We learn image adaptive filters. This generalizes DenseCRF and enables bilateral CNNs.

Code: http://bilateralnn.is.tuebingen.mpg.de

Learning Sparse High Dimensional Filters: Image Filtering, Dense CRFs and Bilateral Neural Networks

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1 Sparse High Dimensional Filtering

Problem: Learn filters in high dimensional space

For example, Bilateral Filtering an input $v$, and features $f_v$:

A common choice is pixel position and color: $f = (x, y, r, g, b)$.

2 Learning Permutohedral Lattice Filters

We use the permutohedral lattice from [2].

Parameterize the filter kernel instead of using Gaussian. We also generalize to non-separable filters.

Learn permutohedral filter via stochastic gradient descent.

3 Single Filter Applications

1. Joint Bilateral Upsampling: Upsample a low-resolution result using a high-resolution guidance image [3].

2. 3D Mesh Denoising

Mean-field inference in densely connected CRFs is tractable [4]. It reduces to bilateral filtering:

In [4]: Gaussian edge potentials:

$\psi_v(x, z) = \frac{1}{\sqrt{2\pi \sigma}} \exp(-\frac{(x-z)^2}{2\sigma^2})$.

4 Generalization of DenseCRF

In [4]: Gaussian edge potentials:

$\psi_v(x, z) = \frac{1}{\sqrt{2\pi \sigma}} \exp(-\frac{(x-z)^2}{2\sigma^2})$.

Here: Learn pairwise potentials with back-propagation through truncated message passing.