Implicit Representations for Constrained Image Segmentation

Jan Philipp Schneider[1] Mishal Fatima[1] Jovita Lukasik[1]
Andreas Kolb[1] Margret Keuper[1,2,3] Michael Moeller[1]

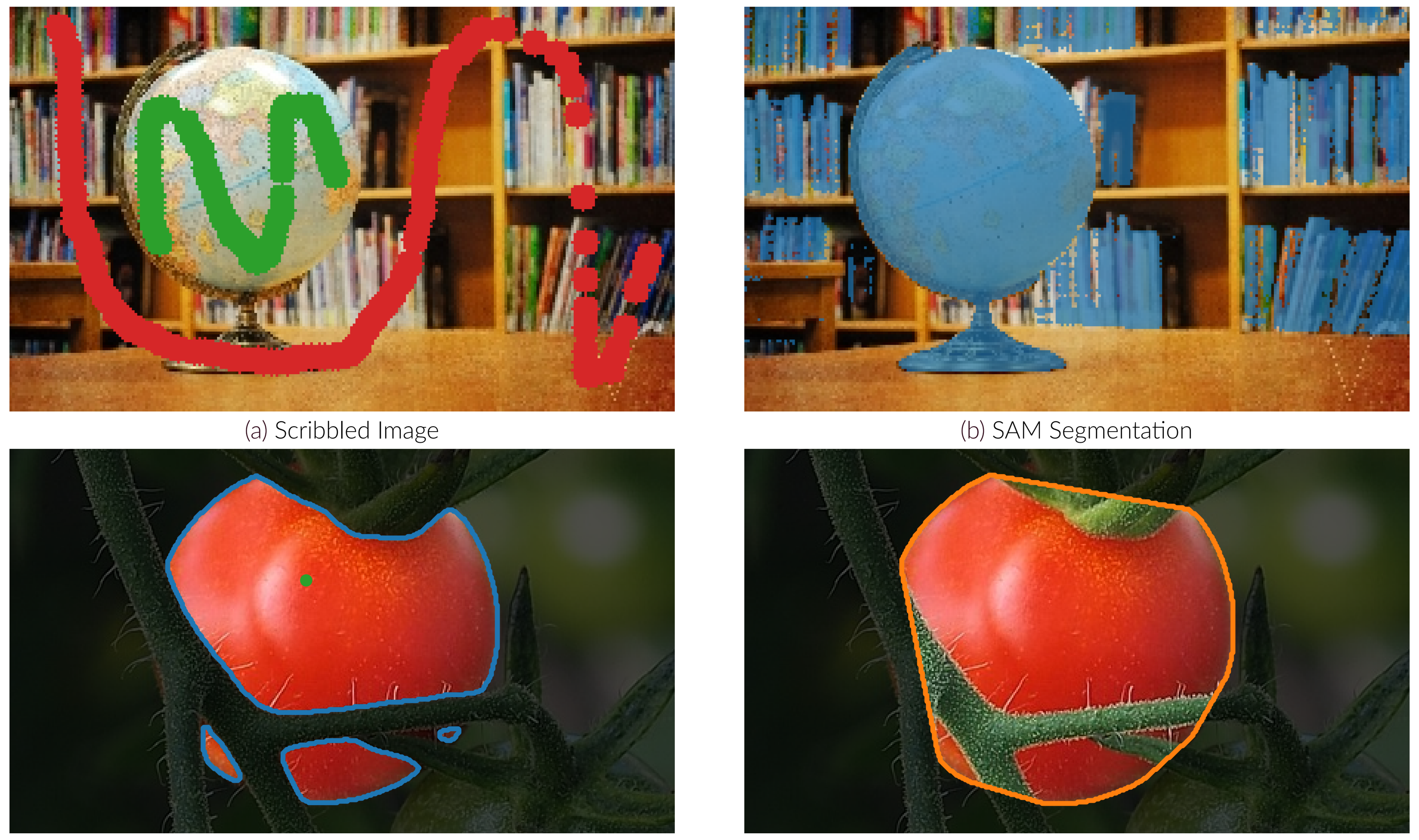
[1] University of Siegen [2] University of Mannheim [3] Max-Planck-Institute for Informatics, Saarland Informatics Campus

Motivation

Segmentation **Foundation Models**, like Segment Anything (SAM) [2], can still **fail if**:

- Data is scarce
- Objects are occluded
- Examples are out-of-distribution

Also: The prior knowledge of geometric properties is rarely considered in image segmentation
But: **Provably** ensuring constraints is hard and costly



(a) Scribbled Image (b) SAM Segmentation
(c) Occluded Tomato (d) Convex Hull of Tomato

Figure 1. Segmenting a scribbled image (a). with SAM (b) leads to a scattered result. The partial occlusion of a tomato (c) leads to a disjointed segmentation in SAM, while for volume estimation, a volume-preserving segmentation (d) would be advantageous.

Can provable geometric constraints improve segmentation quality?

Proposal

Implicit Segmentation Representations (ISR)

- Mapping spatial coordinates to fore- or background
- Foreground is **provably** assured to have one of the properties:
  Convex, Star-Shaped, Mirror & Rotational Symmetric or Path-Connected

Regularization for Shapes

- Using a input convex neural network (ICNN) [3], different input coordinate systems or diffeomorphism + ICNN
- Goes with any prediction architecture: Constrained ISR is used as a regularizer
- Capable of joint optimization

Figure 2. Naïve segmentations (blue) and learned convex, star-shaped, mirror-symmetric, and path-connected ISRs (orange).

Method

Constraint ISR

- Represent segmentations as a *function* $\mathcal{G}_\nu(x) : \mathbb{R}^2 \to \mathbb{R}$ *implicitly* via a neural network
  $\Rightarrow \mathcal{G}_\nu(x)$ maps every pixel to its foreground likeliness
- Operating in the (image) coordinate system $x = c(f), x \in \mathbb{R}^2$ for an image $f \in \mathbb{R}^{n_y \times n_x \times 3}$
- Optional: coordinate transform function $c : \Omega \subset \mathbb{R}^2 \to \mathbb{R}^2$ mapping spatial image domain Ω
- For complete definitions and proofs of all ISRs we refer to our paper [4].

Project or Regularize

Given:

- Segmentation predictor $\mathcal{N}_\theta(f) \in [0,1]^{n_y \times n_x}$; can be any neural network, or simple unaries
- One of our proposed constrained ISRs $\mathcal{G}_\nu$

The output of $\mathcal{N}_\theta$ can be *projected* on $\mathcal{G}_\nu$ by:

$$\text{dist}(\mathcal{N}_\theta(f), S) = \min_\nu \|\sigma(\mathcal{N}_\theta(f)) - \sigma(\mathcal{G}_\nu(c(f)))\| \tag{1}$$

for S as the set of functions represented by $\mathcal{G}_\nu$, and σ beeing the sigmoid function.
Further: (1) can be used as a **regularizer** during training of $\mathcal{N}_\theta \Rightarrow$ optimizing θ and ν *jointly*

Numerical Experiments

- Convex ISR is investigated using a scribble-based convexity dataset and two simple architectures for $\mathcal{N}_\theta$ [1]:
  1. Convolutional Neural Network (CNN)
  2. Fully Connected Network (FCN)
- Using RGB, spatial, and/or semantic input features per pixel

Table 1. Intersection over union (IoU) of foreground objects with predictors $\mathcal{N}_\theta$ and our proposed convex ISR

	RGB+semantic		RGB+spatial+semantic	
	CNN / convex	FCN / convex	CNN / convex	FCN / convex
seq.	0.726 / **0.843**	0.714 / **0.851**	**0.778** / 0.766	0.736 / **0.746**
joint	0.818 / **0.899**	0.635 / **0.894**	0.805 / **0.809**	0.768 / **0.769**

(a) Scribbled Image (b) Segmentation (c) Seq. Projection (d) Joint Projection

Figure 3. Results of the FCN architecture, trained on scribbles with RGB + semantic features.

- Path-connected ISR was evaluated on the FBMS-59 dataset
- Primary predictor $\mathcal{N}_\theta$ is a UNet with training scheme proposed by [5]
- Sequential fit yields 1 %, joint projection 2%, IoU increase over baseline across all image sequences
- Path-Connected ISR is particularly useful when $\mathcal{N}_\theta$ segments multiple objects. In joint training, these disappear completely, see Fig. 4.

Figure 4. Left: Sequential prediction (blue) and projection (orange), Right: Both, after joint training. ISR enforces $\mathcal{N}_\theta$ to focus on the right car and accuracy increases significantly.

Numerical Experiments Cont.

- Constraint ISRs are not limited to spatial image dimensions
- The input x of $\mathcal{G}_\nu$ can be configured to include further features like depth or time

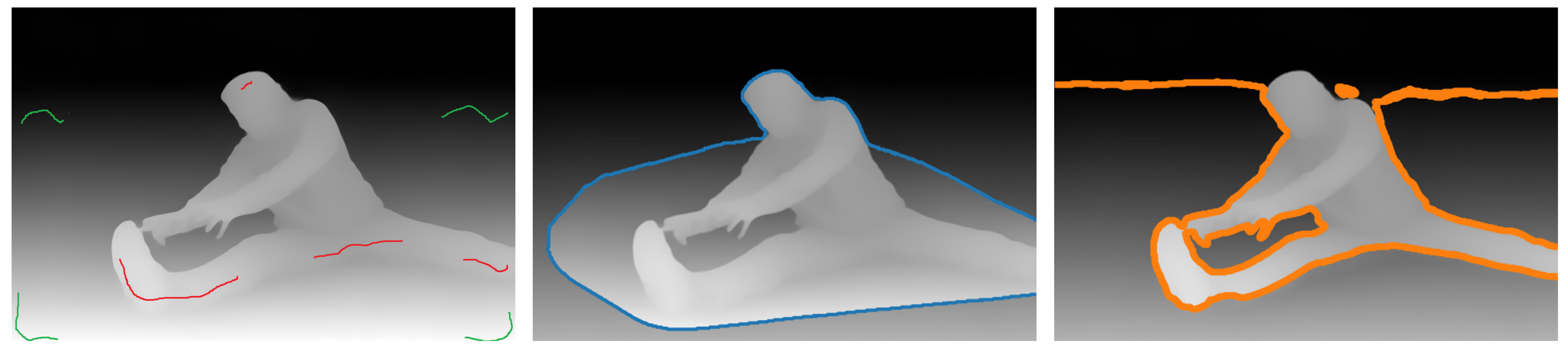


Figure 5. Illustrating of a naïve segmentation (blue) and convex ISR (orange) in $(x,\ y,$ depth)-space. For the ISR, we segment the floor "plane", which is convex in (x, y, depth).

- Combining spatial image dimensions, time, and the path-connected ISR yields a provable spatio-temporal path-connected ISR
- Allows for accurate super-resolution in space and time (Fig. 6)
- Particularly advantageous if the unaries are noisy or the objects are occluded or covered (Fig. 7)
- Could be in-depth explored in segmentation object-trackers in the future, to increase object awareness

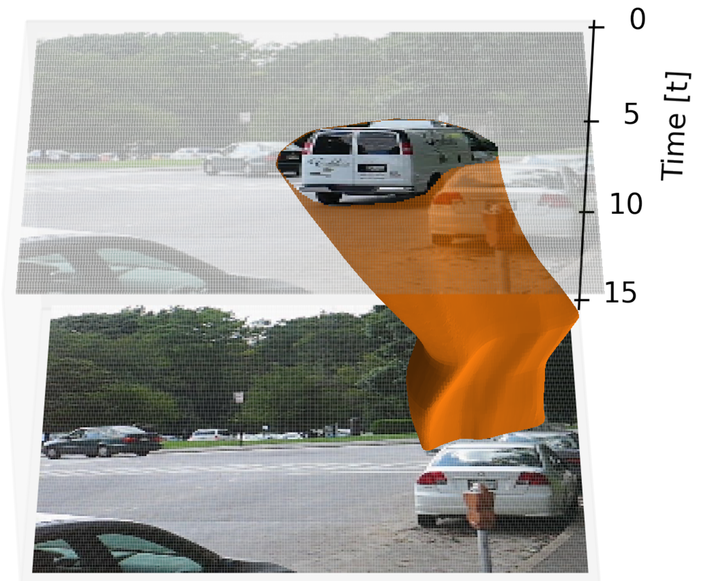


Figure 6. Spatio-temporal path-connected ISR along an image sequence. ISR was 6x super-resolved in time.

Figure 7. Spatio-temporal path-connected ISR, when trained on unaries which were partially (20 %) replaced by pure noise. The frames shown are index 10 to 14 of the *cars3* sequence.

Conclusion

- Proposed a variety of **provable** geometric constraints using *Implicit Representations* for image segmentation
- The ISRs with **implicitly enforced constraints can improve the results**:
  Especially if the missing condition is the main point of failure
- The **joint fit is superior** to a sequential one
- ISRs can be used in a variety of ways and further extended beyond segmentations in the spatial image domain

References

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For the code and link to our paper, scan the QR-Code or visit: `https://github.com/jp-schneider/awesome`