ENHANCING AND REVEALING HIDDEN IMAGE DETAILS

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MOTIVATION

To see more in an image than initially possible. In countless real-world scenarios, image details are deliberately or unintentionally obscured, creating significant challenges for accurate interpretation. In Formula 1, as an example, teams strategically release promotional images of their cars during the development period to excite the fans while concealing key aerodynamic and mechanical developments from their competition. Strategies include camouflage liveries, plays on perspective, deepening of shadows, and simply applying blur to a specific portion of the image. In a similar vein but without intention, forensic experts often rely on low-quality surveillance footage to capture vehicles and subjects of interest. However, footage quality can be so poor that crucial details, such as vehicle make, model, and license plate and subject identifying features and clothing patterns, are indiscernible. The need is to enhance aspects of the images that allow extraction of critical details. The challenge lies in developing a robust computational method that sharpens the desired targets while minimizing hallucinated artifacts. This project aims to explore methods of image enhancement to reveal hidden features of images while maintaining authenticity and fidelity.

RELATED WORK

Several computational imaging techniques, ranging in complexity, exist for sharpening and recovering obscured features in images. One category of techniques is filtering. On the simpler end of the range, gaussian filters (local, linear smoothing) or median filters (local, nonlinear) can improve an image perceptually but do not often enhance features already obscured. Slightly more sophisticated filters that emphasize edges include anisotropic filters, which utilize orthogonal convolution, bilateral (or neighborhood) filters, which consider local neighborhoods and similar intensities, and non-local means filters, which exploit natural patterns in images [1, 2]. Further complexity and performance can be found in the block matching 3D (BM3D) method which finds similar image patches and groups them into blocks which undergo discrete cosine transforms, thresholding, and inverse transforms [3].

Another category of image enhancing is deblurring. Weiner deconvolution is a common technique which combines inverse filtering with an SNR damping factor. An alternative approach, the Richardson-Lucy (RL) deconvolution works iteratively assuming a Poisson noise model found in low-light conditions [4, 5]. These techniques suffer from needing to know information about the noise kernel. Blind deconvolution techniques attempt to amend this prior by using a normalized sparsity regularizer, iteratively [6].

A third category of image enhancement is tone mapping and frequency enhancement for improved contrast and edges. Tone mapping filters include the previously discussed bilateral filter and the more advanced local Laplacian filter [7,8]. Tone mapping techniques can also be examined in stages to extract details without the effect of color or base layers [7]. Similarly, a weighted least squares tone mapping approach coarsen images iteratively to extract multi-scale details [9]. Frequency methods include targeting specific spatial frequencies that are filtered out or amplified (ex. unsharp masking).

A final category of image enhancement (*not included in this project)* is the use of neural networks or numerical optimization algorithms for any of the previous objectives mentioned. Supervised learning models can work especially well for reconstruction (inpainting) of constrained cases, such as license plate reading, but are prone to hallucinations in the face of untrained objectives. More complex CNN's (particularly deep CNN's) can deblur, denoise, and even super resolve images [10-12]. Combining optimization methods, such as the half-quadratic splitting (HQS) method [13] or alternating direction method of multipliers (ADMM) [14], with different regularizers [15] or with dCNN's also works effectively for image enhancement.

Project Overview

The final goal of this project is to compile a set of image enhancement tools that can be effectively implemented across a number of real-world scenarios. Performance of each tool will be evaluated via PSNR, SSIM, and perceptual quality of a targeted area.

Timeline

- **Week 1** – Select dataset for real-world examples. Determine effectiveness of deconvolution with unknown noise. Implement filtering methods, gaussian, median, bilateral, anisotropic, and non-local means. **Stretch Goal:** Implement BM3D.
- **Week 2** – Implement tone mapping techniques of bilateral and local Laplacian. Inspect tone mapped layers and frequency information of images. **Stretch Goal:** Weighted least squares tone mapping.
- **Week 3** – Refine previous methods and attempt stretch goal(s). Compare results with defined measures. Prepare presentation and write-up of project.

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