Patches, Planes and Probabilities: A Non-local Prior for Volumetric 3D Reconstruction

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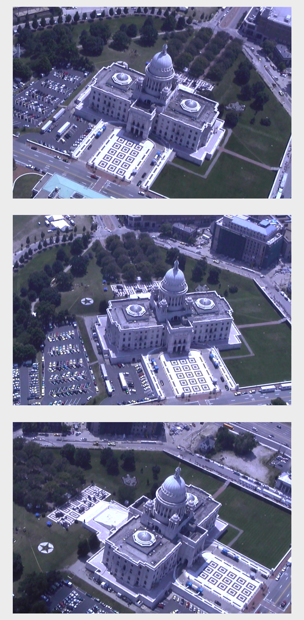
Introduction

Textureless or reflective surfaces cause fundamental ambiguities in 3D reconstruction from images.



input images

probabilistic volumetric reconstruction [1]

probability of occupancy

empty occupied

probabilistic 3D model

[1] is able to expose the reconstruction ambiguity but cannot resolve it without priors. Results show that pairwise priors cannot regularize large ambiguities common in MVS.

Contribution: a non-local prior formulation that encourages piecewise planarity in volumetric 3D reconstruction.

Probabilistic Foundation for MVS [1]

Each voxels contains two r.v.:

$o_i \in \{0,1\}$ occupancy

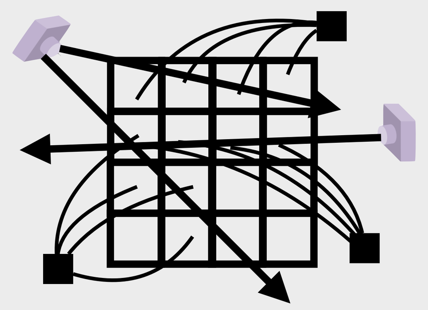
$a_i \in \mathbb{R}$ cont. color

Image formation:

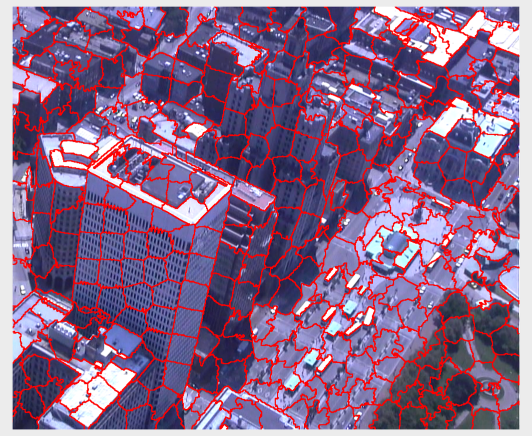
pixel records first occupied voxel's color

Ray potentials penalize deviations of the model from the input images:

$$\psi^{\mathbf{a}}_r(\mathbf{o}_r,\mathbf{a}_r) = \rho(I_r - \mathbf{I}(\mathbf{o}_r,\mathbf{a}_r))$$



Model



superpixel segmentation

Each segment $s \in \mathcal{S}$ contains two r.v.:

$p_s \in \{0,1\}$ planarity

$\mathbf{n}_s \in \mathbb{R}^3$ plane parameters

Each pixel contains a depth r.v.: d_r

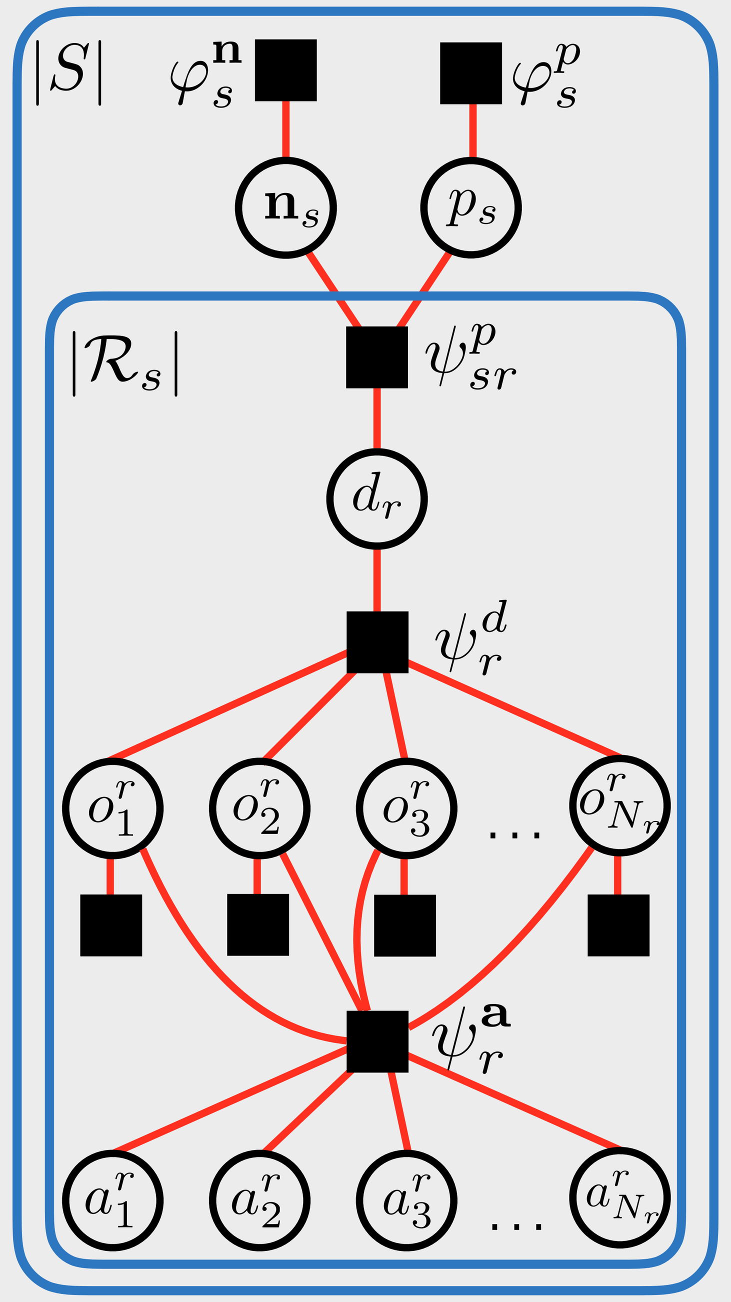
plane-depth potential
$$\psi^p_{sr}(d_r,p_s,\mathbf{n}_s) = \begin{cases}\exp(-\lambda_p\,\eta(d_r - D_r(\mathbf{n}_s))) & \text{if } p_s = 1\\ 1 & \text{otherw.}\end{cases}$$

depth-ray potential
$$\psi^d_r(\mathbf{o}_r,d_r) = \begin{cases}1 & \text{if } d_r = \sum_{i=1}^{N_r} o^r_i \prod_{j<i}(1-o^r_j)\, d_{ri}\\ 0 & \text{otherwise}\end{cases}$$

plane pose prior
$$\varphi^{\mathbf{n}}_s(\mathbf{n}_s) = \sum_{k=1}^{K} w_k\, \mathcal{M}\left(\frac{\mathbf{n}_s}{\|\mathbf{n}_s\|}\,\middle|\,\mu_k,\kappa_k\right)$$

$\mathcal{M}$: Von Mises-Fisher distribution

segment planarity prior
$$\varphi^p_s(p_s) = \exp(\lambda_s\,|\mathcal{R}_s|\,p_s)$$



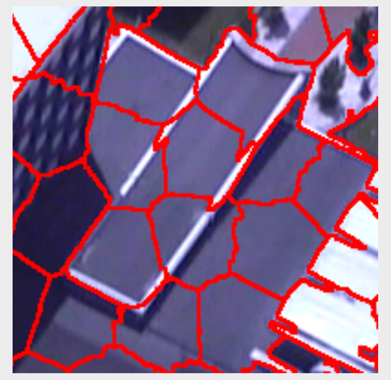
$$p(\mathbf{o},\mathbf{a},\mathbf{d},\mathbf{p},\mathbf{n}) = \frac{1}{Z}\underbrace{\prod_{i\in\mathcal{X}}\varphi^o_i(o_i)\prod_{r\in\mathcal{R}}\psi^{\mathbf{a}}_r(\mathbf{o}_r,\mathbf{a}_r)}_{[1]}\prod_{s\in\mathcal{S}}\underbrace{\varphi^p_s(p_s)}_{\text{planarity prior}}\underbrace{\varphi^{\mathbf{n}}_s(\mathbf{n}_s)}_{\text{plane pose prior}}\prod_{r\in\mathcal{R}_s}\underbrace{\psi^d_{sr}(d_r,p_s,\mathbf{n}_s)}_{\text{plane-depth potential}}\underbrace{\psi^d_r(\mathbf{o}_r,d_r)}_{\text{depth-occupancy potential}}$$

Inference

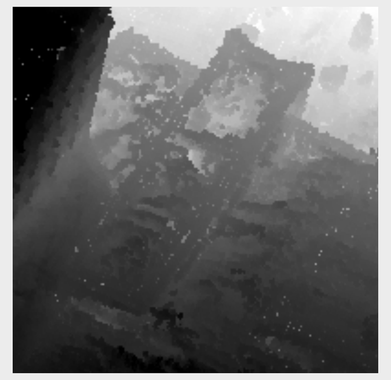
We use discrete-continuous sum-product belief propagation for inference.

For the cont. plane parameters, we use particle BP. Plane particles are generated by

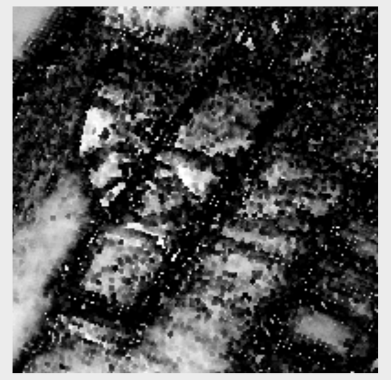
- Sampling from plane pose prior
- Fitting planes to the current depth estimates in the segment



segmentation



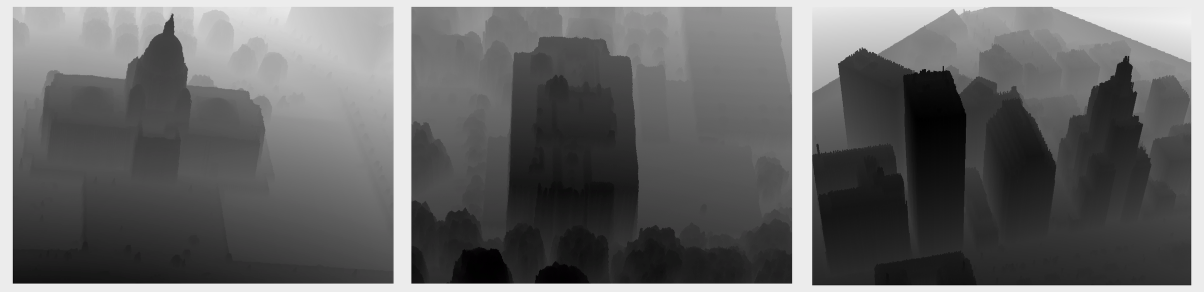
depth map

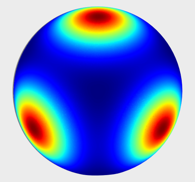


depth entropy

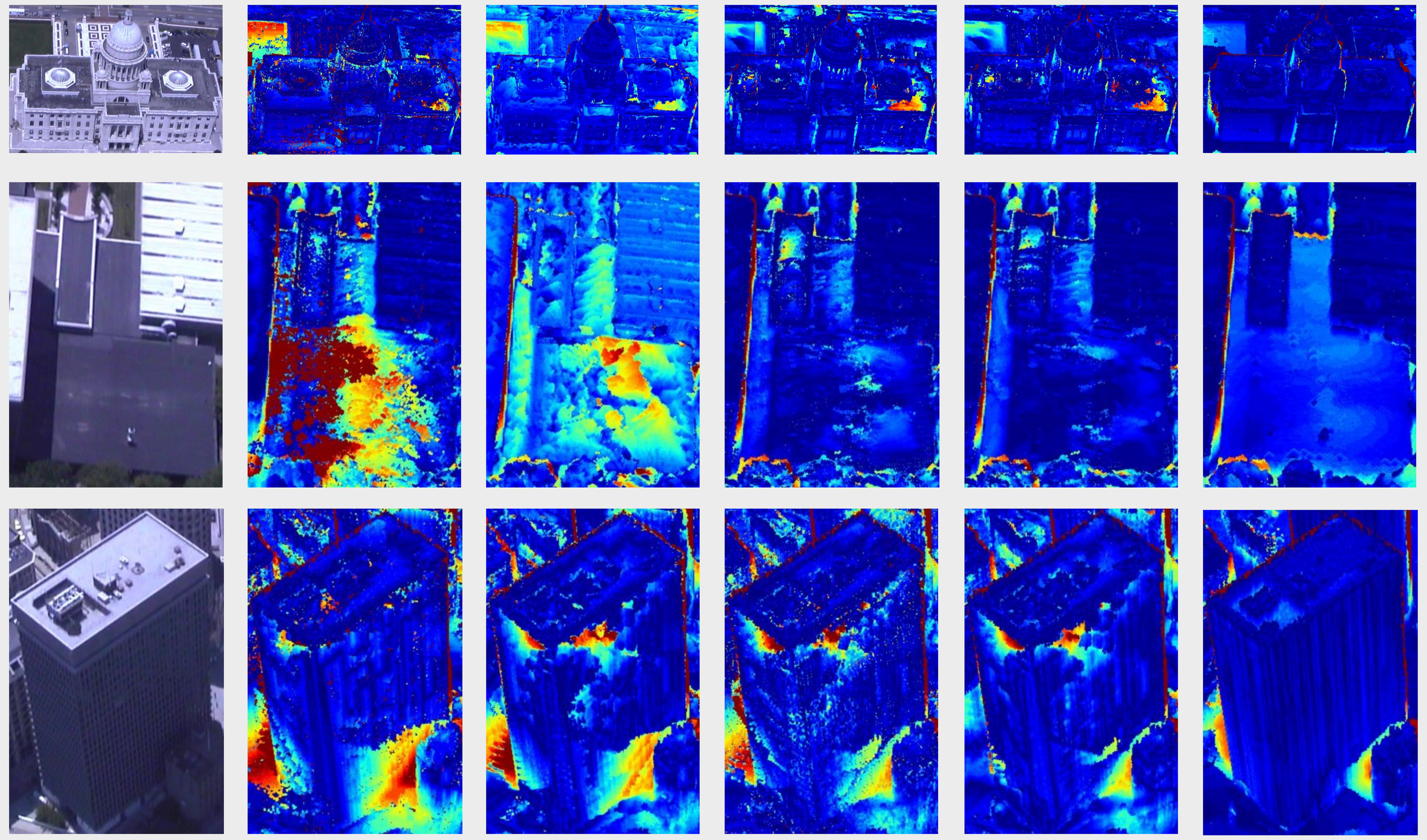
Experiments

Aerial datasets
~200 images
LIDAR ground-truth



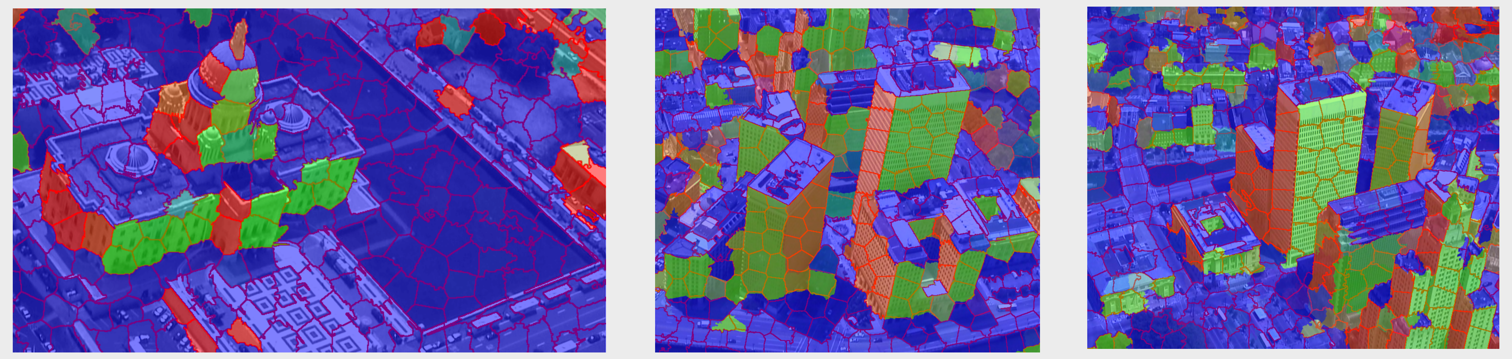


Manhattan world plane pose prior



Ref. image [3] [2] [1] [1]+Pairwise Ours

Most likely plane normal visualization



References

[1] Ulusoy, Geiger and Black: Towards Probabilistic Volumetric Reconstruction using Ray Potentials; 3DV 2015 - Best Paper Award

[2] Pollard and Mundy: Change detection in a 3-d world; CVPR 2007

[3] Liu and Cooper: Statistical Inverse Ray Tracing for Image-Based 3D Modeling; PAMI 2014

code online