SaiNet: Stereo aware inpainting behind objects with generative networks

CVSSP Centre for Vision, Speech and Signal Processing

BBC R&D

UNIVERSITY OF SURREY

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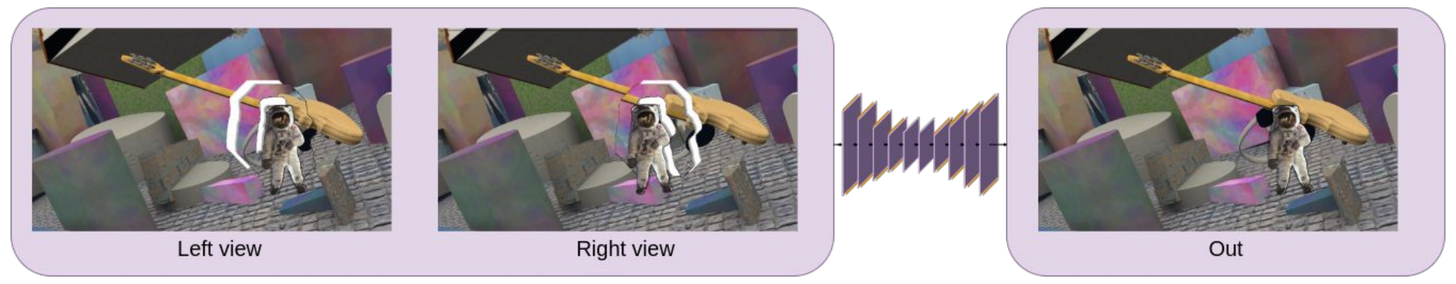
What do we do?

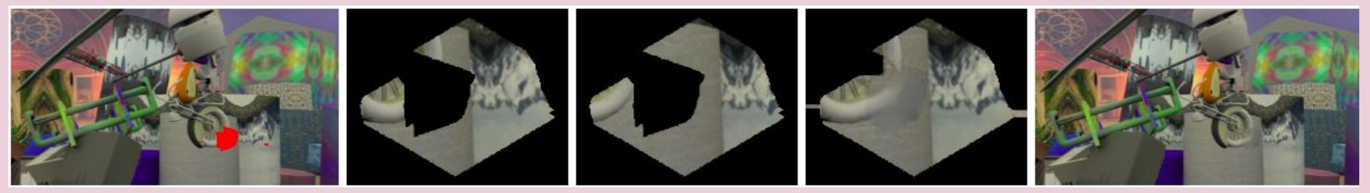


In multi-view settings we want to recover the missing information due to object disocclusions in a reasonable and cross-camera consistent way. Our approach uses object background information and stereo consistency to inpaint behind objects. In addition, our model converts a difficult unsupervised problem into an easier supervised one. Making it possible to train on larger stereo datasets.

Datasets

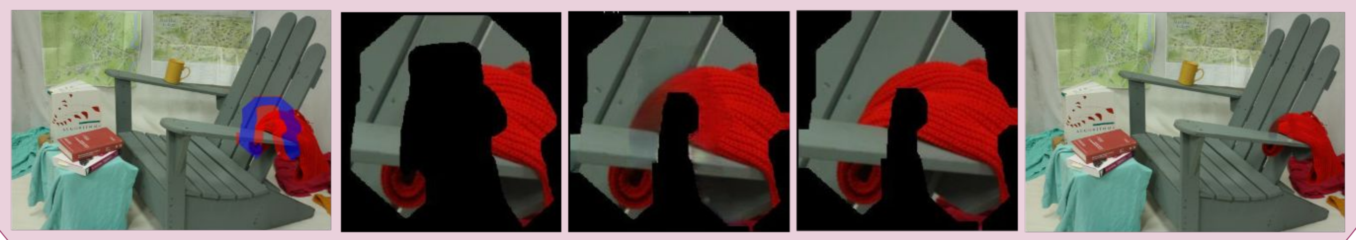
- Good quality, natural stereo datasets are very hard to come by.
- Random sampling of context-synthesis areas performs **data augmentation**.

FlyingThings3D[4] containing a variety of objects flying around in a randomised way.



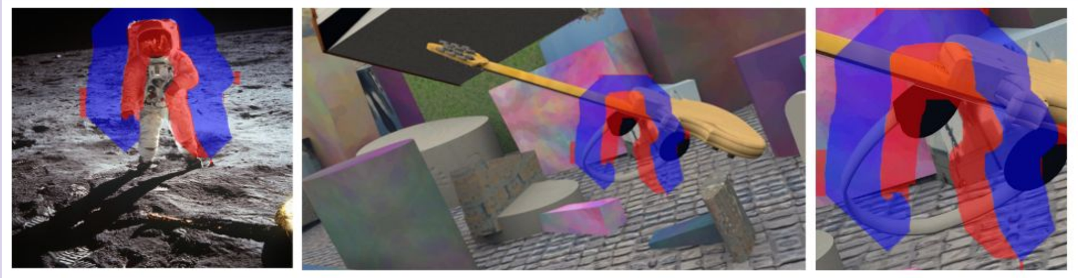
Driving[4] naturalistic-looking dynamic street scene resembling the *KITTI* dataset.

Middlebury[5] 33 natural scenes.

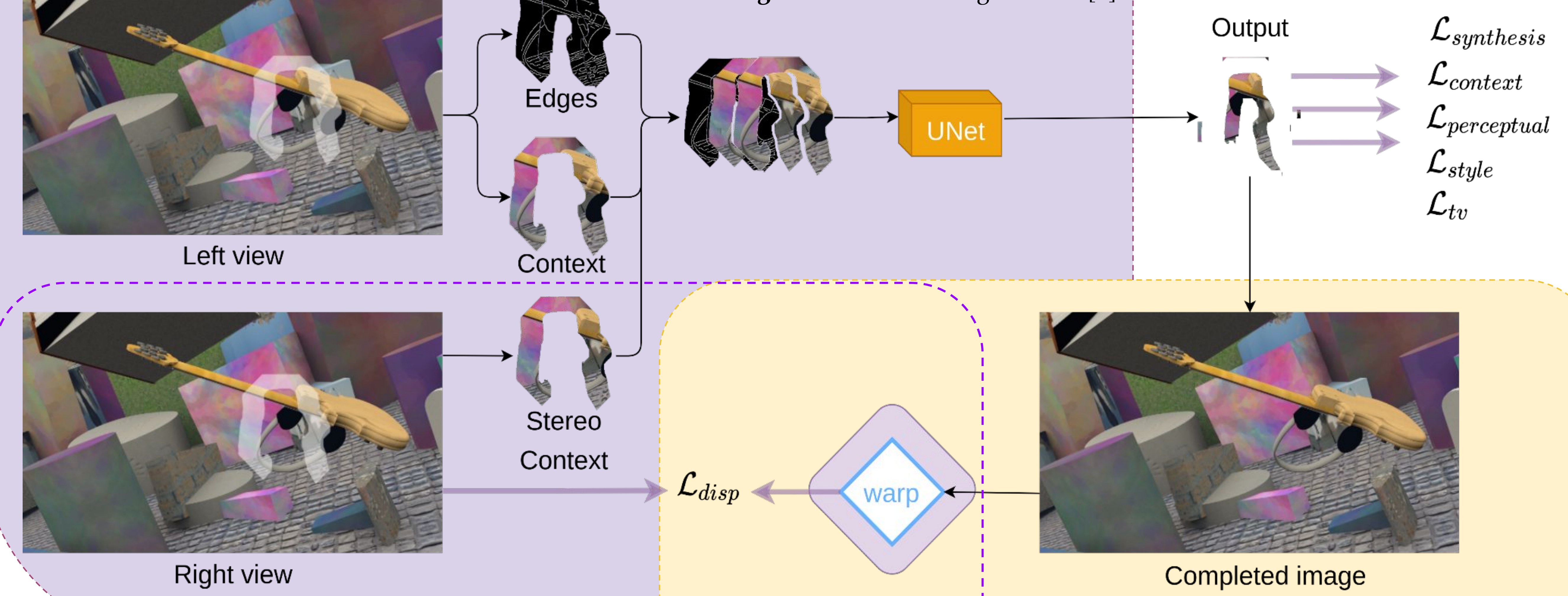


How do we do it?

Object occlusion regions



- Represent real objects
- More challenging as not necessarily bounded
- Generate masks from object boundaries:
  - **context** is the background around the object
  - **synthesis** is the hole behind the object
- Data augmentation:
  - Random sampling of context-synthesis areas
  - Sample from stereo view using disparity
- Input to the nextwork
  - RGB **context**
  - RGB stereo-**context**
  - Colour **edges** for structural guidance[3]



- Enforce local consistency with a disparity loss.
- Measures the consistency between inpainted patch in one view and the GT in the other

Stereo awareness

Stereo consistency

What is new?

Problem	Solution
Novel view synthesis requires peeking behind objects and trying to recover information which is not present in an image	Leverage information from stereo-views
Stereo data is scarce	Perform data augmentation
Most inpainting approaches focus on randomly shaped inpainting masks of limited complexity	Use geometrically-meaningful object masks
Inpainting large and irregular non-bounded holes is a difficult problem	Use structure guided inpainting and extra stereo-information

Conclusions

- **Novel** stereo-aware learned inpainting model.
- Enforces **stereo consistency**
- Trained in a **self-supervision** fashion
- Uses **geometrically meaningful masks** representing object occlusions.
- Improvement over state-of-the-art models by up to **50% PSNR**.
- Good performance over several **diverse datasets**.
- Possible future work: extend model to cope with the challenges of wide-baseline non-parallel cameras.

Quantitative results

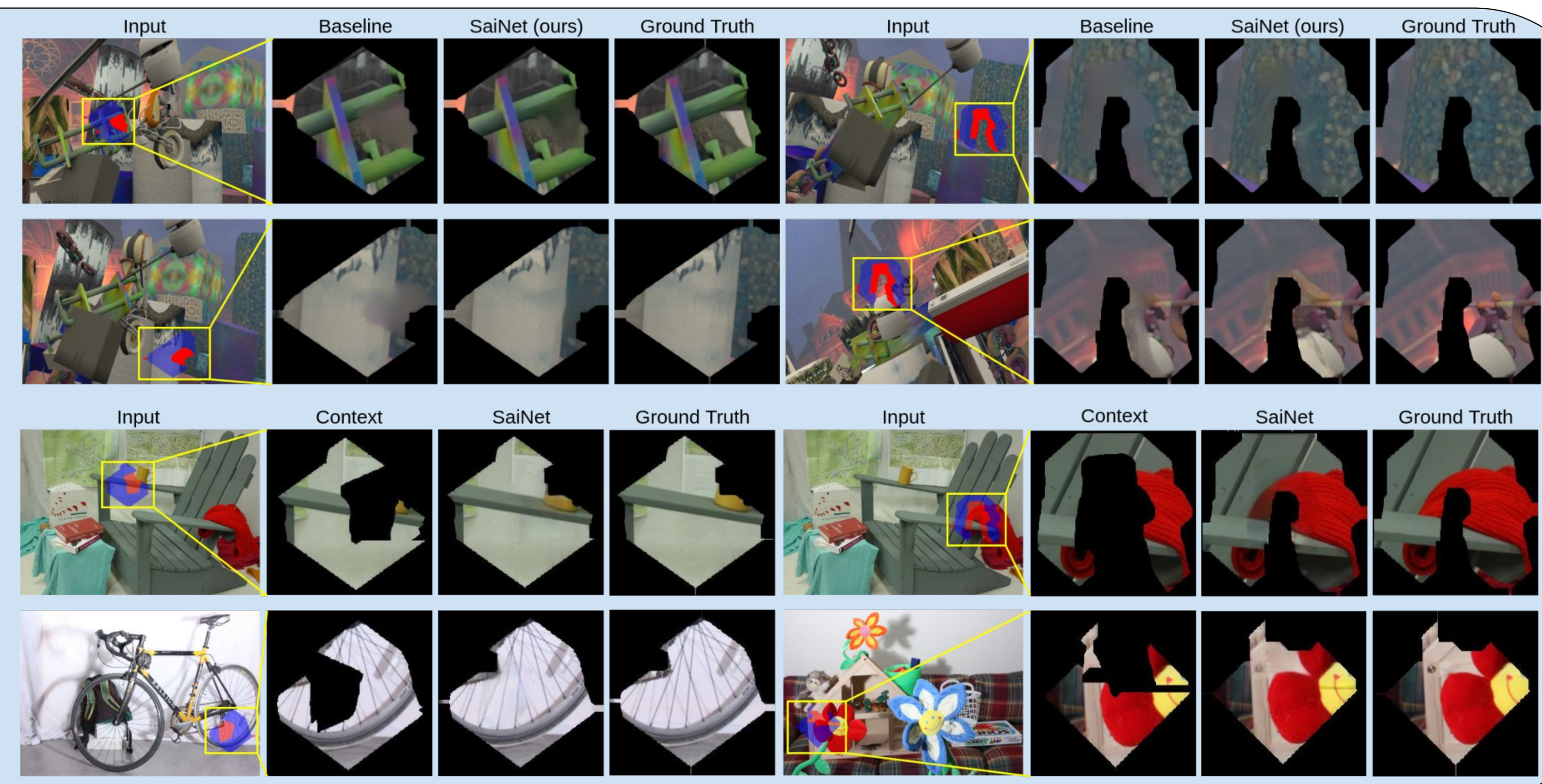
- Better across all metrics.
- Competitive consistency in more challenging problem.

Table 1. **Quantitative results.** Image quality & stereo consistency of different models. **Bold** is best. ⋆ values are from their paper.

Dataset	Model	PSNR↑	SSIM↑	LPIPS↓	DispE (%)↓
FlyingThings3D	Shih *et al.*[1]	28.32	0.8589	0.0707	7.96
	Ours	**30.50**	**0.8643**	**0.0556**	**7.67**
Driving	Shih *et al.*[1]	30.46	0.969	0.1141	9.94
	Chen *et al.*[6]⋆	22.38	0.959	-	7.79
	Ma *et al.*[7]⋆	23.20	0.964	-	**4.72**
	Ours	**34.94**	**0.977**	**0.0628**	8.01

Qualitative results

- Superior image quality.
- More challenging masks.
- Sharp edges.
- Visually pleasing.
- Struggle with intricate unseen structures.



References

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