Investigating Image Inpainting via the Alternating Direction Method of Multipliers

EE 367, Course Project Proposal

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Due Friday, 2/10/2017, at 12:00pm

1 Motivation

In many imaging applications, there exists potential for corruption of the images by sources of noise that completely lose original pixel information. It is important to be able to reconstruct the image as accurately as possible, to be able to convey the original image information. This process of reconstructing images that have large portions of their image completely lost, known as image inpainting, allows for the estimation and restoration of those missing pixels. A simple example of image inpainting can be seen below [1]. As can be seen in the image below, the inpainting process may leave some artifacts behind and is not usually perfect; in fact, the accuracy of the inpainting is typically related to one's choice of prior (*i.e.*, a total variation prior will typically work better on an image with sparse gradients than a least-squares prior will.)

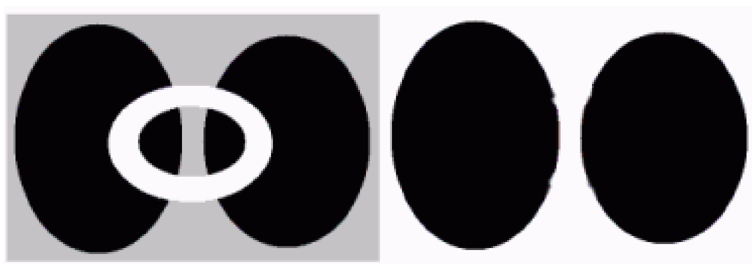

Figure 1: Two images of a pair of ovals, one with a white donut ring (left) and its inpainted counterpart (right.) Note the artifacts along the boundary of the inpainted ovals where the donut was inpainted.

2 Related Work

Recent work has been done in the field of efficient algorithms, and the alternating direction method of multipliers (ADMM) has been one of the more widespread algorithms used in the past few years [2], finding many applications in imaging, such as in deconvolution [3]. In addition, ADMM has been used as a solution guaranteeing fixed-point convergence for many denoising algorithms satisfying certain criteria [4]. These past works suggest that using ADMM in an image inpainting framework would yield an accurate solution to the image restoration problem for many classes of images (*e.g.*, for images with sparse gradients.)

3 Project Overview

In this project, I shall investigate image inpainting by investigating various priors — such as (but not limited to) the total-variation (TV) prior and the sparse (L1) prior — and developing optimization problems for the various priors. The choices of priors will be dependent on the classes of images used in this project. These priors will be used to formulate an optimization problem that will then be solved using ADMM. For each of these priors, and possibly a combination of them, I will implement the ADMM algorithm and compare it against competing algorithms for image inpainting. The metrics of comparison to be used will be the peak signal-to-noise ratio (PSNR) of the reconstructed image compared to the undistorted image, and the computation speed. In addition, the structural similarity index (SSIM) will be used as an alternative metric to quantify the similarities between the reconstructed image and the original image [5].

4 Milestones, Timeline, and Goals

4.1 Week 1

This week will be used to determine proper priors and images to investigate, and understanding their effect on the formulated optimization problem. By the end of this week, the goal will be to have a list of priors and a corresponding list of images (with different structures) to try to apply to the optimization algorithm.

4.2 Week 2

This week will be devoted to implementing the algorithms and determining which priors work best, and how a possible combination of priors can be used to make a more accurate reconstructed image. In addition, I will be testing the priors on various images to see if certain priors work significantly better on certain classes of images. By the end of this week, the optimization problem should be completely formulated.

4.3 Week 3

This week will be devoted to comparing the formulated optimization problem to other variations of the optimization problem and formally acquiring the metrics discussed in the Project Overview. In addition, work on the report and poster presentation will start in this week. By the end of this week, the goal is to be completely finished with the project's technical work.

4.4 Week 4

By the start of this week, the technical work on this project should be complete. This week will focus on finishing the report and poster presentation.

References

[1] A. Telea, "An image inpainting technique based on the fast marching method.," *Journal of Graphics Tools*, vol. 9, no. 1, pp. 23–34, 2004.

[2] S. Boyd, N. Parikh, E. Chu, B. Peleato, and J. Eckstein, "Distributed optimization and statistical learning via the alternating direction method of multipliers," *Found. Trends Mach. Learn.*, vol. 3, pp. 1–122, Jan. 2011.

[3] G. Wetzstein, "EE 367 / CS 448I Computational Imaging and Display (Winter 2017) Notes: Image Deconvolution (lecture 6)," January 2017.

[4] S. H. Chan, X. Wang, and O. A. Elgendy, "Plug-and-play ADMM for image restoration: Fixed point convergence and applications," *CoRR*, vol. abs/1605.01710, 2016.

[5] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, "Image quality assessment: From error visibility to structural similarity," *IEEE Transactions on Image Processing*, vol. 13, no. 4, pp. 600–612, 2004.