Markov Random Fields and Gibbs Sampling for Image De-noising

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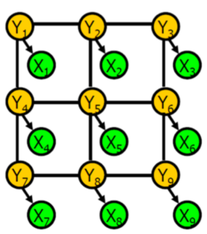
Motivation

- High-order MRFs are more expressive.
- Filters like Gaussian blur are deterministic. Gradient ascent needs careful initialization and converges to suboptimal. Gibbs Sampling provides exploration, and does not require sophisticated initialization.
- There might be some patterns that pixels within a window tend to show.

p($y|x$)



Related Work

- MRF: $\mathrm{p}(Y_{ij}) = \frac{1}{Z}\exp\left(-E(Y_{ij})\right)$.
- Metropolis-Hastings for Markov Chain Monte Carlo. $A(x'|x) = \min\left(1, \frac{P(x')Q(x|x')}{P(x)Q(x'|x)}\right)$.
- Ising, Potts, hierarchical MRF models.
- Roth & Black: Fields of experts for learning image priors.
- McAuley et al: High-order MRF priors of color image.
- Barbu: Active Random Fields.

New Technique

- Tested different neighbor sizes, found that using 9 neighbors (3×3) is generally better than using 5 (pairwise) or 25 (5×5).
- Define energy as loss + prior + score.
- $E(Y_{ij}) = \sum_{X\in N(Y_{ij})} \| Y_{ij} - X \|_{n_1}^{n_1} + \lambda \sum_{Z\in N(Y_{ij})\setminus X_{ij}} \| Y_{ij} - Z \|_{n_2}^{n_2} + \beta\, \psi(Y_{ij})$.
- For loss, L_1 norm has higher PSNR, but L_2 norm has better visualization. Lorentzian is robust to outliers, and can provide smoothing.
- Applied sparse gradient and close-to-mean-of-neighbors priors.
- With the assumption that pixels within a window tend to have some patterns, defined 'score' as the dot product of patterns (filters) and pixels in window.
- By using first n principal components as filters and weighting dot products by variance explained, found that 'close to center' prior gives improvements.

Experimental Results