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Investigating Image Quality Loss in Filtering Gaussian Noise from Grayscale Low-light Photography

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ABSTRACT. Statisticians, as well as machine learning and computer vision experts, have been studying image enhancement through denoising different domains of photography, such as textual documentation, tomography, astronomical, and low-light photography. With the surge of interest in machine- and deep-learning, many in the computer vision field feel that current approaches for effective image denoising are moving away from statistical inference methods and, instead, moving into these subfields of artificial intelligence. However, this paper sheds some light on current applications that show how statistical inference-based methods and frameworks that rely on conditional probability and Bayes theorem are still prevalent today. We reconstruct a few inferential kernel filters in the R and python languages and compare their effectiveness in denoising RAW images. In doing so, we also surveyed Elon students about their opinion of a single filtered photo using the various methods. Many scientists believe that noise filters cause blurring and image quality loss so we investigated whether or not people felt as though improved denoising causes any quality loss as compared to their original images. Individuals assigned scores indicating the image quality of a denoised photo compared to its true no-noise image on a 1 to 10 scale. Survey scores for the various methods are compared to benchmark tests, such as peak signal-to-noise ratio, mean squared error, and r-squared, to determine if there were any correlations between visual scores and the benchmark results.

1. Introduction

We are surrounded by many naturally-occurring signals produced by our environment. As photographers, we specifically try to capture light signals during exposure. Even with the immense collection of advanced electronics found in today's average digital camera, these captured light signals are still prone to random noise from sources such as the camera's sensor or circuitry and as a response to qualities of the environment, like temperature. Of the environments in which photographers love to shoot, none resist noise as poorly as low-light environments do. As popular of a time as dusk is to capture, it can also be the most detrimental to image quality. Many researchers have spent much of their lifetime investigating methods for properly denoising image signals []. In doing so, standardized formulas have been developed for validating the effectiveness of these methods. However, past studies have reported that the benchmark scores typically associated with these methods are uncorrelated with the opinions of unbiased observers []. This was a motivation for our investigation of image quality.

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In studying image quality, we found that there is a void in computer vision literature surrounding visual perception of image quality in denoising methods. Additionally, our study differs from past work for three main reasons. First, we focus on the subdomain of low-light photography due to current interests surrounding this setting. This lead us to creating our own low-light image dataset to suit our environment. Second, we investigate quality of filtered grayscale images and from the perceptions of college students. This was for convenience and to offer a different perspective than previous studies have had. Lastly, we include the proprietary image denoising method in Adobe's creative cloud. This is by far the most accessible method to photographers and has also received a fair amount of criticism in the photography community, which made it an interesting addition to us.

In this paper, we evaluate five filter methods' performance on a single noisy photo. After implementing these filtering methods on a single image from our low-light dataset, we compare the benchmark scores of the filtered images, as well as perform a one-way ANOVA test on college students unbiased visual perception scores about the image quality of a filtered image in relation to its desired non-noisy state.

This paper is organized in the following way. In section 2, we describe the background surrounding the subdomain of signal denoising in computer vision and, in doing so, share the methods performed on our test image. Section 3 elaborates on our methodology and experimental design, which includes the benchmark dataset we created, the R Shiny App survey that was built, and the process in which are experiment was performed. Section 4 shares the results of the benchmark tests on the single image as well as survey participants perception of the filtered photos. Finally, in section 5 we discuss the conclusions that we draw from the study.

1.1. Background

Computer vision is believed to be driven by two main pursuits for knowledge. From one perspective, scientists look to model human vision processes. Interest surrounds mimicking common human ability and understanding how human perception and comprehension occurs. On the other end of spectrum, scientists look to improve autonomy in machines and perform advance tasks, such as identifying objects or understanding dynamically-changing scenes, unrelated to understanding how human vision works (Zhang, 2015). They inevitably overlap at times, but these motivators are what drive the study of vision in computer science. The field is said to have emerged partly as a result of Larry Robert's thesis at MIT, where he introduced the concept of extracting 3-dimensional shapes from 2-dimensional images using "line drawing" to retrieve edge information (Roberts, 1963). Many scientists would follow in his footsteps in studying a subdomain of computer vision that is today known as edge detection. Self-driving vehicles are some of the newest technology that require advanced methods for scene understanding that mimic human perception, while also performing many other processes that go beyond our human capability, like tracking distance from other vehicles.

The study of noise removal would be motivated by the latter pursuit. Signal denoising experts look to filter noise to improve pre-processing for machine autonomy and a broad scope of other science processes. Image denoising has been used to cleanup tomographic photos for electron identification (Fernandez, 2009). It has also been used to process and cleanup many other signals, including electronic hisses, magnetized particles from magnetic film, tendrils and candlesticks from stock market data, and grain from satellite images. The specific study of digital image denoising emerged following the invention of the first charge-couple device camera in 1975. (NEED TO ADD MORE ON THIS HERE)

There are many heuristic methods for noise removal, but none have been able to fully denoise a scene to this date. Competition in the field emerged for the title of ”best-approach”. Noise reduction is computationally demanding though so methods are judged by both, their effectiveness and running-time. (NEED TO ADD MORE ON THIS HERE)

In this paper, we explore the effectiveness of a few of the most common noise removal methods shared by all sciences, but for the purpose of cleaning up Gaussian noise grain from low-light images.

1.2. Filter Methods

As mentioned earlier, the study was conducted using five of the most common image denoising methods. They include the bilateral filter, the non-local means filter, the three-by-three mean filter, and two levels (50% and 100%) of the Adobe Lightroom CC denoise filter. Each method will be dissected in this section

2. Methodology

Insert. (Include study conducted under IRB approval)

3. Experiment Results

4. Discussion

5. Conclusion and Future Work

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The work on this article would not be possible without the work of all the people involved in LaTeX typesetting.

Appendix A. Some additional comments

If something needs to go in the appendix, it comes here.

Appendix B. Even additional comments

If one appendix is not enough, additional material can be put here.

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