An Overview and Categorization of Bayesian Priors in Computational Imaging Applications

proposal by
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Introduction:

Some of the most common estimation and reconstruction problems in Computational Imaging are inverse problems, such as de-noising or de-blurring. These problems involve estimating or reconstructing an image after it has been exposed to a set of transformation. Often these problems end up becoming optimization problems. One of the most powerful additions and controls in the solutions to these problems, whether direct or iterative, are priors. Priors are mathematical representations of certain inferred or expected characteristics of an image. By adding these terms to the objective, one can tune the recovered image in powerful ways. However, there an enormous number of priors used in numerous applications. They range from simple magnitude regularization to more complex and recent priors. With such a large variety of priors, I believe it is important to categorize and compare how they may be used in common problems to see which perform best in which contexts. Furthermore, exploring which priors perform well together will also help provide a useful reference for individuals seeking to approach these pervasive and important inverse problems.

Related Work:

An enormous amount of work has been done in developing priors in Computational Imaging. The particular sources I will discuss are just simple examples that demonstrate the ubiquity of priors in computational imaging examples. The Venkatakrishnan et al example illustrates how many tradeoffs exist depending on which priors are used. The closest project I have found to this one is the work of Venkatakrishnan et al. I will describe how I will utilize their work in the methodology sections.

In addition to the **TV** prior, **Tikhonov** prior, and others discussed in class, here are two quick priors that are used in computational imaging application:

EPP – Edge Preserving Prior
For this prior I refer to Raj et al in their paper describing a method to help reduce noise and artifacts in MRI scan images. They discuss EPP as a spatial prior that specifically aids removing aliasing artifacts past the capabilities of the conventional spatial prior. While the common prior does an effective job in helping smooth the result, it does not have the precision that EPP has in still preserving edges.

SGLI – Spatial Gradient and Local Inhomogeneity prior
For this prior I refer to the Cheolkon et al paper. In this they utilize the SGLI prior. The first part of this simply uses the gradient in x and y to measure discontinuity. The more interesting part is the local inhomogeneity which uses a

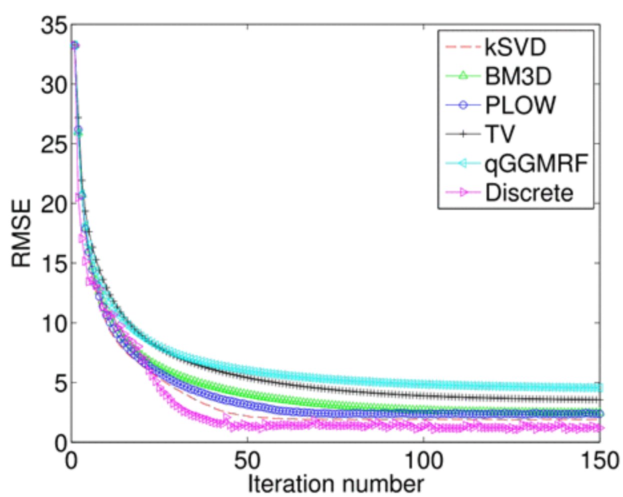
nonlinear transformation to extract a measure of inhomogeneity between local pixels. This prior is applied to reducing ringing artifacts in JPEG images.

Methodology:

First, I would like to briefly discuss the work done by Venkatakrishnan et al. They offer a close look at an approach I can take in my project. Although there work is in building an actually framework for applying priors, they still demonstrate categorization. I can use some of the approaches in their methodology of categorizing the six priors they look at.

Specifically, the main inspiration I take from the paper is the decision to apply various priors to the exact problem, data, and solution framework. This is how I will proceed with my categorization:

I will take priors that assume similar characteristics of an image and classify them into groups. Group by group, I will compare their results quantitatively by looking at RMSE and PSNR relative to a ground truth image. Additionally, I will do qualitative analysis on the resulting images by looking at them. Once I have tested the individual groups on a single problem with multiple images, I will change the type of problem/framework and try all the groups again. Additionally, I will mix and match different groups of priors to see how the combination of them does for certain problems. Finally, I will discuss the pairs of priors, problems, and frameworks that worked particularly well and make some hypothesis to why. I will categorize the rest for further reference.



An example from Venkatakrishnan et al. of what my analysis may look like. This is the comparison of the RSME convergence of six different priors that they compared on a denoising problem.

Milestones:

By the end of week 7

-I would like to have all the priors I am looking at categorized by type

-Furthermore, I would like to have collected a group of papers that explain how to implement each prior in a certain framework

By the end of week 8

-I would like to have implemented all the priors on at least one type of problem.

-I may use a problem from one of the homeworks to get started but would ideally like to use a larger scale problem

By the end of week 9

-I would like to have all the priors tested on multiple problems with combinations of priors where appropriate.

-I would also like to have begun starting on the report, putting together plots, images, and descriptions.

References:

1) Raj, A. , Singh, G. , Zabih, R. , Kressler, B. , Wang, Y. , Schuff, N. and Weiner, M. (2007), Bayesian parallel imaging with edge-preserving priors. Magn. Reson. Med., 57: 8-21. doi:10.1002/mrm.21012

2) S. V. Venkatakrishnan, C. A. Bouman and B. Wohlberg, "Plug-and-Play priors for model based reconstruction," *2013 IEEE Global Conference on Signal and Information Processing*, Austin, TX, 2013, pp. 945-948.

3) C. Jung and L. C. Jiao, "Ringing artifact reduction of JPEG images using a SGLI prior," *2011 IEEE International Workshop on Machine Learning for Signal Processing*, Santander, 2011, pp. 1-4.