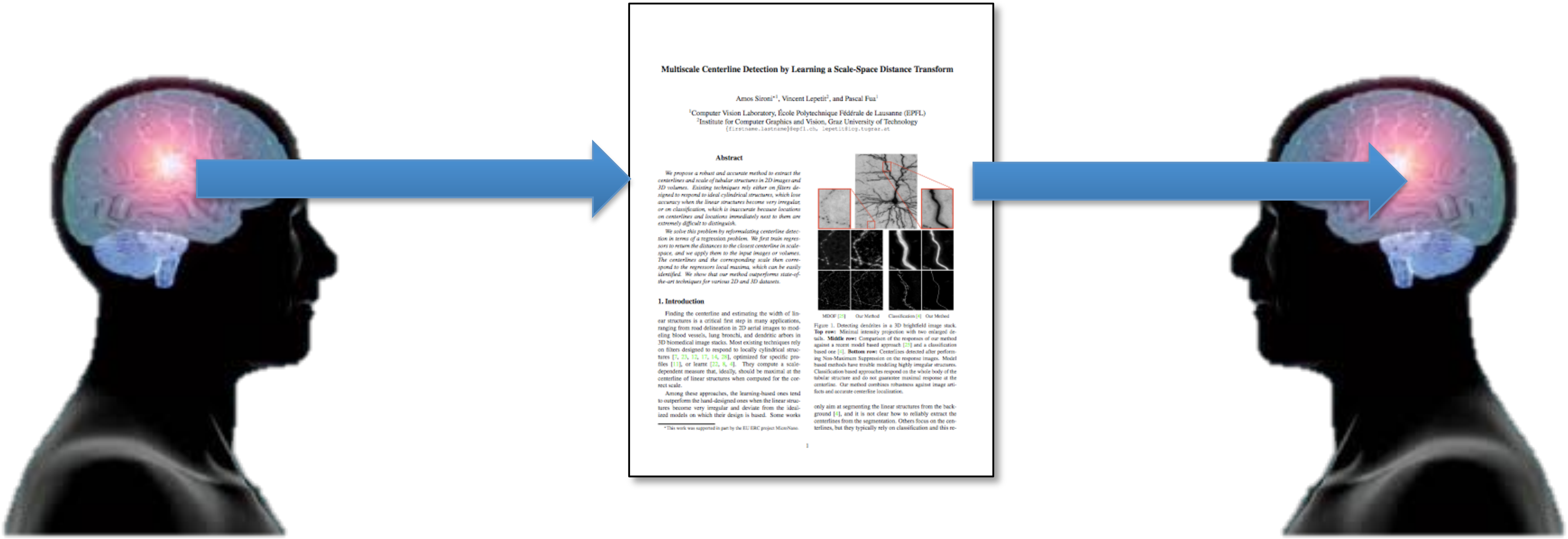
Today

First, you need:

- a contribution (a new theorem, a new method, etc.);
- results (a theoretical proof, empirical results, etc.);
- comparison with previous methods (discussion, empirical comparison, etc.).



Your paper is the only thing the reviewers (and the readers) see of your work

They do not care about the quality of your code, the technical problems you encounter, …

→ your paper should be as good as possible

Conferences

1. Program Chairs (PCs, ~3 persons) select the Area Chairs and the reviewers;
2. PCs assign the papers to the Area Chairs (~20 papers / AC);
3. the ACs assign each of "their" papers to 2-5 reviewers;
4. the reviewers read the papers and give back their reviews to the AC;
5. if the reviews are not consistent, the AC can ask the reviewers to discuss together;

Conferences

6. The reviews are sent to the authors;
7. Some conferences allow the authors to respond (rebuttal). The AC should ask the reviewers to read the rebuttal and see if they want to change their review;
8. The AC decides if the paper should be accepted or not, together with the other ACs.

Conferences

9. The AC writes a short metareview to explain why the paper was accepted and rejected.
10. Some authors complain when their paper is rejected – does not work most of the time

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Reviews are Generally Blinded

- Double blind process:
  - the reviewers do not know who the author is and
  - the authors do not know who the reviewers are. That way only the merits of the paper are evaluated.
- Reviewer's identity usually will not be released to authors;
- Intended to shield reviewers and allow them to provide critical and honest reviews.

Questions to reviewers for a recent Computer Vision conference

- Briefly describe the contributions of the paper to computer vision.

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- Comment on the paper's overall novelty, significance, and its potential impact on the field.

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- Include an explicit list of the paper's strengths.

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- Comment on the paper's overall novelty, significance, and its potential impact on the field.
- Include an explicit list of the paper's strengths.
- Provide an explicit list of the paper's main weaknesses, referring to novelty, significance, potential impact, experimental work, and technical correctness as appropriate.

- Is the paper technically sound? (Definitely correct / Probably correct / Has minor problems / has major problems)

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- Is the experimental evaluation sufficient?

Different papers need different levels of evaluation: A theoretical paper may require no experiments, while a paper presenting a new approach to a well-known problem may require thorough comparisons to existing methods.

Please comment if the paper is lacking in its experimental evaluation.

A Convincing Paper

Rule #1: Be as clear as possible

A Convincing Paper

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- imagine you are a reader who knows nothing about your work;

A Convincing Paper

Rule #1: Be as clear as possible

- imagine you are a reader who knows nothing about your work;
- don't obfuscate.

Conveying the Idea

- Here is a problem
  - It is an interesting problem
  - It is an unsolved problem

get the reader hooked

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- Here is my idea

  makes the reader understand your idea and think it is ingenious

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- My idea works (details, data)
- Here is how my idea compares to other people's approaches

theoretical and/or empirical proofs, and comparisons with previous methods

All this takes time (and experience).

Be prepared to

- get many corrections from your advisor,
- do more experiments to make your point, correct,
- get more corrections,
- re-write again,
- *get feedback from your colleagues*,
- correct,
- proof-read,
- …

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The Different Parts of a Paper

- Title
- Abstract
- Introduction
- Related work
- (possibly an introduction to specific existing techniques)
- Method
- Results
- Discussion / conclusion / future work

Title

- kind of important (it is the first thing the reviewer reads from your paper), but not critical;

- try to be descriptive but short.

Abstract

- I like writing the abstract first. It helps to crystalize the ideas, and to give a general direction to the paper.
- Others write it last.
- Should be concise, but still have all the points to convey the idea:
  - Here is a problem
    - It is an interesting problem
    - It is an unsolved problem
  - Here is my idea
  - My idea works (details, data)
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We propose a robust and accurate method to extract the centerlines and scale of tubular structures in 2D images and 3D volumes. Existing techniques rely either on filters designed to respond to ideal cylindrical structures, which lose accuracy when the linear structures become very irregular, or on classification, which is inaccurate because locations on centerlines and locations immediately next to them are extremely difficult to distinguish.

We solve this problem by reformulating centerline detection in terms of a *regression* problem. We first train regressors to return the distances to the closest centerline in scale-space, and we apply them to the input images or volumes. The centerlines and the corresponding scale then correspond to the regressors local maxima, which can be easily identified. We show that our method outperforms state-of-the-art techniques for various 2D and 3D datasets.

don't lose time with generalities

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description of the contribution, give the intuition but don't be vague

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the proposed method outperforms the state-of-the-art

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Introduction

again, same but long version:

- Here is a problem
  - It is an interesting problem
  - It is an unsolved problem
- Here is my idea
- My idea works (details, data)
- Here is how my idea compares to other people's approaches

Finding the centerline and estimating the width of linear structures is a critical first step in many applications, ranging from road delineation in 2D aerial images to modeling blood vessels, lung bronchi, and dendritic arbors in 3D biomedical image stacks. Most existing techniques rely on filters designed to respond to locally cylindrical structures [1, 2, 3, 4], optimized for specific profiles [5], or learnt [6, 7, 8]. They compute a scale-dependent measure that, ideally, should be maximal at the centerline of linear structures when computed for the correct scale.

Among these approaches, the learning-based ones tend to outperform the hand-designed ones when the linear structures become very irregular and deviate from the idealized models on which their design is based. Some works only aim at segmenting the linear structures from the background [6], and it is not clear how to reliably extract the centerlines from the segmentation. Others focus on the centerlines, but they typically rely on classification and this results in poor localization accuracy. This is because it is hard for the classifier to distinguish points on the centerline itself from those immediately next to it.

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- *important, yet unsolved problen*
- *you know the state-of-the-art*

In this paper, we show that this problem can be solved by reformulating centerline detection in terms of a regression problem. More precisely, we train scale regressors to return distances to the closest centerline in scale-space. In this way, performing non-maximum suppression on their output yields both centerline locations and corresponding scales. We will show that, on very irregular structures, it outperforms the powerful OOF approach with and without anti-symmetry term [5,6] that is widely acknowledged as one of the best among those relying on hand-designed filters, a very recent extension of it [7] designed to improve its performance on irregular structures, and a similarly recent classification-based method [8].

State the contribution explicitly. Give the intuition but don't be vague

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you compared against the state-of-the-art

- Do not leave the reader guessing what your contributions are!
- Make the contribution clear. If you have several contributions, you can use a bullet list.
- It is better to have one good, clear and strong contribution than several minor contributions.

In the remainder of the paper, we first review related work in Section 2. Then, in Section 3 we describe our method. Finally, in Section 4 we present the results obtained on four challenging datasets and prove the superiority of our approach over the state-of-the-art.

not really important to me, but some readers expect this

Multiscale Centerline Detection by Learning a Scale-Space Distance Transform

Amos Sironi*[1], Vincent Lepetit[2], and Pascal Fua[1]

[1]Computer Vision Laboratory, École Polytechnique Fédérale de Lausanne (EPFL)
[2]Institute for Computer Graphics and Vision, Graz University of Technology
{firstname.lastname}@epfl.ch, lepetit@icg.tugraz.at

Abstract

We propose a robust and accurate method to extract the centerlines and scale of tubular structures in 2D images and 3D volumes. Existing techniques rely either on filters designed to respond to ideal cylindrical structures, which lose accuracy when the linear structures become very irregular, or on classification, which is inaccurate because locations on centerlines and locations immediately next to them are extremely difficult to distinguish.

We solve this problem by reformulating centerline detection in terms of a regression problem. We first train regressors to return the distances to the closest centerline in scale-space, and we apply them to the input images or volumes. The centerlines and the corresponding scale then correspond to the regressors local maxima, which can be easily identified. We show that our method outperforms state-of-the-art techniques for various 2D and 3D datasets.

1. Introduction

Finding the centerline and estimating the width of linear structures is a critical first step in many applications, ranging from road delineation in 2D aerial images to modeling blood vessels, lung bronchi, and dendritic arbors in 3D biomedical image stacks. Most existing techniques rely on filters designed to respond to locally cylindrical structures [7, 23, 12, 17, 14, 28], optimized for specific profiles [11], or learnt [22, 8, 4]. They compute a scale-dependent measure that, ideally, should be maximal at the centerline of linear structures when computed for the correct scale.

Among these approaches, the learning-based ones tend to outperform the hand-designed ones when the linear structures become very irregular and deviate from the ideal-ized models on which their design is based. Some works

*This work was supported in part by the EU ERC project MicroNano.

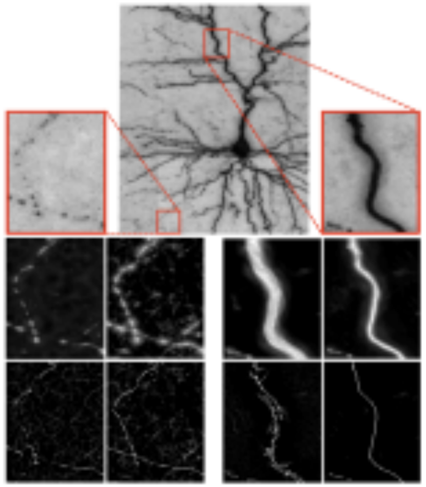

Figure 1. Detecting dendrites in a 3D brightfield image stack. **Top row:** Minimal intensity projection with two enlarged details. **Middle row:** Comparison of the responses of our method against a recent model based approach [25] and a classification based one [4]. **Bottom row:** Centerlines detected after performing Non-Maximum Suppression on the response images. Model based methods have trouble modeling highly irregular structures. Classification based approaches respond on the whole body of the tubular structure and do not guarantee maximal response at the centerline. Our method combines robustness against image artifacts and accurate centerline localization.

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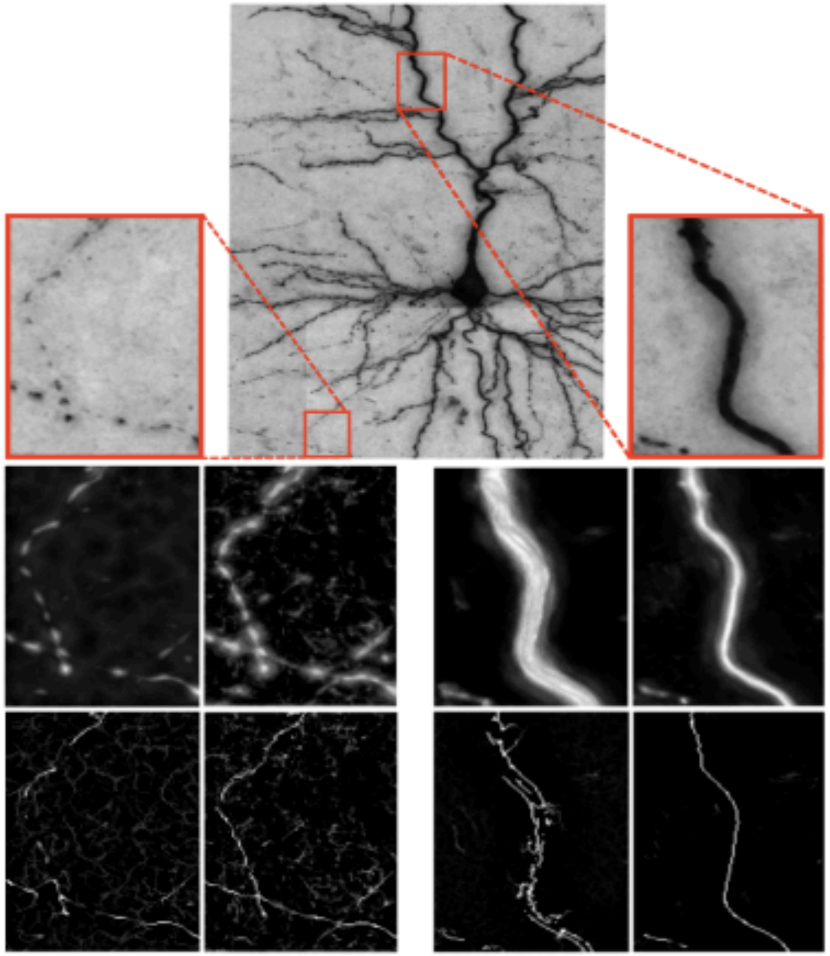
1

and a teaser, not mandatory but very helpful



MDOF [25] Our Method Classification [4] Our Method

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the reader should be able to understand the contribution of the paper from the teaser only

After reading the introduction, the reviewer should already know (maybe only unconsciously) (s)he will accept your paper

(if nothing is technically wrong in the method section)

Related Work

Not a mere description of the state-of-the art!

Serves two purposes:

- show you know the state-of-the-art;
- show your method solves
  - aspects of the problem that were not solved before, or
  - a new problem.

Anticipate a link to previous papers the reviewer can make.

Explain why it is not actually related.

2. Related Work

short introduction describing the structure of the section

Centerline detection methods can be classified into two main categories, those that use hand-designed filters and those that learn them from training data. We briefly review both kinds below.

Hand-Designed Filters [...]

All the chapters should start with a short overview of the chapter.

You can write it after writing the chapter itself.

2. Related Work

short introduction describing the structure of the section

Centerline detection methods can be classified into two main categories, those that use hand-designed filters and those that learn them from training data. We briefly review both kinds below.

short description of a family of methods

Hand-Designed Filters Such filters also fall into two main categories. The first is made of Hessian-based approaches [1, 2, 3] that combine the eigenvalues of the Hessian to estimate the probability that a pixel or voxel lies on a centerline. The main drawback of these approaches is that the required amount of Gaussian blur to compute the Hessian may result in confusion between adjacent structures, especially when they are thick.

[…]

- *For each method, explain why they are not as good as your method, but be fair!*
- *Be accurate, the authors are likely to be your reviewers!*

Method Section

Do NOT describe your algorithm / method step by step! You would quickly lose your reader in technical details.

Instead:

- Start with an overview of the section;
- then, give a general description of the method;
- end with the technical details.

→ Always from the more general to the more detailed explanation

[*overview*]

3.1 Learning a Regressor for Fixed Radius Structures

Let us momentarily assume that the linear struct
Let C be the set of centerline points and
Euclidean distance transform, that is, $\calD_C(\
location $\bx$ to the closest location in C.

…

Second, a regressor trained to associate to a feature vector $f e value of
$d(\bx)$ can only do so approximately. As a result, th refore no
guarantee that its maximum is exactly on the centerline. To obustness
to noise, we have therefore found it effective to train our reg reproduce
a distance function whose extremum is better
implementation, we take it to be

…

3.2 Handling Structures of Arbitrary Radius

In the previous section, we focused on structures of known n general,
however, structures of many different radii are present. To generalize our
approach to this multi-scale situation, …

More general, simpler problem

More detailed

Notations

- Don't start the description of the method with a list of notations!
- Introduce the notations only when needed:

Given training samples $\{(f_i, y_i)\}_i$, where $f_i = f(\mathbf{x}_i, I_i) \in \mathbb{R}^M$ is the feature vector corresponding to a point $\mathbf{x}_i$ in image I_i and $y_i = d(\mathbf{x}_i)$, GradientBoost approximates $y(\cdot)$ by a function of the form

$$\varphi(f(\mathbf{x}, I)) = \sum_{k=1}^{K} \alpha_k h_k(f(\mathbf{x}, I)) , \tag{4}$$

where $h_k : \mathbb{R}^M \to \mathbb{R}$ are weak learners and $\alpha_k \in \mathbb{R}$ are weights. Function φ is built iteratively, selecting one weak learner and its weight at each iteration, to minimize a loss function $\mathcal{L}$ of the form $\mathcal{L} = \sum_i L(d_i, \varphi(f_i))$. We use the

Notations

Consider adding a table summarizing the notations if you need complex notations:

TABLE 1: Main mathematical notations used in the paper.

Notation	**Meaning**
$I(\mathbf{x})$	Input image (resp. volume) at pixel (resp. voxel) $\mathbf{x}$
$f(\mathbf{x}, I)$	Feature vector computed on image I, at pixel $\mathbf{x}$
C	Set of centerline points for a given image
$y(f(\mathbf{x}, I))$	Ideal classifier output: $y(f(\mathbf{x}, I)) = 1$ iff $x \in C$
$\mathcal{D}_C(\mathbf{x})$	Euclidean distance transform of the set C at pixel $\mathbf{x}$
$d(\mathbf{x})$	Ideal regressor response. Exponential scaling of $\mathcal{D}_C$
$\varphi^{(m)}(f(\mathbf{x}, I))$	Actual regressor response for iterative regression, at iteration m
$g(\mathbf{x}, \varphi^{(m)})$	Feature vector for iterative regression, computed on score image $\varphi^{(m)}$ at pixel $\mathbf{x}$
$y(\cdot; r), \mathcal{D}_C(\cdot; r), d(\cdot; r), \varphi_r^{(m)}$	As above, but for centerlines corresponding to tubular structures of radius r
$\Phi(\mathbf{x}, r)$	Multiscale regressor, used as final approximation

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Results Section

- Starts with an overview;
- Experiments that will show your approach is correct;
- Needs comparisons with previous methods.

5. Conclusion

We have introduced an efficient regression-based approach to centerline detection, which we showed to outperform both methods based on hand-designed filters and classification-based approaches.

We believe our approach to be very general and applicable to other linear structure detection tasks when training data is available. For example, given a training set of natural images and the contours of the objects present in the images, our framework should be able to learn to detect such contours in new images as was done in [10]. This is a direction we will explore in future work.

if you think

- your approach can be applied to other problems, or
- points to new research directions,

mention it and explain why.

References

[1] G. Agam and C. Wu. Probabilistic Modeling-Based Vessel Enhancement in Thoracic CT Scans. In CVPR, 2005.

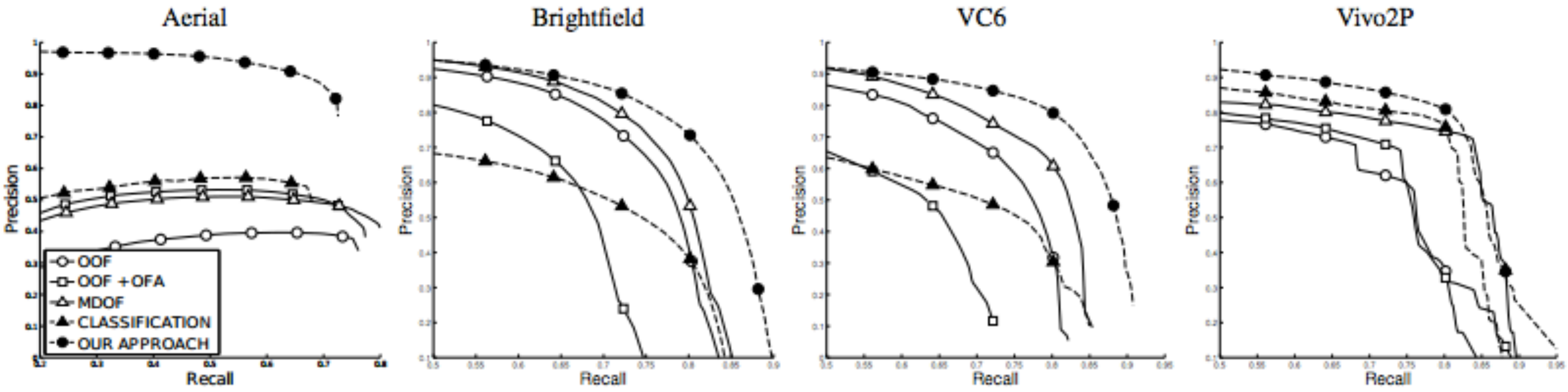
[2] P. Arbelaez, M. Maire, C. Fowlkes, and J. Malik. Contour Detection and Hierarchical Image Segmentation. PAMI, 33(5):898--916, 2011.

[3] C. Becker, R. Rigamonti, V. Lepetit, and P. Fua. Supervised Feature Learning for Curvilinear Structure Segmentation. In MICCAI, 2013.

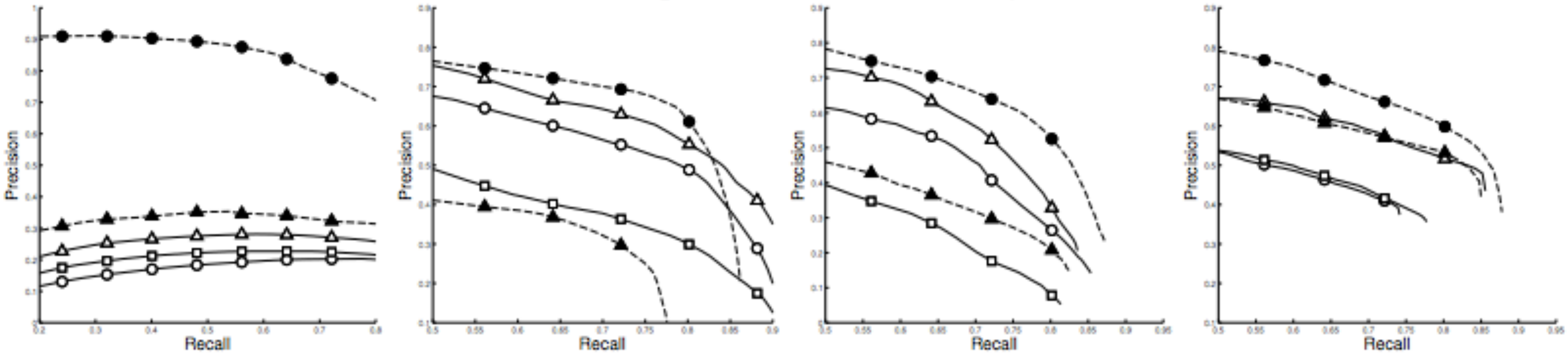
Be consistent, it looks more professional.

For me, the name of the conference and the year are enough.

Figures



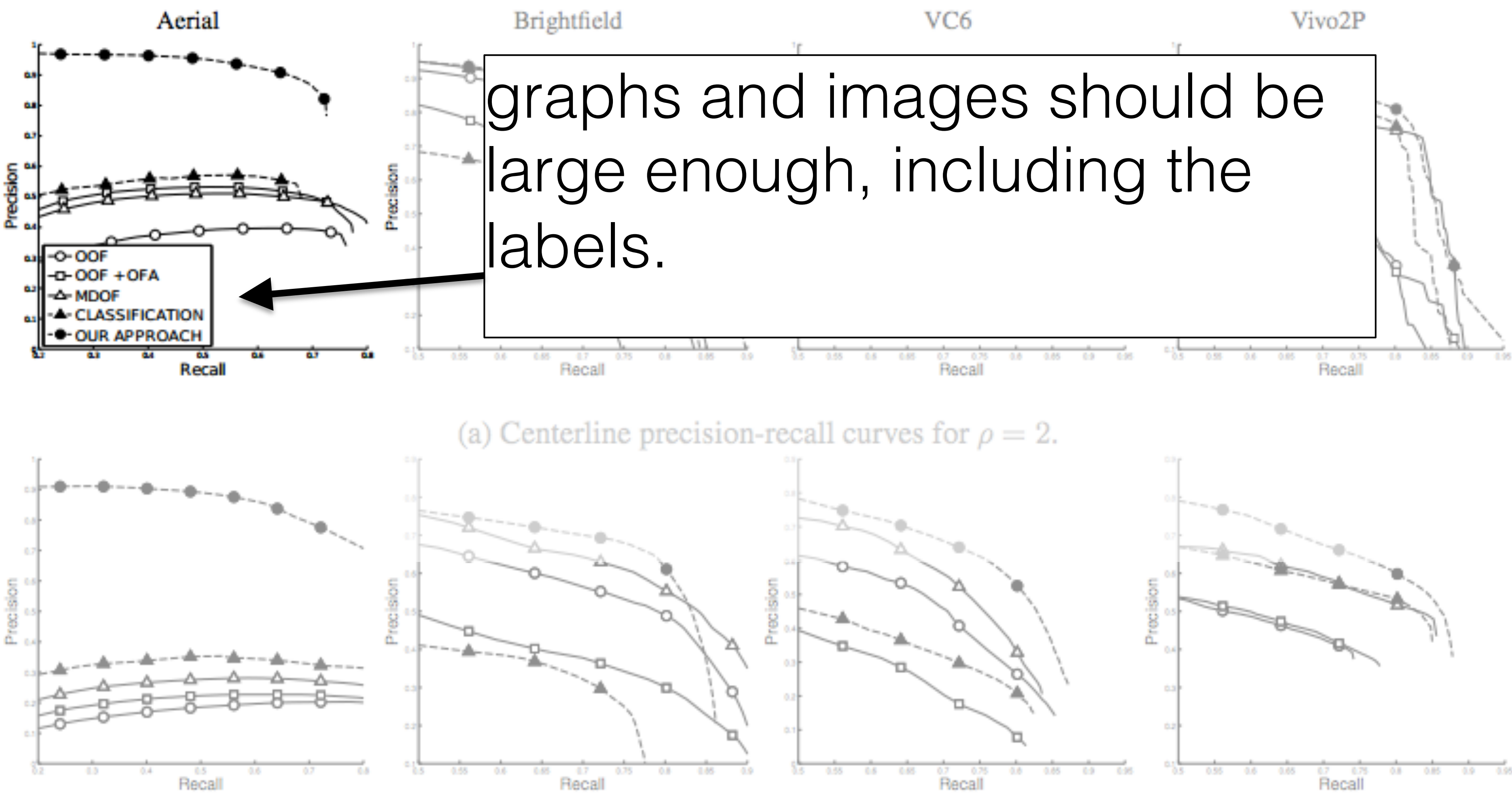
(a) Centerline precision-recall curves for $\rho = 2$.



(b) Segmentation precision-recall curves for $\delta = 0.4$.

Figure 8. Precision Recall curves. Our method outperforms the others on all the datasets we considered, both for centerline detection and joint centerline and radius estimation.

Figures



graphs and images should be large enough, including the labels.

(b) Segmentation precision-recall curves for $\delta = 0.4$.

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Figures

Figure 8. Precision Recall curves. Our method outperforms the others on all the datasets we considered, both for centerline detection and joint centerline and radius estimation.

Caption should start with the name of the figure AND a description.

The reader should understand the figure without having to read the paper. Tell the reader what (s)he should look at.

Referencing Figures

- Use figures to explain difficult aspects.
- Reference the figure at the beginning of the explanations, not at the end, *i.e.* not:

Then, we can rely on simple non-maximum suppression to localize the centerlines. We will show in the next section that this solution is significantly more robust than both classification-based and filter-based methods (see Fig. 3).

no!

but:

Then, as shown in Fig. 3, we can rely on simple non-maximum suppression to localize the centerlines. We will show in the next section that this solution is significantly more robust than both classification-based and filter-based methods.

yes

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Tables

Caption: descriptive, same as for figures.

Table 2. Results on the UIUC Car Detection dataset. Performance shown as recall at recall-precision equal-error-rate, as in [8].

Method	Single-scale	Multi-scale
Xu et al. [30]†	99.5%	98%
Tivive et al. [26]†	99%	98%
Saberian et al. [24]	99.0%	92.1%
Karlinsky et al. [11]	99.5%	98.0%
Mutch et al. [20]	99.9%	90.6%
Lampert et al. [13]	98.5%	**98.6%**
Gall et al. [8]	98.5%	**98.6%**
Our approach ($\mathbf{x}_A$)	**100%**	97.2%
Our approach ($\mathbf{x}_B$)	99.5%	**98.6%**

write the best values in bold

State clearly which line(s) correspond(s) to your method.

Default tables in LaTeX look ugly.

I like the style described in:

http://www.inf.ethz.ch/personal/markusp/teaching/guides/guide-tables.pdf

signal processing concept	algebraic concept (coordinate free)	in coordinates
fi lter	$h \in \mathcal{A}$ (algebra)	$\phi(h) \in \mathbb{C}^{I \times I}$
signal	$s = \sum s_i b_i \in \mathcal{M}$ ($\mathcal{A}$-module)	$\mathbf{s} = (s_i)_{i \in I} \in \mathbb{C}^I$
fi ltering	$h \cdot s$	$\phi(h) \cdot \mathbf{s}$
impulse	base vector $b_i \in \mathcal{M}$	$\mathbf{b}_i = (\dots, 0, 1, 0 \dots)^T \in \mathbb{C}^I$
impulse response of $h \in \mathcal{A}$	$h \cdot b_i \in \mathcal{M}$	$\phi(h) \cdot \mathbf{b}_i = (\dots, h_{-1}, h_0, h_1, \dots)^T \in \mathbb{C}^I$
Fourier transform	$\Delta: \mathcal{M} \to \bigoplus_{\omega \in W} \mathcal{M}_\omega$	$\mathcal{F}: \mathbb{C}^I \to \bigoplus_{\omega \in W} \mathbb{C}^{d_\omega}$ $\Leftrightarrow \phi \to \bigoplus_{\omega \in W} \phi_\omega$
spectrum of signal	$\Delta(s) = (s_\omega)_{\omega \in W} = \omega \mapsto s_\omega$	$\mathcal{F}(\mathbf{s}) = (\mathbf{s}_\omega)_{\omega \in W} = \omega \mapsto \mathbf{s}_\omega$
frequency response of $h \in \mathcal{A}$		$(\phi_\omega(h))_{\omega \in W} = \omega \mapsto \phi_\omega(h)$

signal processing concept	**algebraic concept (coordinate free)**	**in coordinates**
filter	$h \in \mathcal{A}$ (algebra)	$\phi(h) \in \mathbb{C}^{I \times I}$
signal	$s = \sum s_i b_i \in \mathcal{M}$ ($\mathcal{A}$-module)	$\mathbf{s} = (s_i)_{i \in I} \in \mathbb{C}^I$
filtering	$h \cdot s$	$\phi(h) \cdot \mathbf{s}$
impulse	base vector $b_i \in \mathcal{M}$	$\mathbf{b}_i = (\dots, 0, 1, 0, \dots)^T \in \mathbb{C}^I$
impulse response of $h \in \mathcal{A}$	$h \cdot b_i \in \mathcal{M}$	$\phi(h) \cdot \mathbf{b}_i = (\dots, h_{-1}, h_0, h_1, \dots)^T \in \mathbb{C}^I$
Fourier transform	$\Delta: \mathcal{M} \to \bigoplus_{\omega \in W} \mathcal{M}_\omega$	$\mathcal{F}: \mathbb{C}^I \to \bigoplus_{\omega \in W} \mathbb{C}^{d_\omega} \Leftrightarrow \phi \to \bigoplus_{\omega \in W} \phi_\omega$
spectrum of signal	$\Delta(s) = (s_\omega)_{\omega \in W} = \omega \mapsto s_\omega$	$\mathcal{F}(\mathbf{s}) = (\mathbf{s}_\omega)_{\omega \in W} = \omega \mapsto \mathbf{s}_\omega$
frequency response of $h \in \mathcal{A}$	n.a.	$(\phi_\omega(h))_{\omega \in W} = \omega \mapsto \phi_\omega(h)$

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Use the Active Form

NO	YES
It can be seen that…	We can see that…
34 tests were run	We ran 34 tests
These properties were thought desirable	We wanted to retain these properties

The passive form can be boring and ambiguous.

Use Clear Phrases

- Don't say "This method is called…" if you mean "We call our method…"

- *Don't say 'reflective acoustic wave.' Say 'echo.'* (Richard Feynman)

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Getting Started


Multiscale Centerline Detection by Learning a Scale-Space Distance Transform

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Abstract

1. Introduction

Avoid the writer's block and procrastination:

- start writing without thinking too much about the quality of your text;
- then iterate on your text, making it clearer and more convincing at each iteration:
  - Write the sections' overviews at the beginning of each section,
  - make sure your paragraphs are short,
  - add figures,
  - etc.

- Ask friends and colleagues to read your paper (another reason to start early!)
- Experts are good. Non-experts are also very good.
- Explain carefully what you want ("I got lost here" is much more important than "wibble is mis-spelt")

- Each reader can only read your paper for the first time once! Use them carefully.

- The reviewer is always right! If (s)he did not understand something, it is because you did not explain it clearly enough.

The Ultimate Trick to Get Your Paper Accepted

Don't write anything that can make your paper rejected…

1. Make sure your contribution is novel;

2. No bold claim without experimental backup or formal proof;

3. etc.

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- Use LaTeX;
- Write short sentences and short paragraphs;
- Use a spell-checker;
- Give a strong visual structure to your paper using:
  - sections and sub-sections;
  - itemized lists;
  - …

A Good Rebuttal

- Be polite, but strong!
- Focus
  - on the points from the reviewers that could make your paper rejected, or
  - on the points that can give your paper an oral presentation.
- The number of characters is usually limited, but still keep your rebuttal readable and avoid abbreviations.

```
We would like to thank the reviewers for their
comments, and to address here their concerns.
```

be polite

keep a clear structure

```
* The main concern expressed by R2 and R3 is about
the specificity of our target scenarios:

It is true that we focused in our paper on
detecting flying objects -- not only drones but
also aircrafts of different shapes.  This choice
was primarily motivated by our current project.
However, we also successfully applied our approach
to car detection. We would be happy to add this
experiment to the paper if the reviewers think it
is useful.   […]

* R3 complained about few vital details missing. It
is easy to revise the paper to include these
details:
```

you can promise to update the paper as long as you stay credible