

ECE 6258 Project Progress Report

The goal of this project is to denoise several datasets of images and assess the effectiveness of multiple algorithms. This will be done through several IQA methods including PSNR, SSIM, CW-SSIM, UNIQUE, MS_UNIQUE, CSV, and SUMMER as well as the accuracy of image recognition models.

So far, we have assigned each other two datasets and have downloaded them. Nick will be working on the Cure-OR and SSID datasets while Mohit will be working on the Cure-TSR and Set-12 datasets. We have both downloaded the Cure-TSD dataset and will decide who will be working on this one after we have success with the first two. We have also reviewed and decided on four denoising algorithms: NLM (Non-local means filter), Trilateral Weighted Sparse Coding (TWSC), Multi-channel Weighted Nuclear Norm Minimization (Multi-channel WNNM), and Trainable Nonlinear Reaction Diffusion (TNRD). We divided the algorithms evenly between the two of us and have downloaded and reviewed code from github that implements these algorithms. Lastly, we downloaded and reviewed the two image recognition models that will supplement our IQA methods in deciding algorithm effectiveness through classification accuracy for CURE-OR, CURE-TSR, CURE-TSD.

The denoising algorithms we plan on exploring are Non-local means filter(NLM), Trilateral Weighted Sparse Coding(TWSC), Multi-channel Weighted Nuclear Norm Minimization(WNNM), and Trainable Nonlinear Reaction Diffusion(TNRD). NLM is an algorithm that involves using a NL means filter to generate an output, which then goes through a wavelet decomposition, thresholding, and wavelet reconstruction process [1]. TWSC extends the central assumption of most denoising algorithms, which is that the noise is additive white gaussian noise. It involves using three weight matrices into the data and regularization terms in a linear equality-constrained problem [2]. WNNM involves using non-local self-similarity techniques to create a convex realization of the low rank factorization problem [3]. TNRD involves using optimal nonlinear reaction diffusion models, which is very flexible and efficient to learn on parallel GPUs. The nonlinear differential equation proposed involves propagating the convolution of an image with a proposed image kernel [4]. These denoising algorithms will be explored in depth in the coming weeks so we understand the results when they are applied to our candidate datasets. In addition, these models have several parameters which can be tuned to yield different results; we plan on experimenting with those to gain a better understanding of the strengths and weaknesses of the given approaches.

Our plan moving forward is as follows. The first two weeks we will set up our environments and run the images through our denoising algorithms. The third week, we will run IQA and image recognition on the image outputs. During the fourth week we will collect results, gather insights, and decide if we want to pivot on any algorithms. This will give us two weeks before the project is due to make any tweaks that improve performance, create visualizations, and create our poster and paper.

Mohit Singh, Nick Witten
ECE 6258

Sources

- [1]<https://www.mathworks.com/matlabcentral/fileexchange/44090-image-denoising-based-on-non-local-means-filter-and-its-method-noise-thresholding?focused=3806802&tab=function>
 - [2]https://openaccess.thecvf.com/content_ECCV_2018/papers/XU_JUN_A_Trilateral_Weighted_ECCV_2018_paper.pdf
 - [3] <https://www4.comp.polyu.edu.hk/~cslzhang/paper/WNNM.pdf>
 - [4] <https://arxiv.org/pdf/1508.02848.pdf>
-
- <https://vciba.springeropen.com/articles/10.1186/s42492-019-0016-7>
 - <https://github.com/wenbihan/reproducible-image-denoising-state-of-the-art>