Image Blur Metrics

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Introduction

Blurring in images arises from a variety of sources, like atmospheric scatter, lens defocus, optical aberration, and spatial and temporal sensor integration. [1] Human visual systems are good at perceiving it. But the mechanism of this processing is not completely understood. Therefore, it is difficult to come up with metrics to estimate blur in images.

One can use conventional image quality metrics like Mean Square Error (MSE), Peak-Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) to perceive blur, but they are by definition reference based, which means that the system needs to have an idea of what an un-blurred image is. We therefore need metrics that can come up with absolute values for blur without the use of references.

I studied a set of papers describing reference-free metrics for estimating blur, listed in the references section. Of these papers, I implemented two based on using edge-detection algorithms (like Sobel filters), and then measuring blur based on the degree of smoothness of these edges. These include [3] and [4], which describe metrics based on average edge width, and cumulative probability of blur detection, respectively. I compared their results with each other and the SSIM metric.

Image Set

Currently, my image set consists of only grayscale images. The edge detection filters built into MATLAB detect only drastic changes in luminance, which restricted my set in this regard. In order to perform edge-detection in color images, we could use filtering algorithms that detect for drastic changes in delta E (in LAB colorspace), which correspond to human-perceivable changes in color. It must be noted that the structural similarity index may not work well for some color images, because it ignores color, and is really based on luminance and contrast.

I discuss two sample grayscale images (cameraman, boat) at different levels of blurring and different types of blurring in this report.

Figure 1. Cameraman image: Pillbox filter blurring achieved at filter radius 3 and radius 9.The first type of blurring is achieved by the use of a circular pillbox averaging filter the more the radius of the filter, the greater the blur. Figure 1 illustrates this.

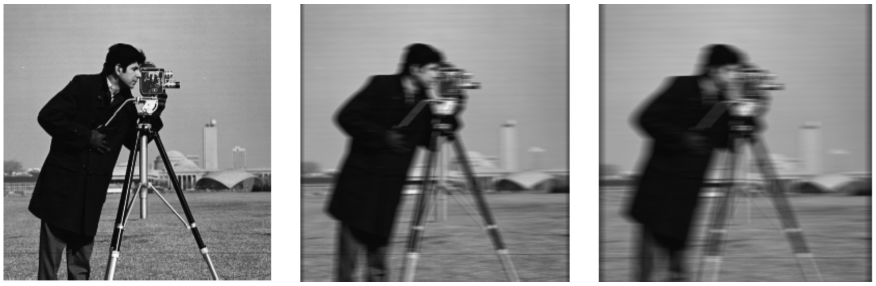


Figure 2. Cameraman image: Motion filter blurring achieved at length 9 and length 15.

The second type of blurring is achieved by the use of a filter that, once convolved with an image, approximates the linear motion of a camera by a certain length of pixels. Figure 2 illustrates this blurring at two different lengths.

Structural Similarity Index (SSIM)

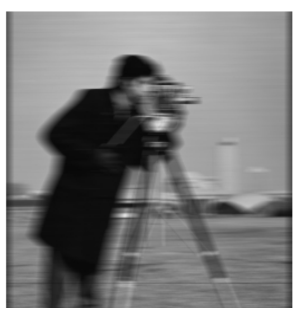
Structural similarity [4] is based on comparing the structure of two images after subtracting luminance, and normalizing variance. It has a good correlation with mean opinion scores, but it is not reference-free. Using the MATLAB code provided by the authors of [4], I obtained the following results for the two images:

(a). 100%

(b). 73%

(c). 54%

(d). 74%



(e). 67%

Figure 3. Cameraman image. Images (b) and (c) are pillbox blurred at radii 3 and 9, while images (d) and (e) are motion blurred at lengths 9 and 15.

Figure 3 illustrates the SSIM estimates for the image of the cameraman. 3(a) is a reference describing a perfect image. We see a good correlation overall ((c) is clearly the most blurred of all the images), but between (b) and (d), it is not immediately clear that (d) is about the same as (b) in terms of blurring. Most people would say (d) is more blurred. Similar results are seen in figure 4, where the 3%