EE367 final project

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1 Motivation

Alternating Direction Method of Multipliers (ADMM) and Half-Quadratic Splitting (HQS) have been shown to perform well in solving the problem of image deconvolution [3]. These algorithms are attractive due to their performance, efficiency, and flexible choice of priors. Simultaneously, diffusion-based models such as StableDiffusion[2] have emerged as powerful tools for text-conditioned computational imaging tasks such as inpainting, denoising, and image generation. As diffusion models are inherently trained to perform denoising, this project seeks to explore their potential in conjunction with ADMM and HQS for image deconvolution.

This project is motivated by the hypothesis that the integration of diffusion models with ADMM and HQS can enhance image deconvolution performance beyond other priors such as total variation and DNCNN by incorporating text prompts. The unique ability of diffusion models to incorporate text-based conditioning offers an additional dimension of contextual information that could be beneficial in challenging deconvolution scenarios. This project aims to systematically evaluate the efficacy of this integration and to understand how text prompts can influence the denoising process.

2 Related Works

Patel et. al.[1] and Zhu et. al[4]. both showed good performance of diffusion models in conjunction with HQS and ADMM respectively for performing image deconvolution. Patel achieved this performance by applying a pretrained diffusion model for a decreasing denoising number of steps as the the number of ADMM iterations increased. However, neither team tested the use of text prompts to condition the denoising networks. We will test if the addition of text prompts help to increase performance.

3 Method

Our method we be done in a few simple steps. First, we will find a suitable dataset of images with text pairings. Most likely, we will use a subset of the

COCO captions dataset. Building off of the starter code for HW6, we will take some baseline statistics of HQS and ADMM with total variation and DCNN recording statistics such as PSNR for the dataset. Once this is complete, we will use pretrained, off-the-shelf versions of diffusion models to try and replicate the results of the related works in using diffusion models as the prior for HQS and ADMM. Finally, we will include the image captions in our dataset as the text prompt for conditioning the pretrained diffusion models and compare the results with the previously established baselines. We will provide both qualitative and quantitative evaluations of performance for all methods.

4 Timeline

- March 1: Establish baselines on COCO and implement ADMM/HQS with diffusion models
- March 8: Have results of baselines + diffusion with and without captions
- March 15: Do experiments modifying prompt structure and other diffusion hyperparameters

References

[1] Zakaria Patel, Akash Haritas, and Kartikaeya Kumar. Deconvolution using admm with diffusion denoising prior, 2022.

[2] Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. High-resolution image synthesis with latent diffusion models. *CoRR*, abs/2112.10752, 2021.

[3] Singanallur V. Venkatakrishnan, Charles A. Bouman, and Brendt Wohlberg. Plug-and-play priors for model based reconstruction. In *2013 IEEE Global Conference on Signal and Information Processing*, pages 945–948, 2013.

[4] Yuanzhi Zhu, Kai Zhang, Jingyun Liang, Jiezhang Cao, Bihan Wen, Radu Timofte, and Luc Van Gool. Denoising diffusion models for plug-and-play image restoration, 2023.