Marked Point Process Model for Curvilinear Structures Extraction

AYIN research team

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Outline

- Introduction
- Marked Point Process modeling
  - MPP revisited
  - Generic model for curvilinear structures
  - Monte Carlo sampler with delayed rejection
- Integration of line hypotheses
- Experimental results
- Summary

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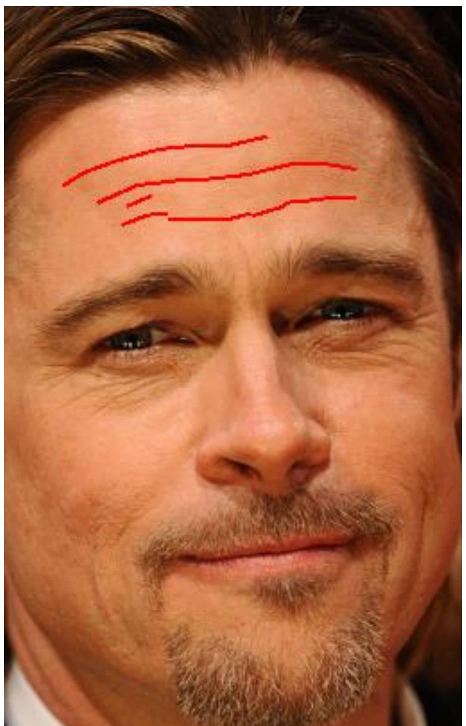
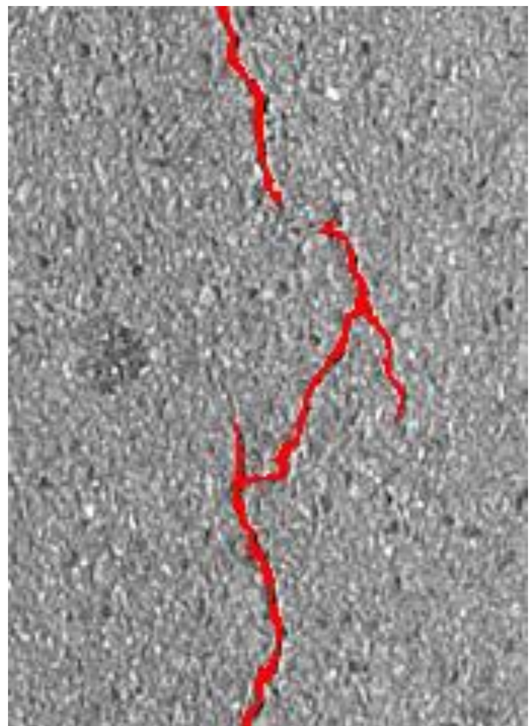
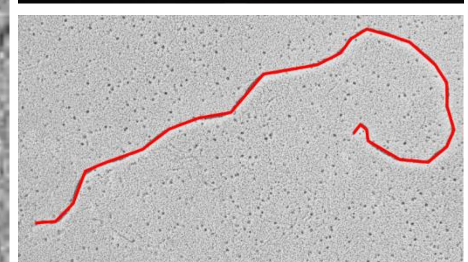
Curvilinear Structure

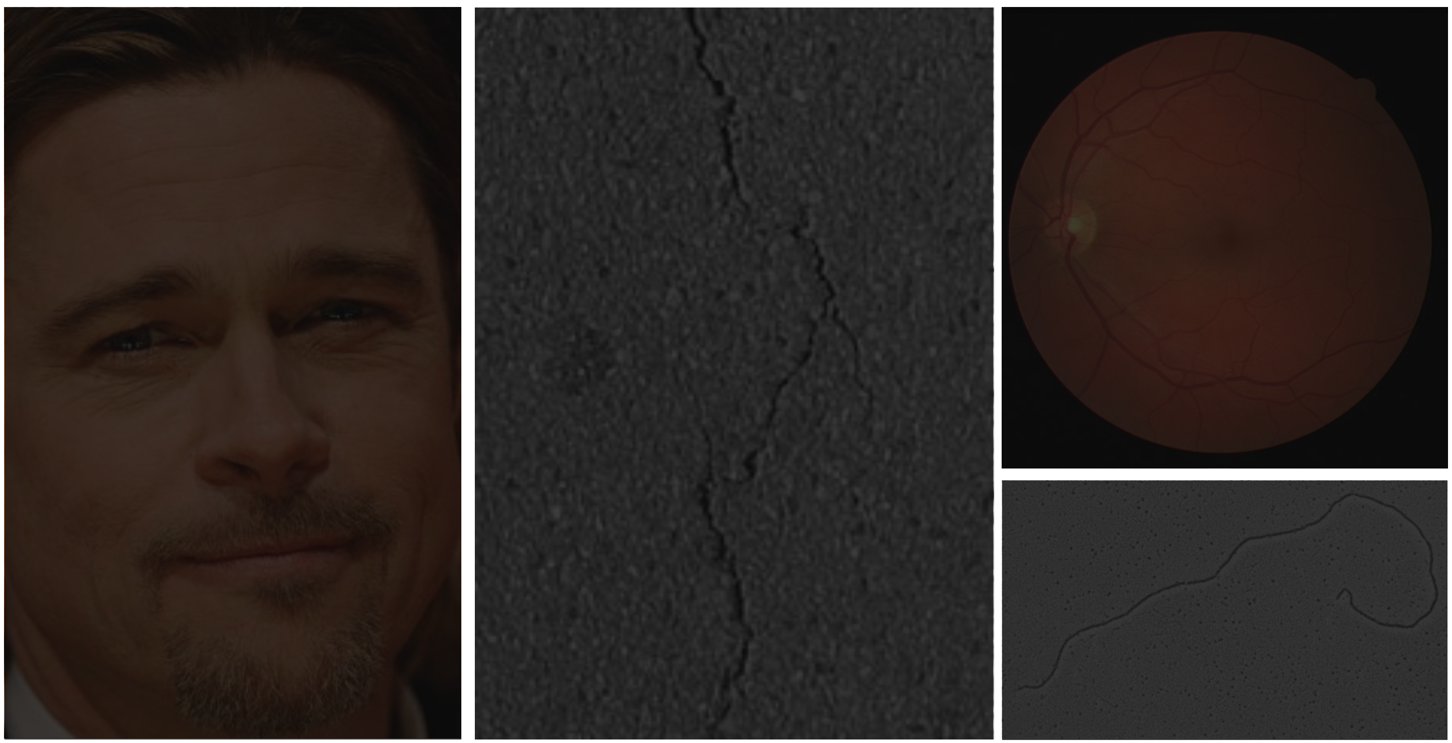
- Goal: **detection** + **localization** of curvilinear structures: wrinkles, road cracks, blood vessels, DNA, ...



Challenges

- **Low contrast** within a homogeneous texture
- Shown in a **complex shape**



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Marked Point Process

- Counting unknown number of objects with **higher order shape constraints**
- Three essentials to realize MPP model:
  1. Parametric object
  2. Probability density
  3. Sampler

Marked Point Process

- Parametric object
  - **Point** (Image site) + **Mark** (Object shape): $s_i \in \mathbb{R}^2 \times \mathbb{M}$
  - e.g.,

Circle $(\mathbf{x}, r)$ tree | Ellipse $(\mathbf{x}, a, b, \theta)$ boat | Rectangle $(\mathbf{x}, w, h, \theta)$ building | Line $(\mathbf{x}, \ell, \theta)$ road

- Probability density $f(\mathbf{s})$
  - Defines distribution of points

$$\hat{\mathbf{s}} = \underset{\mathbf{s}\in\Psi}{\operatorname{argmax}}\, f(\mathbf{s}) = \underset{\mathbf{s}\in\Psi}{\operatorname{argmin}} \sum_{i=1}^{\#(\mathbf{s})} U_d(s_i) + \sum_{i\sim j} U_p(s_i, s_j)$$

Data likelihood: $U_d(s_i)$

Prior energy: $U_p(s_i, s_j)$

Marked Point Process

- Sampler
  - **Goal**: maximize unnormalized probability density over configuration space $\Psi = \cup_{n=0}^{\infty} \mathbf{s}_n, \text{ where } \mathbf{s}_n = \{s_1, \dots, s_n\}$
  - **Difficulties**:
    - $f(\mathrm{s})$ is non-convex
    - Ψ 's dimensionality is unknown
  - **MCMC sampler**
    - Each state of a discrete Markov chain $(X_t)_{t \in \mathbb{N}}$ corresponds to a random configuration on Ψ
    - The Markov chain is **locally perturbed** by **sub-transition kernels** and **converges** toward stationary state

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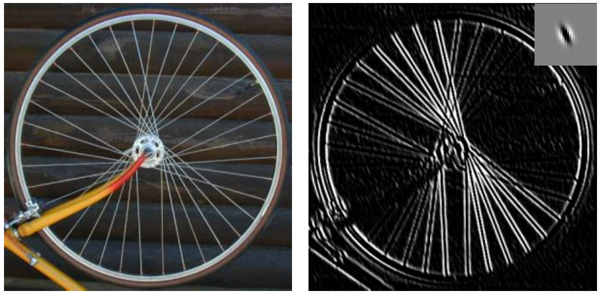
Data Likelihood

- Features for curvilinear structure
  - Gradient magnitude
  - Homogeneity of pixel values

$$U_d(s_i) = \omega_d^m U_d^m(s_i) + \omega_d^v U_d^v(s_i)$$

Gradient magnitude ▲ Intensity variance ▼

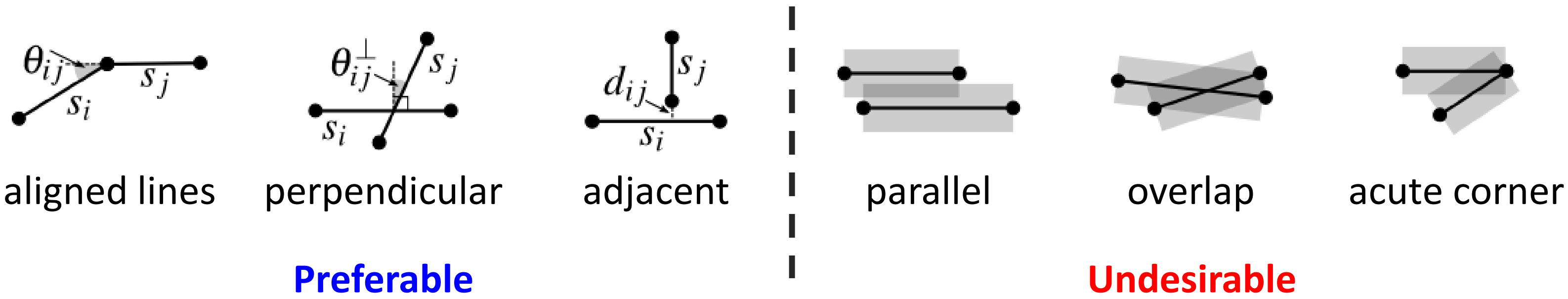
- Steerable filters
  - Linear combination of 2nd derivatives of Gaussian
  - Accentuate gradient magnitudes w.r.t. **orientation**



Input Filtering responses

Prior Energy

- **Spatial interactions** on a local configuration



- Neighborhood system
  - Pairs of line segments, s.t. their center distance is smaller than half the sum of their lengths

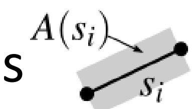
$$i \sim j = \left\{ (s_i, s_j) \in \Psi^2 : 0 < \|\mathbf{x}_i - \mathbf{x}_j\|_2 \leq \frac{\ell_i + \ell_j}{2} + \epsilon \right\}$$

Prior Energy

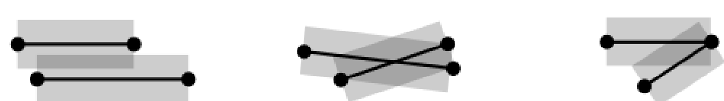
$$U_p(s_i, s_j) = \Upsilon(s_i, s_j) + \mathbf{w}_p^\intercal \mathbf{c}_{ij}$$

Intersection

Coupling energies

- Intersection
  - To **avoid congestion** in a local configuration
    - Dilate line segments 

    - Count the number of pixels falling in the same area
    - Reject configurations if portion of intersection areas ≥ 10%
    - $\Upsilon(s_i, s_j) = \infty$



parallel overlap acute corner

Prior Energy

$$U_p(s_i, s_j) = \Upsilon(s_i, s_j) + \mathbf{w}_p^\mathsf{T} \mathbf{c}_{ij}$$

Intersection   Coupling energies

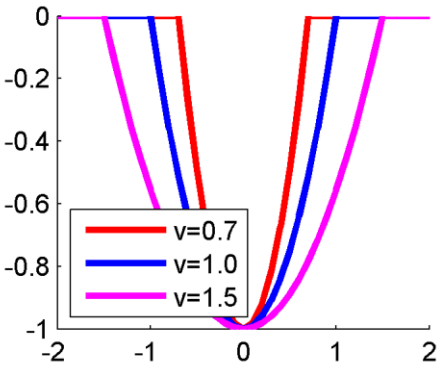
- Coupling energies
  - To obtain **smoothly connected lines**

$$\mathbf{w}_p = [\omega_p^s, \omega_p^c, \omega_p^a, \omega_p^r]^\mathsf{T}$$

$$\mathbf{c}_{ij} = [1, \varphi(d_{ij}, \epsilon), \varphi(\theta_{ij}, \tau), \varphi(\theta_{ij}^\perp, \tau)]^\mathsf{T}$$

    - ω_p^s penalizes single line segment
    - $\omega_p^c \varphi(d_{ij}, \epsilon)$ minimizes gap between lines
    - $\omega_p^a \varphi(\theta_{ij}, \tau)$ prefers small curvature
    - $\omega_p^r \varphi(\theta_{ij}^\perp, \tau)$ allows almost perpendicular lines

$$\varphi|_{|v|} : \mathbb{R} \mapsto [-1, 0]$$



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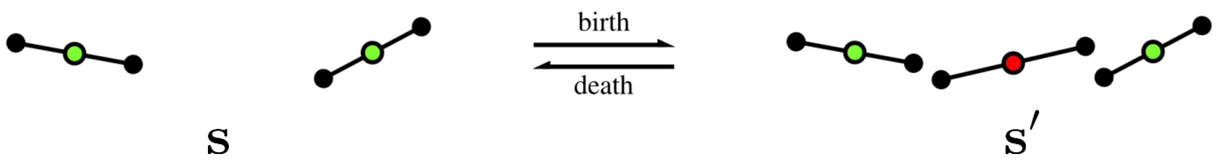
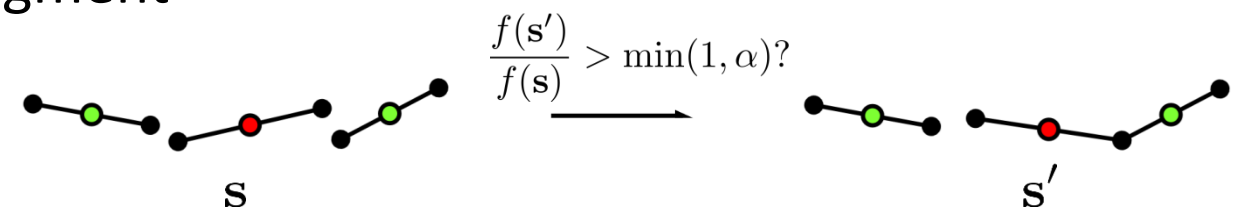
RJMCMC

- Stimulate a discrete Markov chain over the configuration space via **sub-transition kernels**
  - **Birth kernel** proposes a new segment
  - **Death kernel** removes a segment

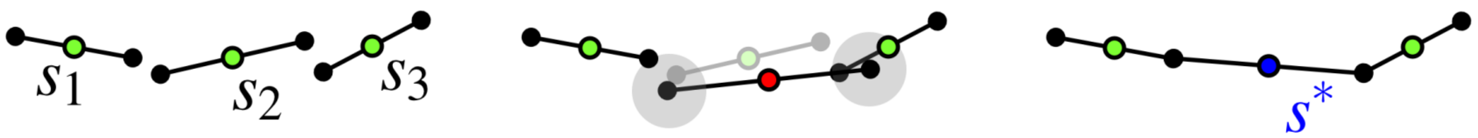


  - **Affine transform** updates intrinsic variables of the segment



Delayed Rejection

- Gives a **second chance** to a rejected configuration **by enforcing the connectivity**



1. Let $\mathbf{s}$=$\{s_1, s_2, s_3\}$ be the current configuration
2. Propose a new configuration via affine transform kernel
3. If s' is rejected, DR kernel searches for the nearest end points in the rest of the line segments
4. An alternative line segment s^* will enforce the connectivity

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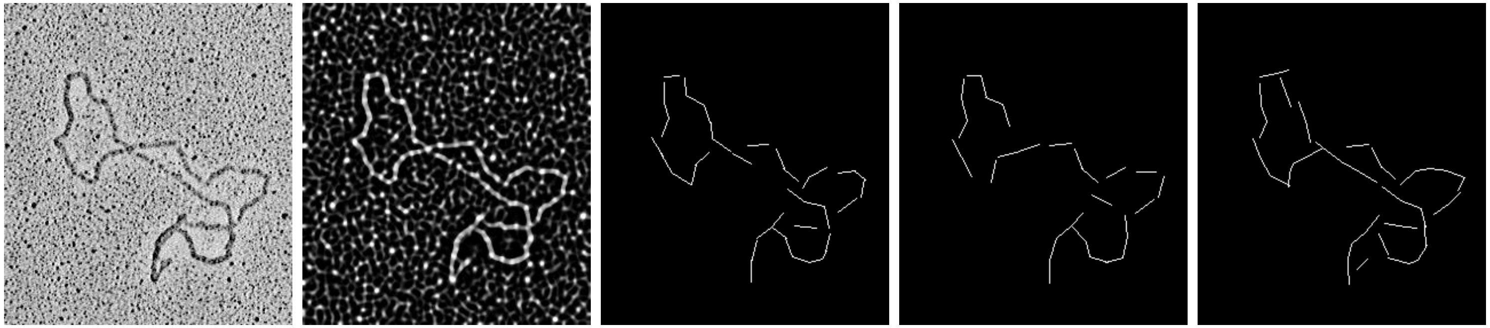
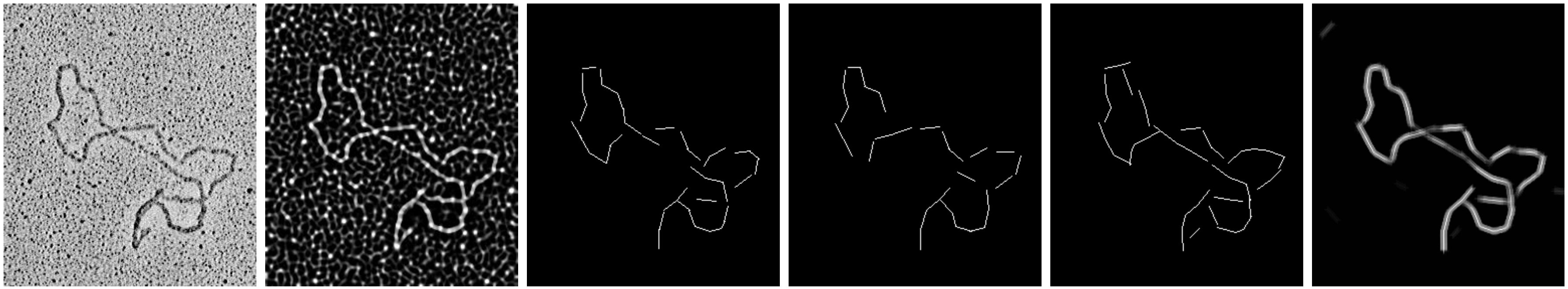
Create Line Hypotheses



Input | Gradient | $\hat{\mathbf{s}}^1$ | $\hat{\mathbf{s}}^2$ | $\hat{\mathbf{s}}^3$

- MPP model is sensitive to the selection of hyperparameter $\mathbf{w} = [\omega_d^m, \omega_d^v, \omega_p^s, \omega_p^c, \omega_p^a, \omega_p^r]^\mathsf{T}$
  - Learning is not feasible
    - Unable to obtain ground truth, e.g., wrinkles
    - Variable for different types of datasets

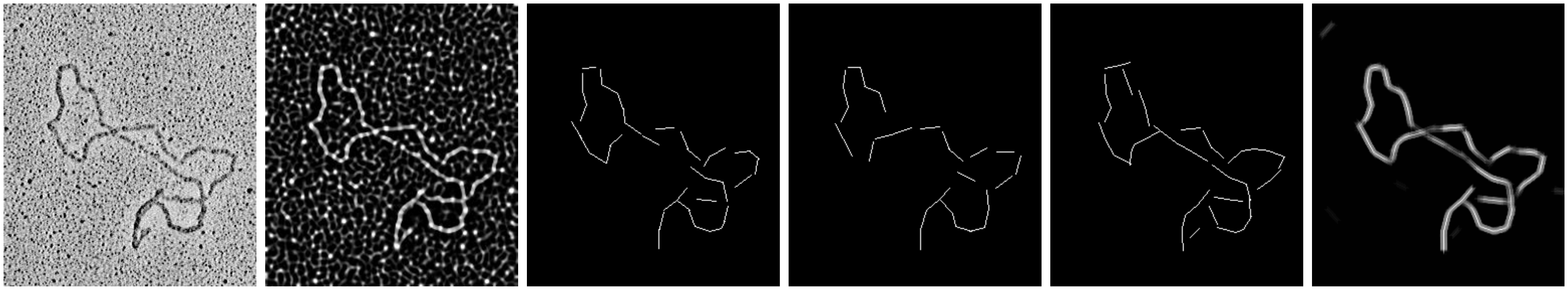
Integrate Line Hypotheses



Input | Gradient | $\hat{\mathbf{s}}^1$ | $\hat{\mathbf{s}}^2$ | $\hat{\mathbf{s}}^3$ | $\mathcal{P}_{\hat{\mathcal{S}}}$

- Assumption
  - Prominent line segment will be observed more frequently
- Mixture density $\mathcal{P}_{\hat{\mathcal{S}}}$
  - Shows consensus between line hypotheses
  - Criterion for hyperparameter vector selection

Integrate Line Hypotheses



Input | Gradient | $\hat{\mathbf{s}}^1$ | $\hat{\mathbf{s}}^2$ | $\hat{\mathbf{s}}^3$ | $\mathcal{P}_{\hat{\mathcal{S}}}$

- Updated data likelihood

$$U'_d(s_i) = U_d(s_i) + U^h_d(s_i)$$

$$U^h_d(s_i) = \int_0^1 -\log \mathcal{P}_{\hat{\mathcal{S}}}(s_i(t))\, dt$$

  - Reduce sampling space
  - Quantifies consensus among line hypotheses w.r.t. s_i

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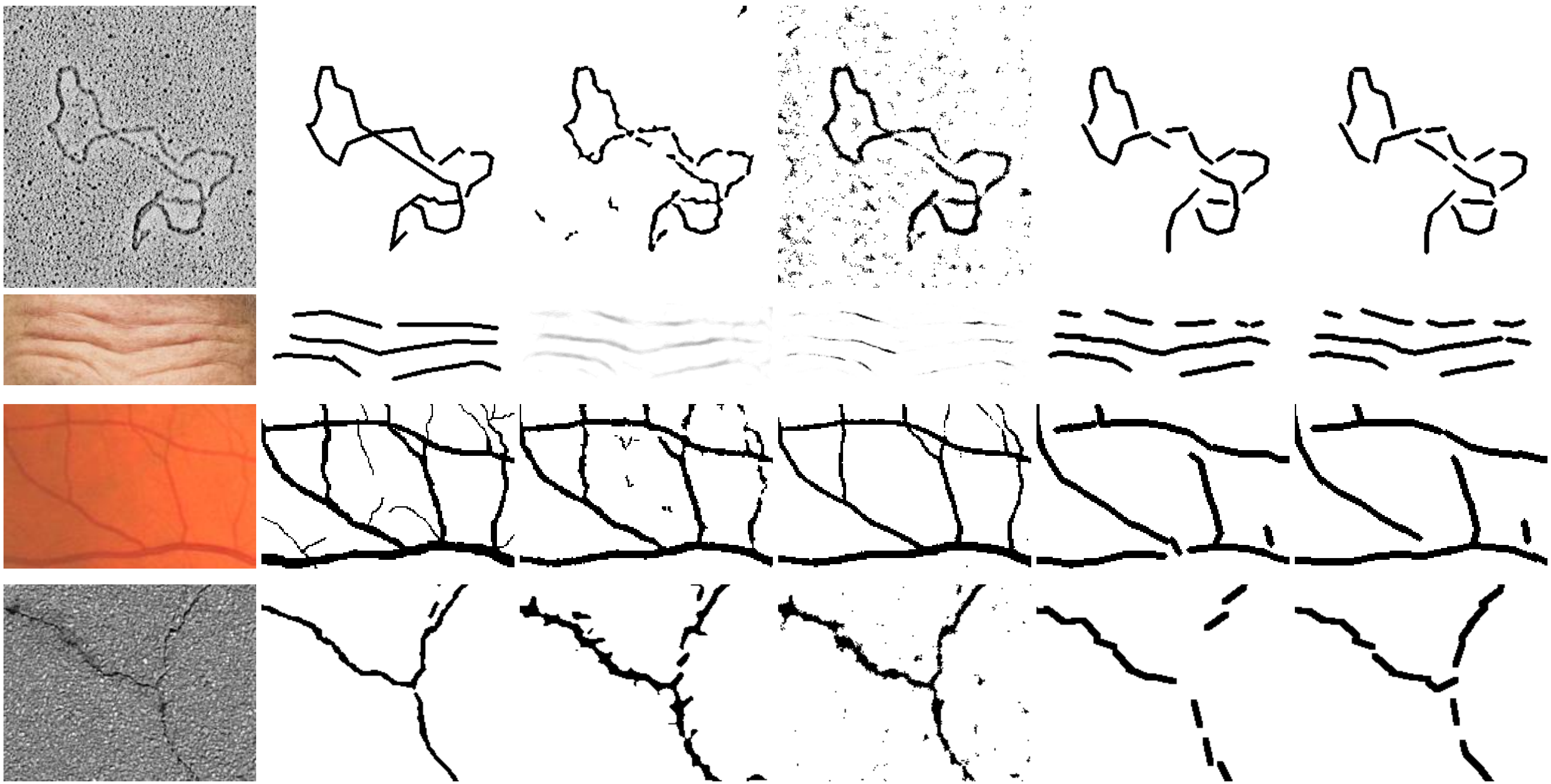
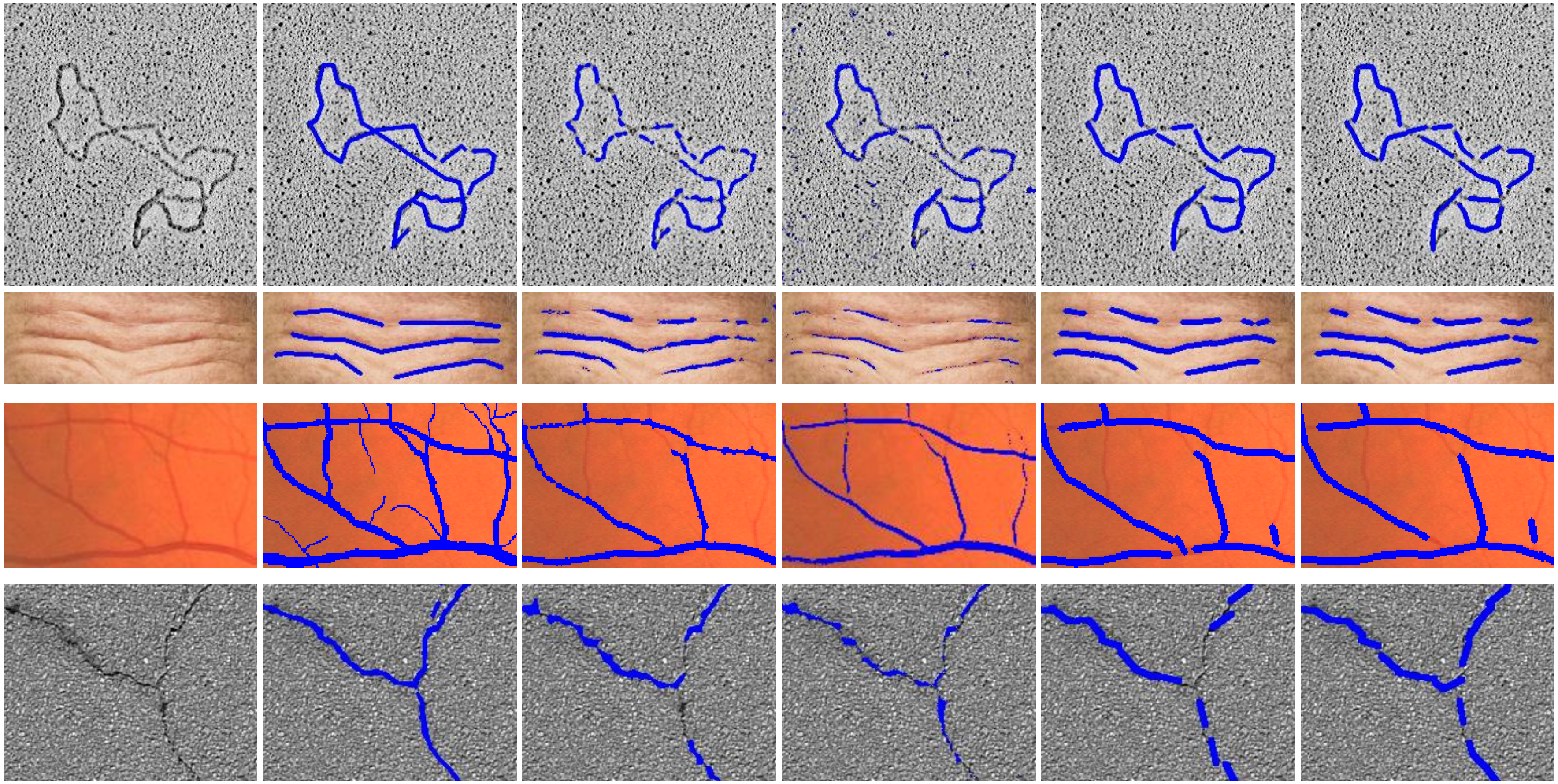
Experimental Results



Input | Ground truth | Path opening* | Learning** | Baseline MPP | Proposed

* H. Talbot *et al.*, “Efficient complete and incomplete path openings and closings,” ICV 2007
** C. Becker *et al.*, “Supervised feature learning for curvilinear structure segmentation,” MICCAI 2013

Experimental Results



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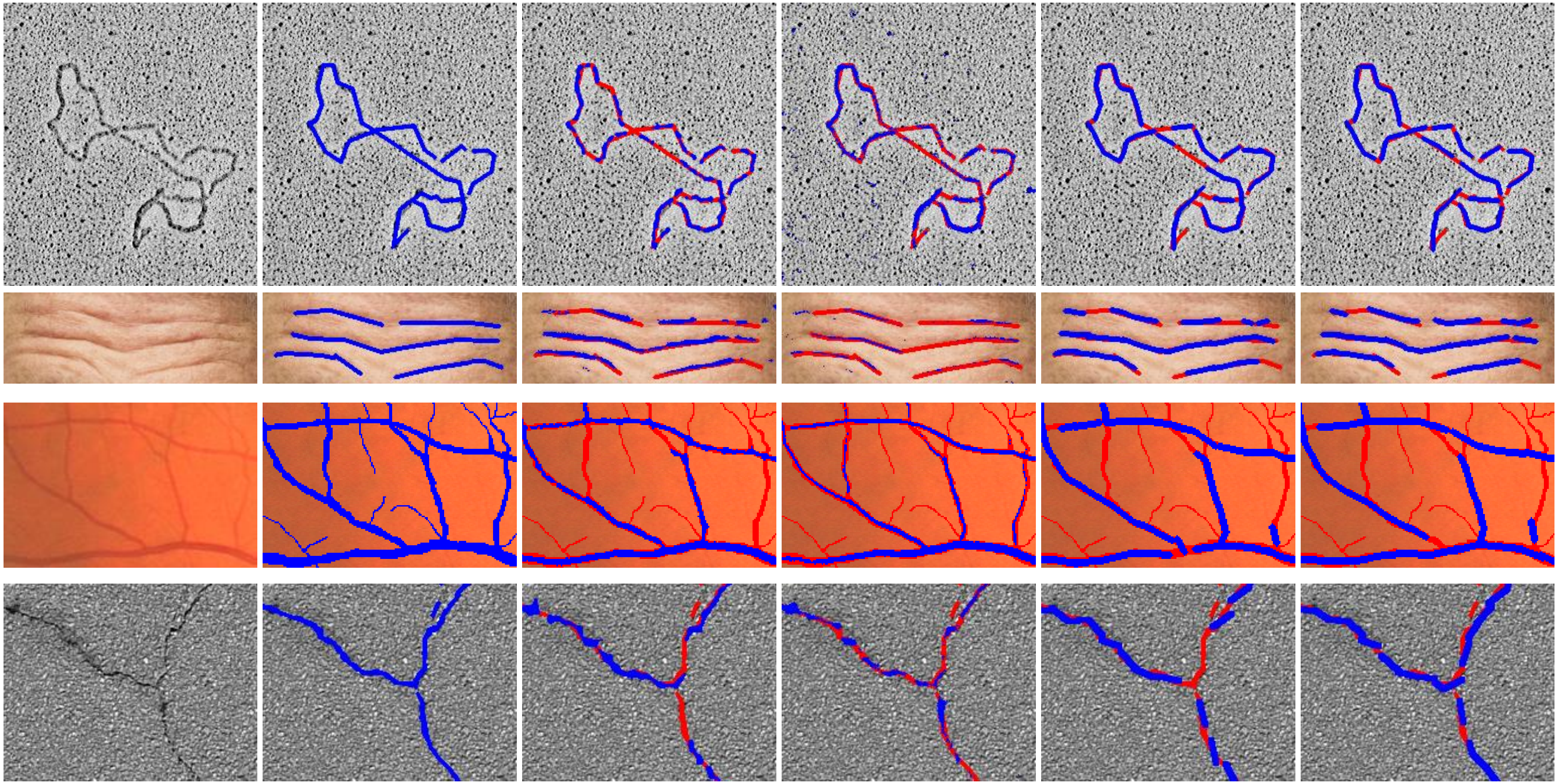
Experimental Results: **missing**



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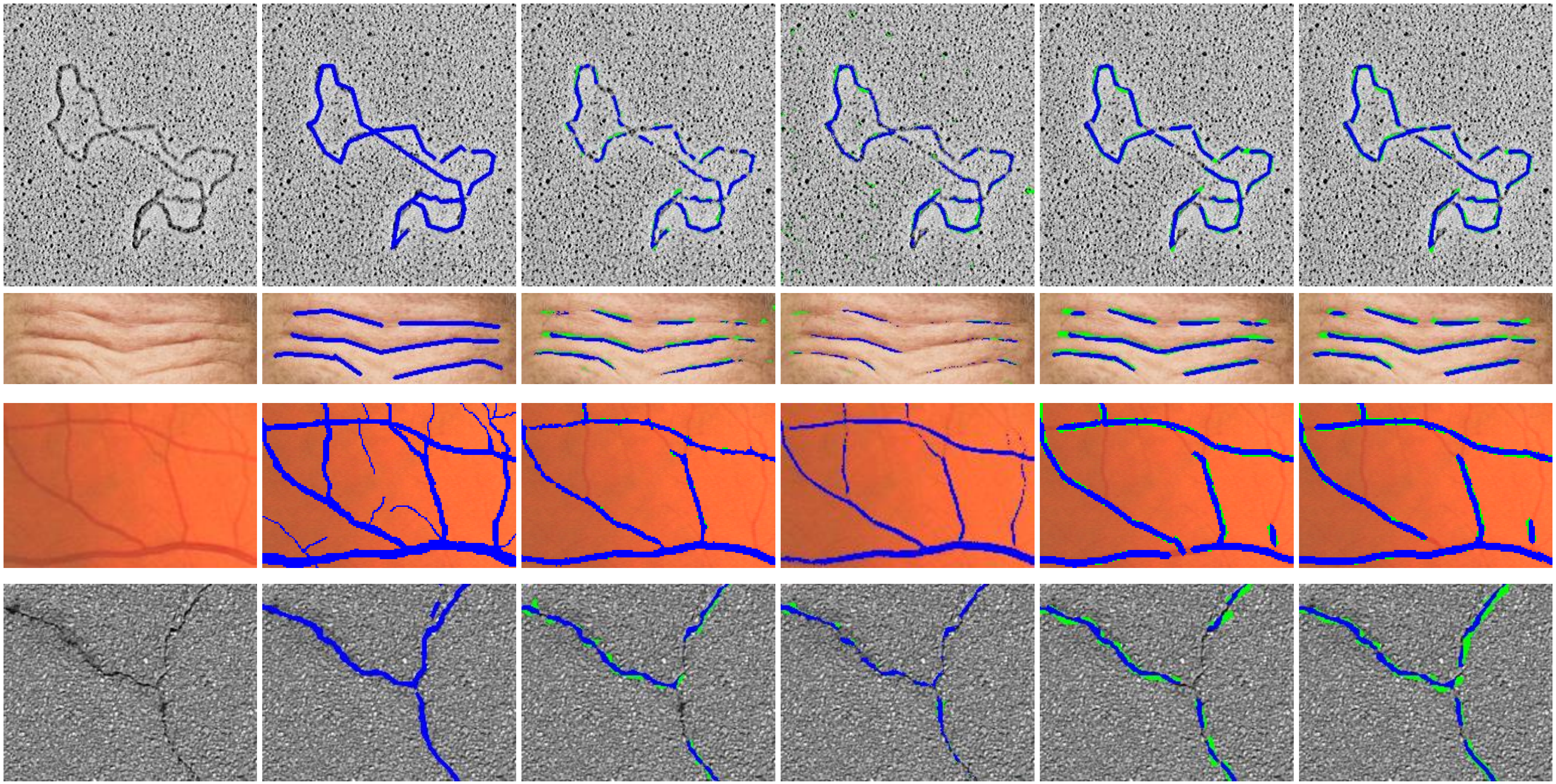
Experimental Results: **over detection**



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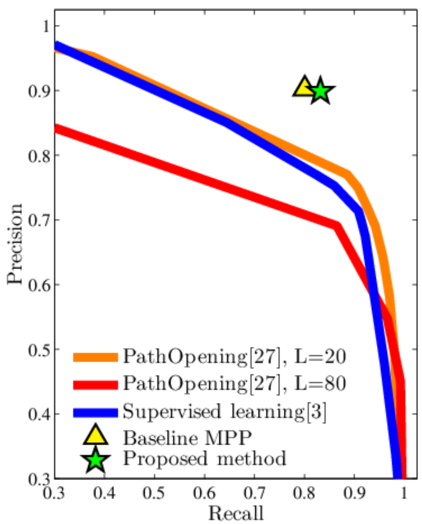
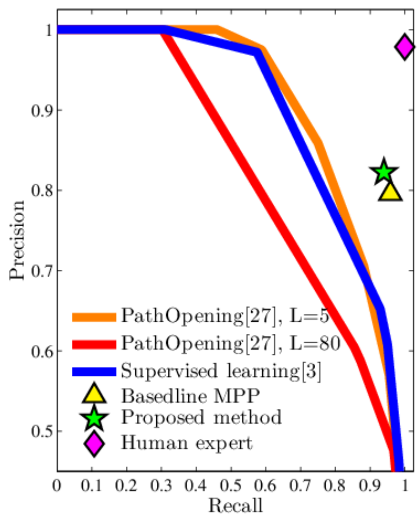
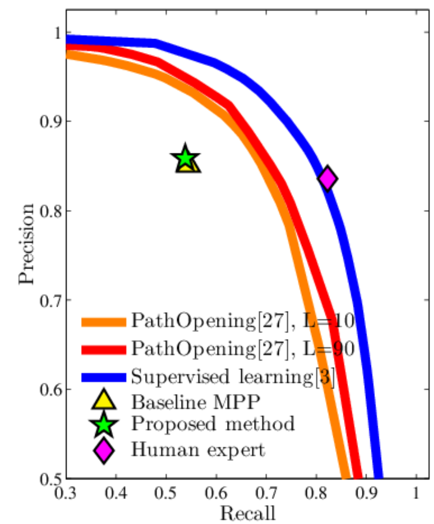
Experimental Results: **Precision-Recall**



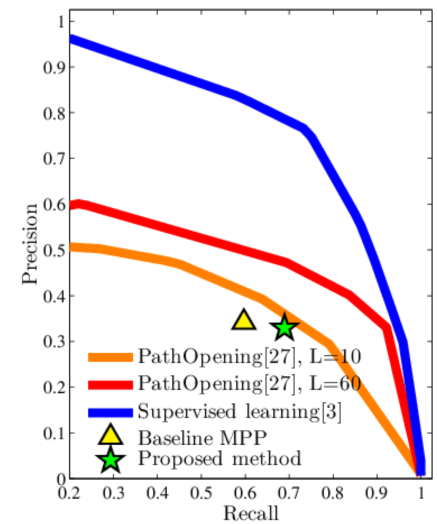
DNA



Wrinkles



Retina



Cracks

+ **Pros**: fully automatic

– **Cons**: varying line width, congestion

Summary

- **Generic MPP model for curvilinear structures**
  - Wrinkles, DNA filaments, road cracks, blood vessels, ...
- Modeling
  - Line segment: length & orientation
  - Data term: image gradient intensity & orientation
  - Prior term: provide smoothly connected lines
- Simulation: RJMCMC with delayed rejection
- **Reduce parameter dependencies** of MPP modeling using hypotheses integration

Thank you!

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