

Massively Parallel Exact Histogram Equalization

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Histogram specification is performed by transforming an image so that the image's histogram matches a target histogram. When the target histogram is uniformly distributed this is called histogram equalization. Histogram equalization is a common technique in increasing the contrast of an image. Besides being used to increase the contrast of an image for human visualization, it is frequently used as an early step in image segmentation, pattern or object recognition, and other similar procedures to increase the quality of the method's results. The classic method of histogram equalization is typically fine for human perception, but it results in a loss of information when applied to digital images. When used as a preprocessing step for algorithms, e.g. image segmentation, it reduces the quality of the results. Exact methods of histogram specification, although much slower, result in much less loss of information (with a goal of losing no information and being a completely invertible operation) and therefore are preferable to the classic method as a preprocessing step. Since exact histogram specification are orders of magnitudes slower than the classical methods, applications such as real-time medical imaging that require histogram equalization as a part of their image processing currently must use the classical method. This project adapts exact histogram equalization methods to run on graphics processing units (GPUs) to greatly increase their speed. The use of the adapted methods would make general applications of histogram equalization less time consuming and make use of exact histogram equalization methods viable for real-time imaging applications along with increasing the speed of large-scale machine learning applications.

Classical exact histogram equalization is completed in two steps. First the transform of an image's histogram to an equalized histogram must be calculated, then the transform can be applied to the image to obtain an equalized image. The first step requires information about every single pixel within the entire image so it cannot be parallelized well. However, the application of the transform to the image is embarrassingly parallelizable. Exact histogram equalization was first solved for digital images in [3]. The general approach is to establish a strict ordering for every single pixel, usually by computing additional information for each pixel. In practice, most methods cannot establish perfect strict orderings for large images, but do establish near-strict orderings. After the strict ordering is established, the pixels are sorted. Finally, the equalization transformation is calculated using the sorted histogram and the transformation is applied to the image. Exact equalization methods are mainly differentiated by the way the pixels are made to be strictly orderable. Every exact histogram specification method can benefit from moving the sorting and application of the transform onto GPUs. GPUs give a great speedup with sorting and the application of the transform can be parallelized by using a binary search for the sorted order for each pixel allowing every pixel to be processed in its own thread. In order to make exact histogram equalization methods benefit even more from running on GPUs, each method's approach to strict ordering must be split into separate smaller processes that can run in parallel on each pixel of an image. The method suggested in [3] uses expanding mean filters to make an image strictly orderable. Instead of computing the mean filters across the entire image, we can compute the mean filter around each pixel in its own thread. Any other exact histogram specification method based on convolutions can use a similar approach. A more modern method tries to reconstruct the original real-valued version of the image using a variational approach based on a very fast minimization method; the iterative nature of

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50 this process allows for improved results with increased iterations [4]. Similar to the first method we must do
51 computation separately around each pixel instead of across the entire image. However, between iterations
52 the GPU must be synchronized across all pixel computations since each iteration requires the previous one's
53 results.

54 There are many different methods of exact histogram equalization such as ones based on convolutions,
55 wavelets, or variational approaches. Since these methods have different approaches, each must be adapted for
56 use on the GPU separately; no single solution will work for all of the exact methods. By using the adapted
57 methods for the GPU, the speed of exact histogram equalization is significantly improved to the point that
58 even very large images (2560x1920) can be processed at 100 frames per second (FPS) while maintaining the
59 quality of the results. Previous implementations only achieved about 0.3 FPS for that size of images.

60 Additional Key Words and Phrases: image processing, strict ordering, exact histogram specification, histogram
61 matching, histogram equalisation, gpu programming

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