A non-invasive approach to noise reduction through image fusion

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Abstract:

Noise is an unavoidable problem in photography caused by a shortage of light reaching the sensor in an image's darker areas. While noise is most often noticed in dark images taken at night or in dimly lit rooms, it's also apparent in the shadow areas of daylight images. As high-quality prints show close to a full luminosity range (~10 to ~243 depending on paper type), any noise present will generally show up in print which presents a problem even in well exposed images. Several methods have been used in the past to reduce noise to include multi-image stacking, classic neighborhood-based noise reduction algorithms, and HDR techniques.

Each of the previous noise reduction techniques can be characterized as opinionated as they either reduce noise at the expense of detail or, in the case of HDR, the input image is dramatically changed. Changing the quality of the input image in a way that is perceptually different from what the camera takes in through the sensor means that photographers must consider and adjust for trade-offs when selecting and applying noise reduction techniques.

One of the answers to this problem used in mobile phone photography is performed by merging multiple identical images taken in a short time period to average out the noise. This has been done to great effect; however, it is limited by the need for many images in order to work effectively.

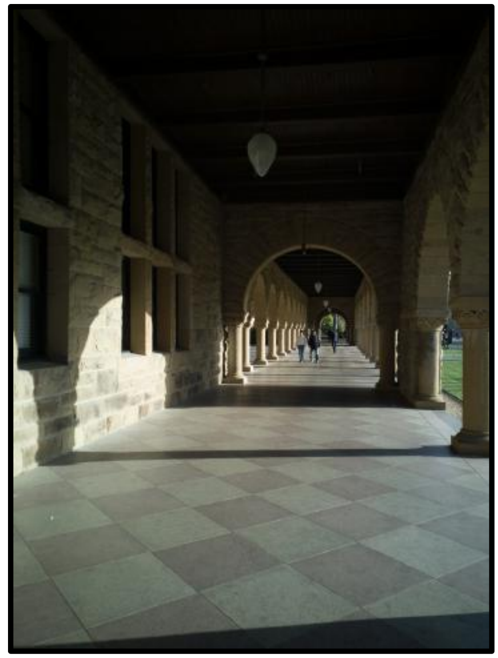
Introduction:

In this research I demonstrate a simple solution to noise reduction that takes advantage of two image frames rather than neighborhood pixel analysis as seen in classic noise reduction techniques. I'll discuss the benefits, drawbacks, and use-cases of my technique after presenting the following method.

The method in this paper evolves and programmatically executes photography methods used in practice for commercial and landscape photography making use of luminosity masks; however, this application in the use of noise reduction is a product of my own experience as an architecture photographer. A luminosity mask is a grayscale image used to target different tonal ranges when editing or blending photos together.

In order to attain the highest image quality when manipulating shadows, a photographer can layer a brighter image into the shadows of an even exposure to bring out shadow detail rather than increasing the brightness of the original image (in turn exposing noise). In a studio this masking technique can produce a very high-quality image without noticeable noise in a controlled environment. The application of this technique in photoshop, however, can be costly in terms of editing time or requires the creation of custom "actions" by those who understand luminosity masks and have a need for this technique. In my research I've modified this technique to make a general-purpose image fusion algorithm that doesn't invasively modify image content and attempts to preserve the original image as it was captured while reducing artifacts and color loss caused by underexposure of the shadows.

The new technique I present will match exposures from an overexposed image to an evenly exposed image using an existing histogram matching function and pull shadow pixels from the overexposed image to be integrated into an evenly exposed image according to a luminosity mask. The resulting output will look nearly identical to the evenly exposed image with two important differences: the output image will contain the same noise levels of the overexposed image, and will bring back color lost from the underexposed areas of the image.



Even Exposure (image 1)

Overexposed (image 2)

Methodology:

To conduct experiments, I've selected suitable images from the google HDR+ Burst Photography Dataset. The requirement for input images to the algorithm are that each set of two input images must be of aligned, different exposures. Because most of the data set consists of repeated single exposures, only six images in the dataset were suitable for testing and four will be showcased as examples here. Future research and improvement to the project will necessitate a larger, more robust dataset.

Input:

The technique presented will require two input images: an evenly exposed image to merge into, and a brighter image to use for source pixels (images 1 and 2).

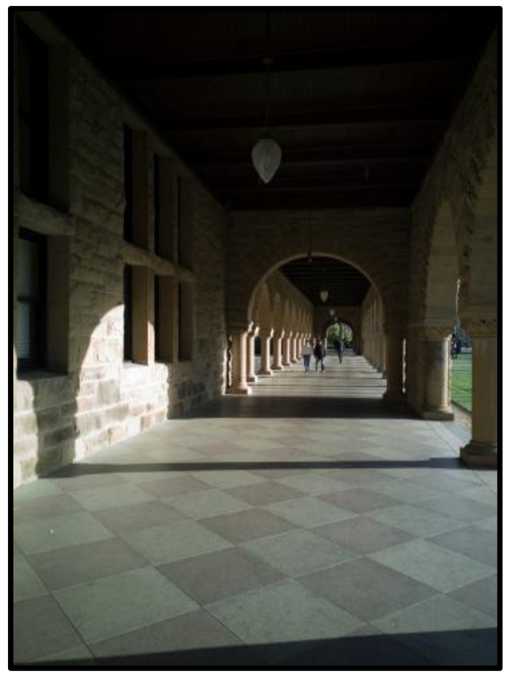
Luminosity / Alpha Mask

After collecting two aligned input files, first create a luminosity mask that targets the shadows and mid-tones of the brighter image without picking up any blown out or clipped pixels and smoothly transitions from blown out areas into the shadows. In OpenCV the easiest way to accomplish this is to convert the color image to grayscale and apply a lookup table that inverts the input image and applies contrast while compressing highlights and shadows. This will effectively prevent blown out areas of the overexposed image from coming through while targeting most of the shadow areas where noise occurs.

The lookup table in these examples is applied with input values of 0, 85, 170, 255, and output values of 255, 230, 35, and 0. These numbers were reached empirically through trial and error based on previous experience evaluating luminosity masks. Following this the points in between input and output are interpolated to generate the final lookup table that will be applied to the image mask (image 3).

Luminosity Mask (3)

Once a luminosity mask is created the next step of the algorithm is to bring the exposure of the overexposed image down to the exposure of the evenly exposed image. To do this I've used the skimage library's match_histogram function. Using this function on a blown-out image will cause artifacts in overexposed areas, however due to the method as seen later these won't be included in the final image.



Matched Exposure (4)

Now that the input images have the same exposure level the luminosity mask can be used to combine the two images together. In order to do this the luminosity mask needs to be normalized by dividing each pixel value by 255. This will allow each pixel in the mask to use a percentage of the pixels in each input image for the result where white pixels in the mask represent 100% and black pixels represent 0%.

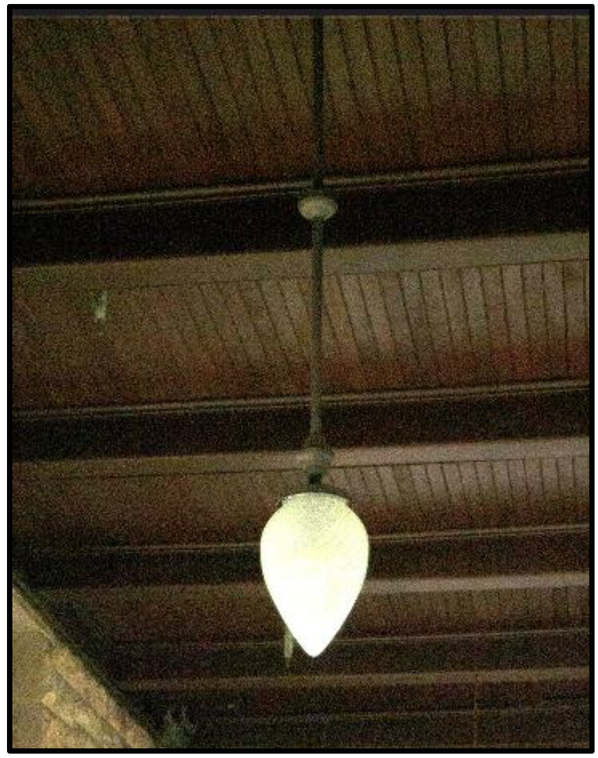
Merging the even exposure with the now-matched brighter exposure using the luminosity mask is represented by the following equation where alpha represents the luminosity mask. If a mask pixel is assigned .3, it will combine the two image pixels using 30% of the overexposed image, and 70% of the evenly exposed image.

merged_image = even_exposure * (1 - alpha) + (matched_exposure * alpha)

The resulting image will maintain the same characteristics as the even exposure with two important distinctions. The result will have less noise than the original image, and it will also contain richer color information in the shadows obtained from the brighter exposure. The image shadows can then be lifted afterwards and will contain the same or similar noise levels as the imported overexposed image. Residual noise patterns will remain in the image in some cases, but their effect is significantly reduced. The input and output images have had their exposure increased for the following example to see differences between input and output noise (Images 5 & 6). Following this page are three more examples. The last set was most likely to show artifacts as the exposures are close together, however no artifacts are apparent after adjusting the lookup table.

The sets are organized as follows: The images in the left column contain inputs and the used luminosity mask. On the right is the merged image at the top followed by the input and output images with identical exposure increases to compare color and noise of the input vs. the result.

Results:



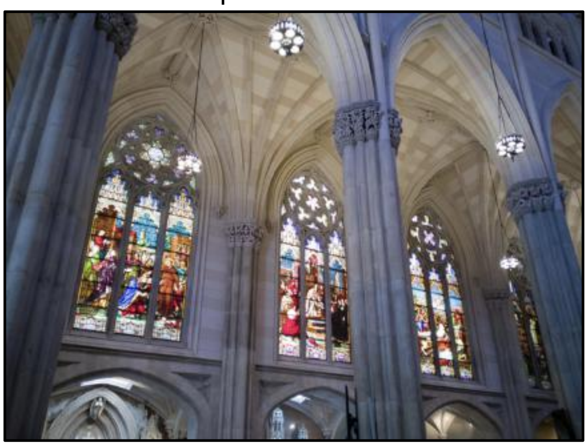
Input Image Brightened (5)

Output Image Brightened (6)

Results continued:


Input 1


Merged Image


Input 2


Brightened Input Crop


Luminosity Mask

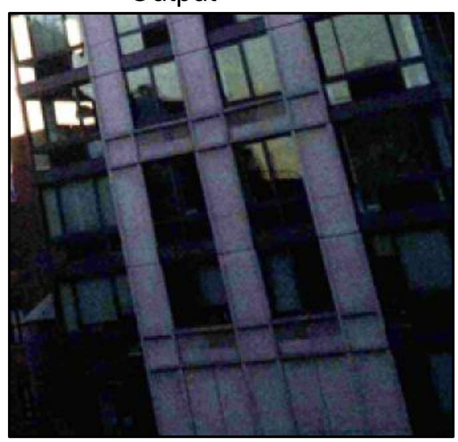

Brightened Output Crop

Results continued:

Input 1

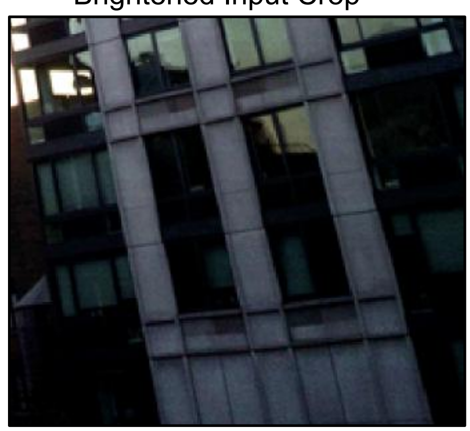
Output

Input 2



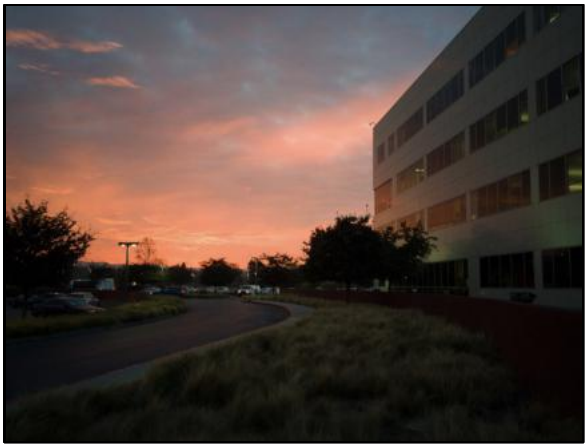
Brightened Input Crop

Luminosity Mask



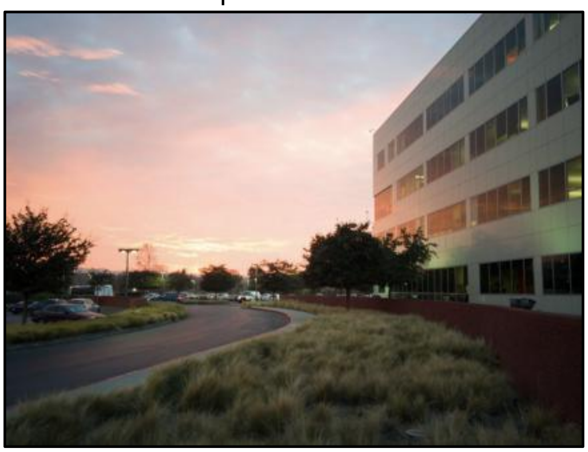
Brightened Output Crop

Results continued:



Input 1

Output



Input 2

Input Brightened

Luminosity Mask

Output Brightened

CONCLUSION

In summary this technique accomplishes noise reduction using the physics of the camera sensor rather than relying on algorithmic neighborhood-based noise reduction methods. Due to this distinction my method exhibits no loss of detail and recovers colors the sensor couldn't pick up well in dimly lit areas using a shorter exposure. From this photographer's perspective the method has no drawbacks when compared to classic noise reduction or multi-image noise reduction. As the resulting information is stored in a jpeg the file becomes much more resistant to degradation through exposure increases.

Given the benefits of the algorithm there are also drawbacks which will be discussed. As such, like any algorithm this is a tool meant to be used in conjunction with others and is not a replacement for other methods by any means.

There are a couple drawbacks to this method. If images are too close together in exposure, artifacts can occur due to the underlying histogram matching process. This has been mitigated in the test set, however it hasn't undergone further testing on a broader set of images. In limited situations it's possible the masking process won't properly isolate the highlights if there are no blown out areas in the brighter exposure. Another drawback is that this algorithm requires pre-alignment of images and doesn't adjust for frame movement or motion in the scene

Benefits to this algorithm are decreased noise, increased detail, increased color retention, lower space requirements than multi-image noise reduction, quicker hardware execution than multi-image noise reduction, and better image flexibility for jpeg format images in a significantly smaller package than raw files.

The last benefit to be mentioned is that the previous attributes are provided in a way that doesn't decide for the photographer what's best for their image and doesn't force compromises. The algorithm accomplishes noise reduction and doesn't get in the way.

Use cases for this algorithm include commercial advertising photography, iPhone photography, landscape photography, and more. The use cases are currently limited to still subjects, however modern deghosting and image aligning techniques could allow this to be used more broadly on moving subjects where sufficient shutter speed is available.

Future research on this project could include the fusion of more images to pull in even more dynamic range. Adding de-ghosting to make the images usable in more dynamic environments would be helpful. Using machine learning to build the correct luminosity mask for a given image would help with precision when deciding what will minimize the most noise without blowing out any highlights. Currently the algorithm is general purpose and doesn't maximize the benefits of this merging technique.

Sources Cited

Data set from Googles HDR+ Burst Photography Dataset: @article{hasinoff2016burst, author = {Samuel W. Hasinoff and Dillon Sharletand Ryan Geiss and Andrew Adams and Jonathan T. Barron and Florian Kainz and Jiawen Chen and Marc Levoy}, title = {Burst photography for high dynamic range and low-light imaging on mobile cameras}, journal = {ACM Transactions on Graphics (Proc. SIGGRAPH Asia)}, volume = {35}, number = {6}, year = {2016}, }