The statistics of real-world images have been extensively investigated, in virtually all cases using low dynamic range (LDR) image databases. The few studies that have considered high dynamic range (HDR) images have performed statistical analysis over illumination maps with HDR from different sets (Dror et al. 2001) or have examined the difference between images captured with HDR techniques against those taken with single-exposure LDR photography (Pouli et al. 2010). In contrast, in this study we investigate the impact of dynamic range upon the statistics of equally created natural images. To do so we consider the HDR database SYNS (Adams et al. 2016). For the distribution of intensity, we observe that the standard deviation of the luminance histograms increases noticeably with dynamic range. Concerning the power spectrum and in accordance with previous findings (Dror et al. 2001), we observe that as the dynamic range increases the 1/f power law rule becomes substantially inaccurate, meaning that HDR images are not scale invariant. We show that a second-order polynomial model is a better fit than a linear model for the power spectrum in log-log axis. A model of the point-spread function of the eye (considering light scattering, pupil size, etc.) has been applied to the datasets creating a reduction of the dynamic range, but the statistical differences between HDR and LDR images persist and further study needs to be performed on this subject. Future avenues of research include utilizing computer generated images, with access to the exact reflectance and illumination distributions and the possibility to generate very large databases with ease, that will help performing more significant statistical analysis.

References


Figure 1. (A) The median luminance of an image after it has been normalized to between zero and one against the dynamic range of the image (\(DR = \text{max}(I)/\text{min}(I)\)) computed prior to normalization. (B) The average histogram for low, median and high dynamic range images using the brackets shown in the inset. Each image has been normalized to between zero and one and the histogram sampling was logarithmic. (C) To be consistent with the literature we compute the histogram of \(\ln(I)\)-mean(\(\ln(I)\)).

Figure 2. We fit a first and second order polynomial to the power spectrum of each image (examples in Figure 3). (A) The best fitting leading coefficient is negatively correlated with dynamic range and substantially below zero for high dynamic range images meaning that such images are not scale invariant. (B) The rms error between the first and second order fits as a function of dynamic range. Clearly the first order fits are poor at high dynamic ranges.

Figure 3. Three example images. In the left column we shown the linear images, in the rightmost column we show the images passed through an exponent of 0.33 to increase the visible information. The central column shows the power spectrum sampled at log intervals (black dots) and the best fitting first order polynomial (red line) and the best fitting second order polynomial (yellow line). The first row shows an image where scale invariance holds, the second row, an image with a mild failure, but no direct light source. Such images are common. The third row, is an image taken into direct sunlight and shows an extreme failure of scale invariance.