Deep Vanishing Point Detection: Geometric priors make dataset variations vanish

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https://github.com/yanconglin/VanishingPoint_HoughTransform_GaussianSphere/

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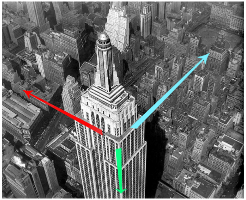
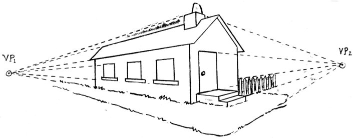
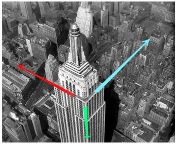
Vanishing Point Detection

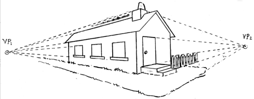




A vanishing point is the intersection of a set of image lines projected from **3D parallel lines**.

Vanishing Point Detection



- SLAM [1];
- Camera calibration [2];
- Scene understanding [3];
- ...

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[1] A. J. Davison, I. D. Reid, N. D. Molton, and O. Stasse (2007). “MonoSLAM: Real-time single camera SLAM”. In:

Current approaches

- Knowledge-based
  - Two-stage: Line segment detector + clustering [4]
  - ◦ pros: unsupervised or little annotation
  - ◦ cons: outlier/noisy lines, performance
- learning-based
  - Conic convolutions [5]
  - ◦ pros: end2end, intuitive, SOTA results
  - ◦ cons: massive labelled data
  - ◦ cons: Manhattan assumption
  - ◦ cons: vulnerable to domain shifts, hampering generalization

[4] H. Li, J. Zhao, J.-C. Bazin, and Y.-H. Liu (2020). "Quasi-globally Optimal and Near/True Real-time Vanishing Point Estimation in Manhattan World". In: *IEEE Transactions on Pattern Analysis and Machine Intelligence*

[5] Y. Zhou, H. Qi, J. Huang, and Y. Ma (2019). "NeurVPS: neural vanishing point scanning via conic convolution". In: *arXiv preprint arXiv:1910.06316*

Contribution: add two geometric priors into CNNs

- Prior 1: *Hough transform* for identifying lines;
- Prior 2: *Gaussian sphere* for localizing vps on a unit hemisphere;
- an *end-to-end* learning framework;
- improved *data efficiency*;
- superior performance *w/o Manhattan assumption*;
- generalization from synthetic to real-world;

Overview of the proposed model

Adding two priors into end2end learning.

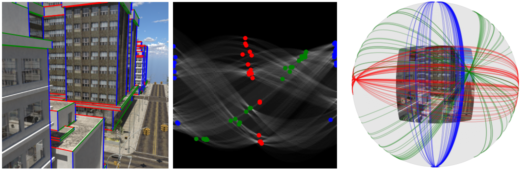
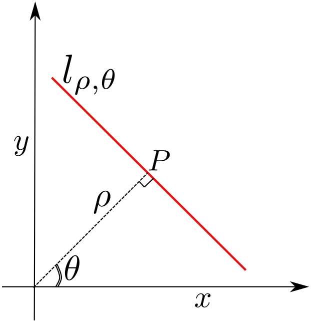


Image domain (i) Hough Transform (ii) Gaussian sphere

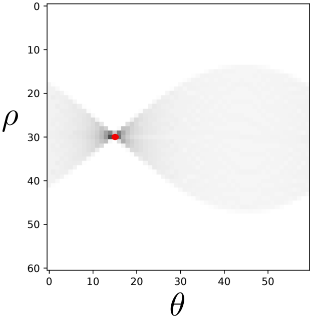
- CNNs for semantic feature learning;
- Hough Transform for line detection;
- Gaussian sphere for VPs detection;

Prior 1: HT (Hough Transform) line priors [6]

- Maps lines to bins in Hough space: a 2D angle-offset histogram;
- Each pixel votes for a number of bins by $\rho = x_i \cos\theta + y_i \sin\theta$;
- Local maxima in Hough space correspond to lines in images



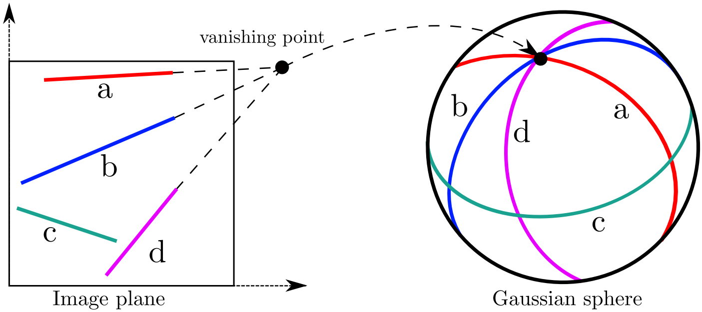
Line



$\mathcal{HT}$ space

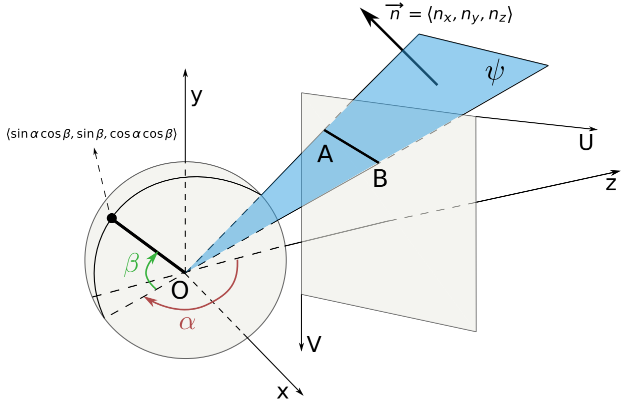
[6] Y. Lin, S. L. Pintea, and J. C. van Gemert (2020). "Deep Hough-Transform Line Priors". In

Prior 2: Gaussian sphere mapping



- VPs are intersections of multiple great circles;
- Spherical convolutions;
- Clustering algorithms to detect multiple unorthoginal VPs.

Prior 2: Gaussian sphere mapping

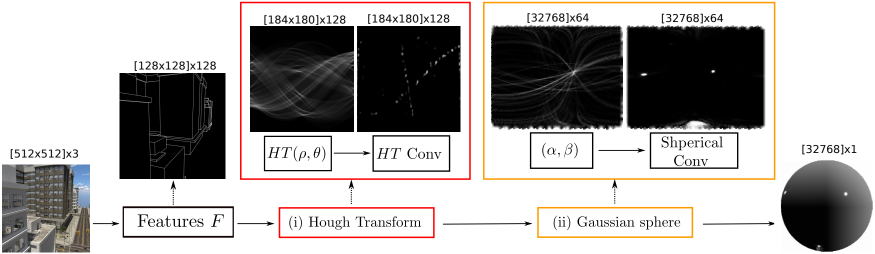


$$\vec{n} = (n_x, n_y, n_z) = \frac{\overrightarrow{OA} \times \overrightarrow{OB}}{\left\| \overrightarrow{OA} \times \overrightarrow{OB} \right\|}. \quad (1)$$

$$\langle \sin\alpha\cos\beta, \sin\beta, \cos\alpha\cos\beta \rangle \langle n_x, n_y, n_z \rangle = 0 \quad (2)$$

Overview of the proposed model

Add two priors into end2end learning.



- CNNs for semantic feature learning;
- Hough Transform for line detection;
- Gaussian sphere for VPs detection;
- Clustering algorithms for detecting unorthoginal VPs (optional).

Experiments: datasets and evaluation

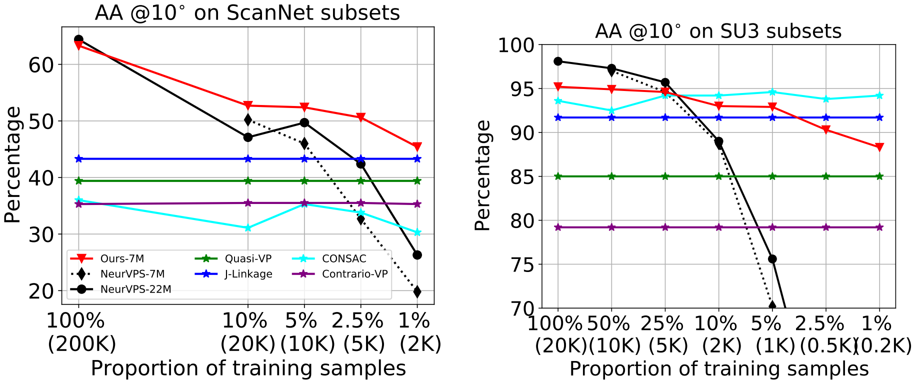
Dataset: Synthetic, Manhattan, non-Manhattan.
Evaluation: angular accuracy (AA) in camera space.
Higher is better.

Visual examples.

Experiments: Improved data efficiency

Comparison with SOTA [7].

Evaluation: angular accuracy (AA), higher is better.

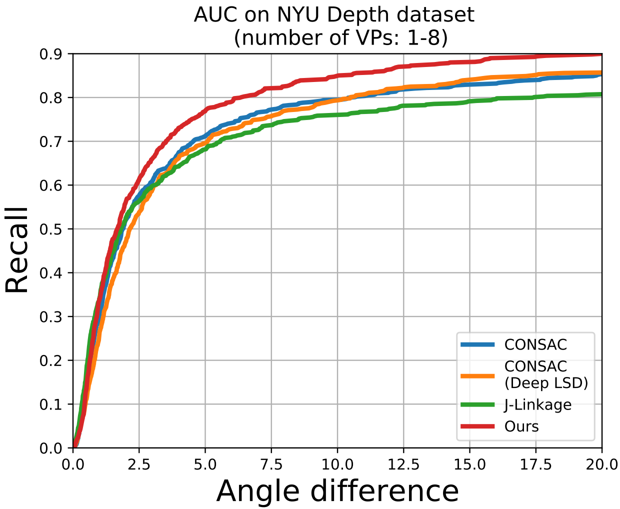


(a) ScanNet (real-world) (b) SU3 (synthetic)

ScanNet: top results on various subsets;

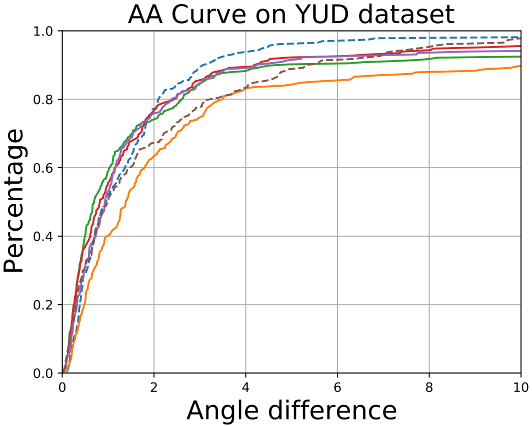
SU3: minor performance decrease when decreasing from 20K to 0.2K.

Experiments: Comparison in *non-Manhattan* world



NYU: consistently outperforms SOTA on detecting multiple unorthogonal VPs.

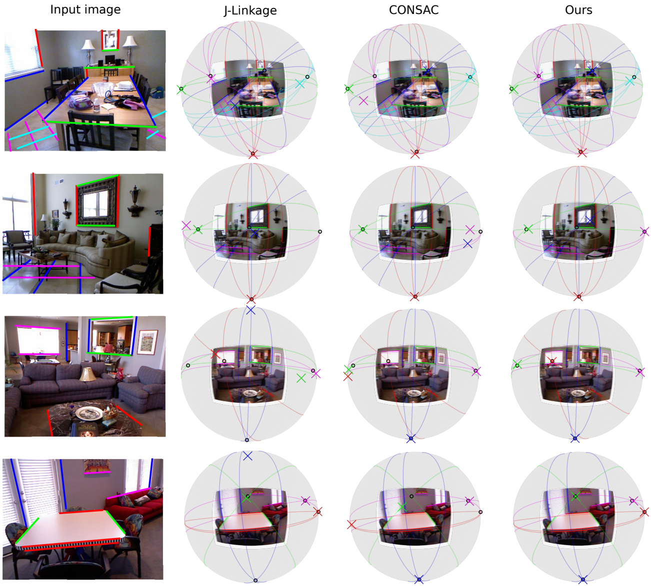
Experiments: Comparison in *Manhattan* world



AA curves on on the ScanNet and YUD.

- On YUD (102 images in total), our model outperforms state-of-the-art *w/o finte-tuning, trained on SU3 (synthetic only)*.

Visualization



Limitations

- Quantization errors (both HT and sphere mapping);
- Dense sampling on the sphere leads to more computation;
- Comparing to classic methods: still need hundreds of training samples.

Conclusions

- Adding two geometric priors:
  Hough Transform and *Gaussian sphere mapping*;
- Improved data efficiency-data efficient learning;
- Applicable in non-Manhattan world;
- Generalizable from synthetic to real-world.

Thank you!

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