GANmouflage: 3D Object Nondetection with Texture Fields

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Motivation

- **Camouflages** are everywhere, on the street, in the forest, under the sea…

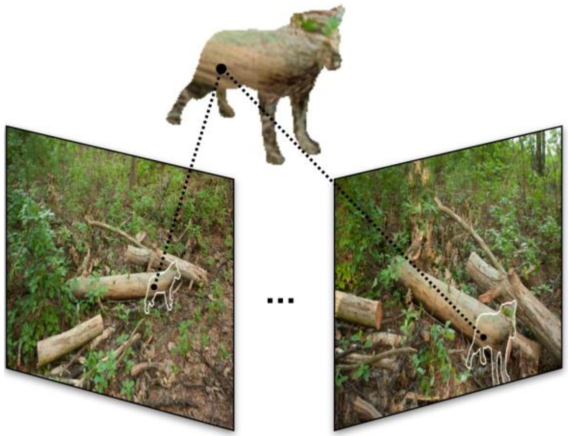
Question: How to follow their design and generate textures as good as them?

Motivation

Challenges:

- ❏ Inconsistency from multiple views.
- ❏ No formal answer to the question, animals act in their own way.

Color an object !

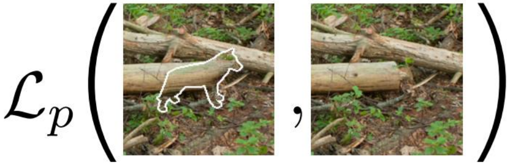


Make it hard to see in multiple views!

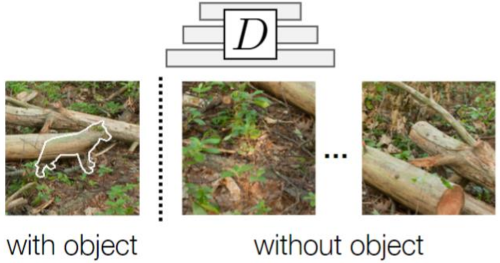
Method

- Modern implicit representations of textures: Texture Fields.
- Learning to camouflage in a self-supervised way.

$$G_\theta(\underbrace{\mathbf{x}}_{\text{Query point}};\ \underbrace{\{\mathbf{I}_j\}}_{\text{Input images}},\ \underbrace{\{\mathbf{P}_j\}}_{\text{Projection Matrices}},\ \underbrace{S}_{\text{Object Shape}})$$



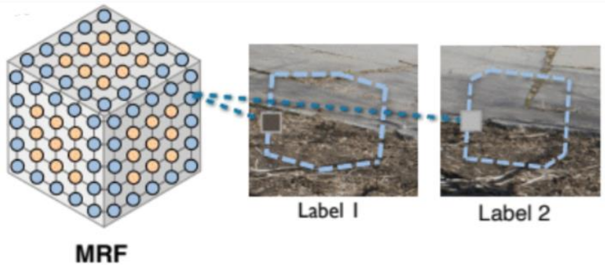
Photoconsistency Loss



Adversarial Loss

Related Work

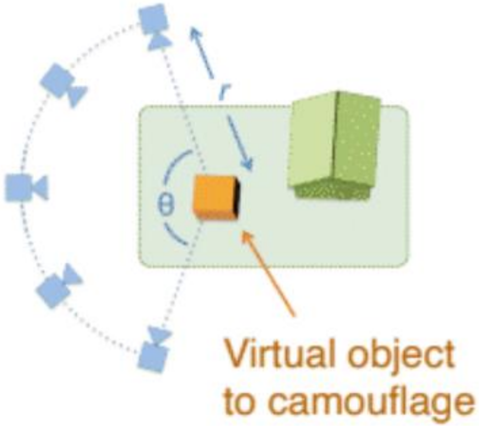
- Owens *et al.* propose to view cuboid surfaces as a graph and optimize camouflage textures as MRF.

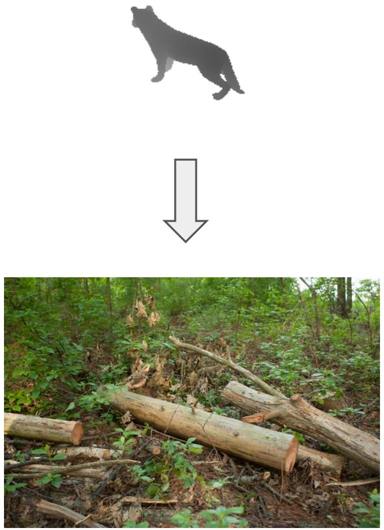


- Reynolds generate 2D camouflage textures using genetic algorithm.

Multi-view Camouflage

- Multiple input views captured around a virtual object.
- Generate camouflage textures for the shape based on the scene and location.



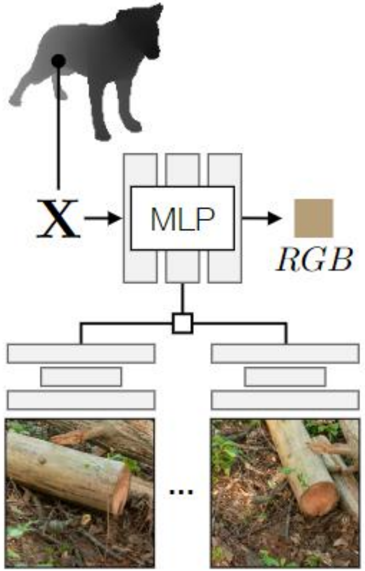


Method

- Texture Field: Multi-Layer Perceptron dependent on scene encodings.

$$\mathbf{c}_i = T(\gamma(\mathbf{x}_i); \{\mathbf{z}_i^{(j)}\}, \{\mathbf{v}_i^{(j)}\}, \{\mathbf{n}_i^{(j)}\})$$

Color for point Query point *i*



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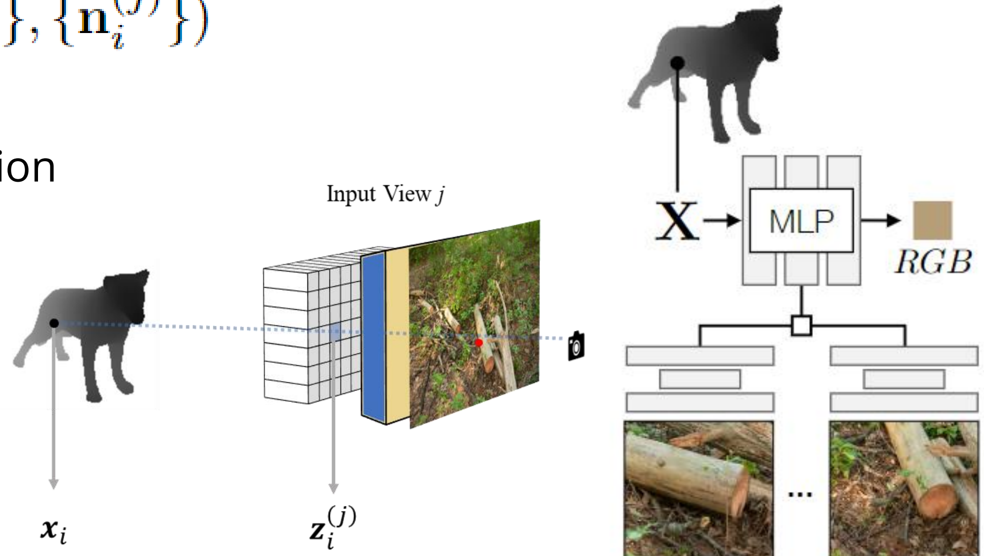
Pixel-aligned image representation

- Image coordinate on input view *j*.

$$\mathbf{u}_i^{(j)} = \pi^{(j)}(\mathbf{x}_i)$$

- Bilinear interpolated image features

$$\mathbf{z}_i^{(j)} = \mathbf{F}^{(j)}(\mathbf{u}_i^{(j)})$$



Method

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$$\mathbf{c}_i = T(\gamma(\mathbf{x}_i); \{\mathbf{z}_i^{(j)}\}, \underbrace{\{\mathbf{v}_i^{(j)}\}, \{\mathbf{n}_i^{(j)}\}}\,)$$

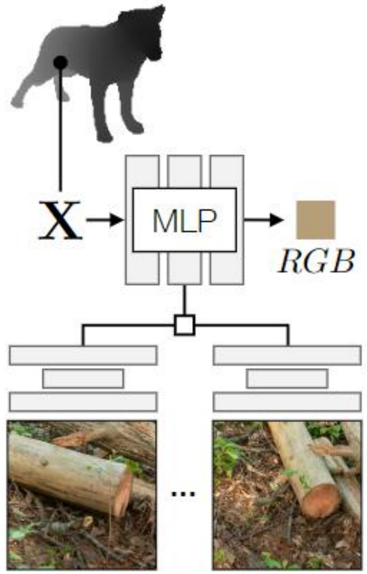
Perspective encoding

- Conveys the local geometry of the object surface and the multi-view setting
- Viewing direction from input view *j*

$$\mathbf{v}_i^{(j)} = \frac{\mathbf{K}_j^{-1}\mathbf{u}_i^{(j)}}{\|\mathbf{K}_j^{-1}\mathbf{u}_i^{(j)}\|_2}$$

- Surface normals in input view *j*

$$\mathbf{n}_i^{(j)} = \mathbf{R}_j \mathbf{n}_i$$



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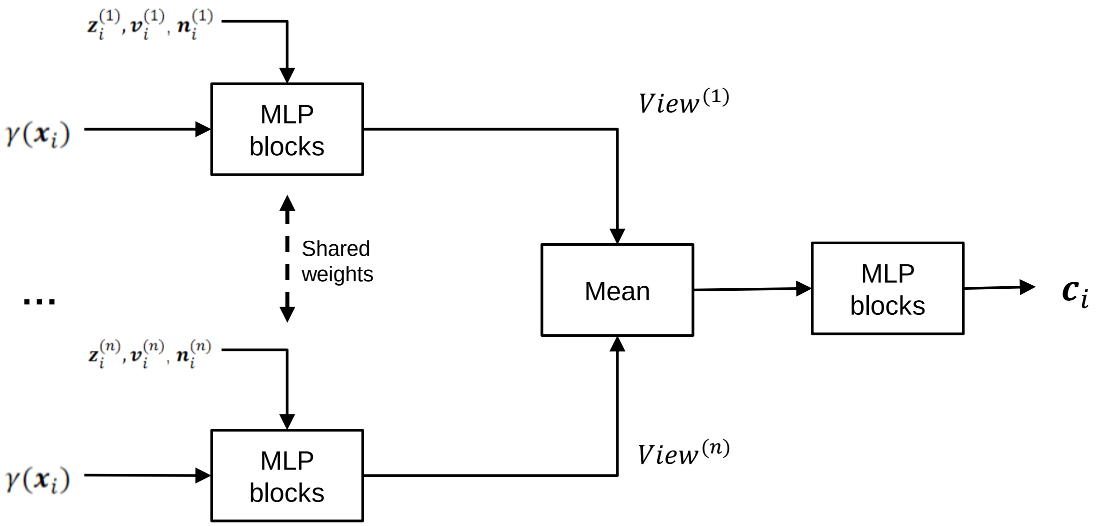
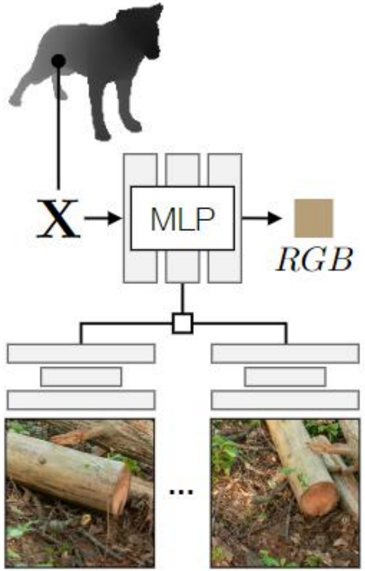
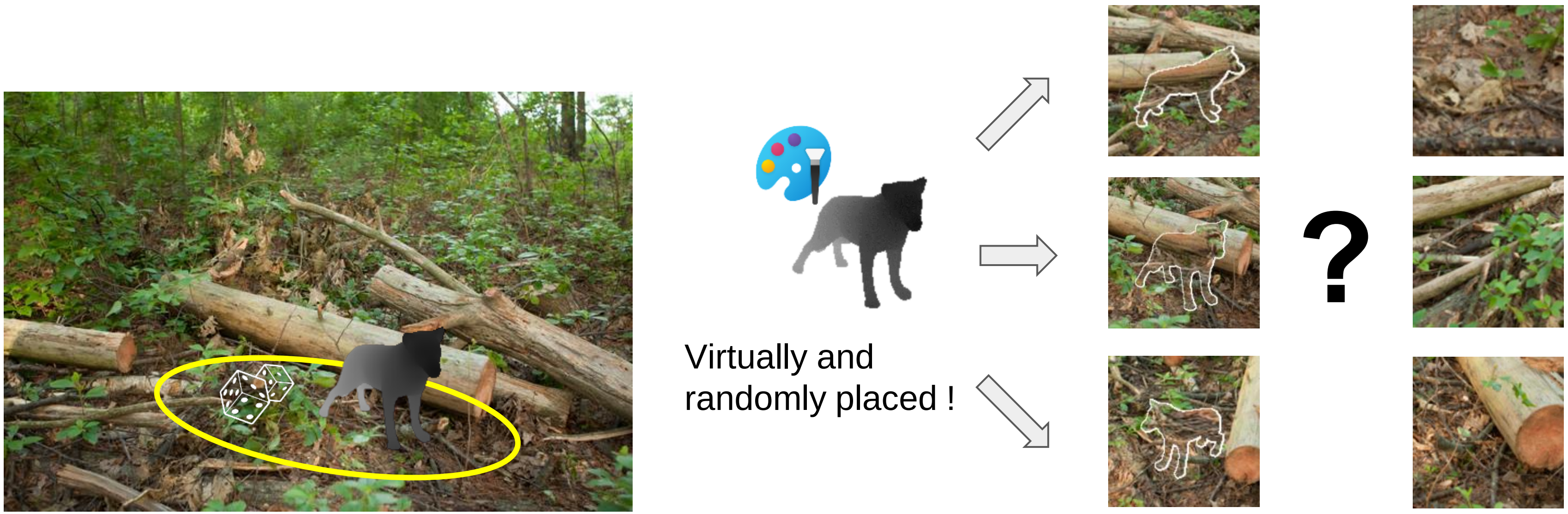




Learning to Camouflage

- Learn how to camouflage through virtually inserting camouflaged objects.



Learning to Camouflage

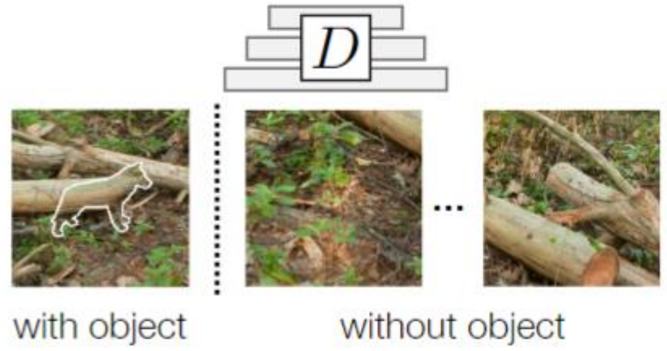
- Photoconsistency Loss:

$$\mathcal{L}_{photo} = \sum_{j \in J} \mathcal{L}_P(\hat{\mathbf{I}}_j, \mathbf{I}_j) = \sum_{j \in J, k \in L} \frac{1}{N_k} \|\phi_k(\hat{\mathbf{I}}_j) - \phi_k(\mathbf{I}_j)\|_1$$

- Adversarial Loss :

$$\mathcal{L}_D = -\mathbb{E}_y[\log D(y)] - \mathbb{E}_{\hat{y}}[\log(1 - D(\hat{y}))]$$

$$\mathcal{L}_{adv} = -\mathbb{E}_{\hat{y}}[\log D(\hat{y})]$$



- Self-supervised camouflage loss

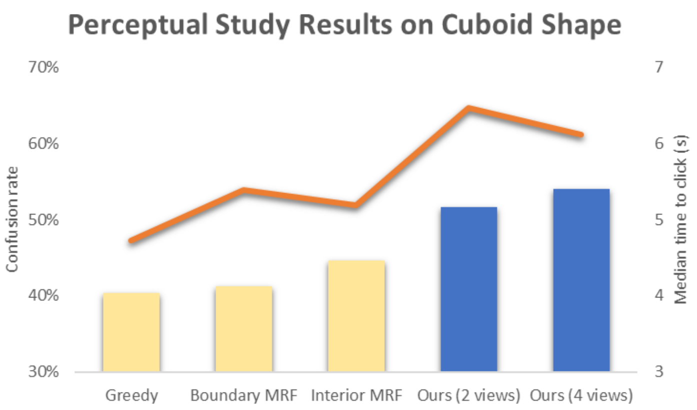
$$\mathcal{L}_G = \mathcal{L}_{photo} + \lambda_{adv}\mathcal{L}_{adv}$$

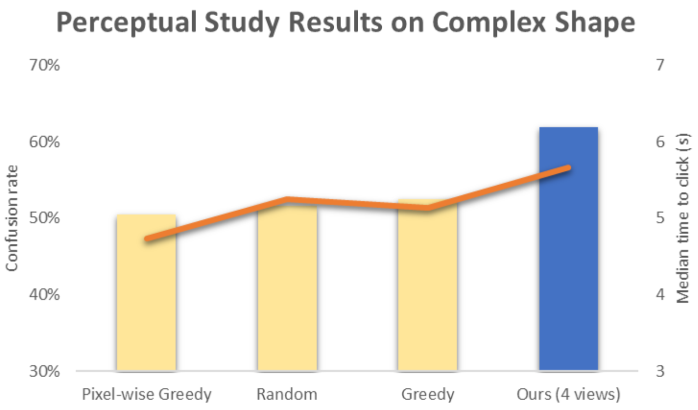
Experiments

- Evaluate our method on 36 scenarios from Owens *et al.*:
  - Render objects after camouflage at the predefined place.
  - Test our method with 2 view input or 4 view input.
  - Test on cuboid and animal shapes.
- Baseline
  - Iterative greedy projection
  - MRF based methods from Owens *et al*.
  - Image inpainting + projection

Result

- Evaluation based on perceptual study.
  - Participants are required to click on the location of camouflaged objects.
  - Confusion rate and click time are recorded for each trial.





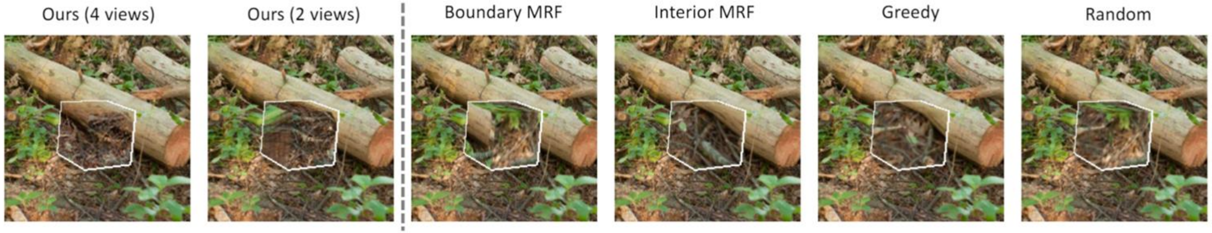
Results

- Automated metrics
  - LPIPS
  - SIFID
- Compared with image inpainting pipeline
- Ablation Study

Model	LPIPS↓	SIFID↓
Boundary MRF [34]	0.1228	0.0867
Interior MRF [34]	0.1185	0.0782
DeepFill v2 [58] + Projection [34]	0.1469	0.1245
LaMa [51] + Projection [34]	0.1263	0.1006
LDM [40] + Projection [34]	0.1305	0.0976
No $\mathcal{L}_{adv}$	0.1064	0.0720
No $\mathcal{L}_{photo}$ on input views	0.1131	0.0856
With pixelNeRF encoder [57]	0.1047	**0.0712**
Ours (2 views)	0.1079	0.0754
Ours (4 views)	**0.1034**	0.0714

Table 3. **Evaluation with automated metrics.** We compare our method to other approaches, and perform ablations.

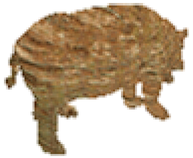
Results



(a) Qualitative results on cubes

(b) Qualitative results on animal shapes

Virtual Tours in the scene



Conclusion

- We propose a method using Texture Fields to generate camouflage texture for objects.
- Our method has more flexibility on input shapes.
- We propose a self-supervised way to train the texturing model.

Reference

[1] Andrew Owens, Connelly Barnes, Alex Flint, Hanumant Singh, and William Freeman. Camouflaging an object from many viewpoints. In *CVPR*, 2014.

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[4] Silvia Zuffi, Angjoo Kanazawa, David Jacobs, and Michael J. Black. 3D menagerie: Modeling the 3D shape and pose of animals. *In IEEE Conf. on Computer Vision and Pattern Recognition (CVPR)*, July 2017.

[5] Richard Zhang, Phillip Isola, Alexei A Efros, Eli Shechtman, and Oliver Wang. The unreasonable effectiveness of deep features as a perceptual metric. In *CVPR*, 2018.

[6] Tamar Rott Shaham, Tali Dekel, and Tomer Michaeli. Singan: Learning a generative model from a single natural image.In *Proceedings of the IEEE International Conference on Computer Vision*, pages 4570–4580, 2019.

Image credit:

https://scswraps.com/utility-box-brick-camouflage/

https://www.mystart.com/blog/the-coolest-camouflage-techniques-used-by-animals

https://www.youtube.com/watch?v=JSq8nghQZqA

Thank you !