Graphical Models for Image Denoising

EE 367 Project Proposal

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1 Motivation

Probabilistic graphical models (PGM) such as Bayesian networks and Markov Random Fields has been widely used in many applications. Inspired from their interpretation power of dependencies, this project will focus on building various graphical models for image denoising tasks, through parameter learning of spatial dependencies in images. We can treat each pixel as a node in the graph, so there are two types of pixels here: the 'true' and the 'observed'. The goal would be to reconstruct each 'true' pixel from the noisy 'observed' ones.

2 Related Work

Markov Random Field (MRF) is a set of random variables (i.e., pixel values) having a Markov property described by an undirected graph [5]. A classic and simple application of MRF in image denoising is to assuming each observed pixel is related to the corresponding true pixel, and each true pixel is related to its four direct neighbors [4]. The next step would be to come up with a joint probabilistic distribution between the values in the noise image and the values in clean image. We either use prior knowledge or data to come up with this probabilistic distribution, and there are lots of models such as Gaussian distribution.

Another good example would be Non-local Bayes (NL-Bayes) [3], an improved variant of Non-local Means (NL-means) [2], by evaluating for each group of similar patches a Gaussian vector model. It achieves a PSNR value close to state of the art algorithms such as BM3D.

Bayesian Network (BN) represents a set of variables and their conditional dependencies via a directed acyclic graph (DAG) [1]. Suffered from the fact that it is more difficult to learn parameters, BN is less common than MRF in this field.

3 Project Overview

This project focuses on building image denoising models for natural images. I will start by comparing existing models. After that, I will try something novel: design and train a MRF that when reconstructing from an observed pixel, can take into consideration not only the four direct neighboring pixels, but also other 'not too far' or even 'any related' pixels as well. The reason is that within a 3 by 3 window of pixels, we can get information of edges, and this could help to avoid smoothing out 'true' sharp edges. The pixels to consider could depend on either location or correlation. A full Maximum A Posteriori (MAP) estimation will be performed for inference. I can start with a very dense one, and prune it while training. Also, the model need not be constrained to PGM, neural networks might help for finding features. I may try CNNs also.

PSNR and RMSE are the two major evaluation metrics, computation efficiency is also considered.

4 Milestones

Week 02/18 - 02/24: Examine and summarize existing works.

Week 02/25 - 03/03: Design Mathematical models for new structures.

Week 03/04 - 03/10: Build and test models.
Week 03/11 - 03/17: Optimization.

References

[1] Irad Ben-Gal. Bayesian networks. *Encyclopedia of statistics in quality and reliability*, 2007.

[2] Antoni Buades, Bartomeu Coll, and J-M Morel. A non-local algorithm for image denoising. In *Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on*, volume 2, pages 60–65. IEEE, 2005.

[3] Marc Lebrun, Antoni Buades, and Jean-Michel Morel. " implementation. *Image Processing On Line*, 2013:1–42, 2013.

[4] Stan Z Li. *Markov random field modeling in image analysis.* Springer Science & Business Media, 2009.

[5] Uwe Schmidt. Learning and evaluating markov random fields for natural images. *Master's thesis*, February 2010.