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There are many algorithms in digital image processing field to enhance the contrast. Most of them can be categorized as linear and non-linear methods. Linear methods are easy to implement and fast as well. However, they cannot enhance the image properly when there is a large variation in intensity across different objects in an image.

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Normalization

How Normalization works?

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Normalization is often used on images acquired with a digital camera. When taking pictures in low light, the exposure time may be increased, which can result in some of the features of the image being too dark while others are too bright. In such cases, normalization can be applied to get rid of this problem. The different features, such as shadows and highlights, may also be normalized individually so that each of them has a value within the set limits.

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Literature review:

"What is the best algorithm to identify optic disc location in fundus images?" Several different methods have been studied to try and solve this problem, but it's hard to say which one is best because there are many different ways that this can be done. The goal of the algorithm is to take an image and segment it into two parts: the retina and everything else. Most methods involve differentiating between the two by using some type of edge detection with a thresholding technique. Most algorithms out there today use morphological operations for their edge detection, but some have used other techniques such as gradient magnitude. Most methods also use a thresholding technique to separate the two parts. There are many different ways this can be done:

Otsu's method is an adaptive threshold, where it analyzes the entire image and figures out what the least significant change in intensity is (darkness) and sets a region around that pixel as white. This isn't a very accurate method because it only finds the minimum value locally, not globally.

There are two more popular methods for accomplishing this task: top hat thresholding and fuzzy c-means clustering.

Top hat thresholding involves taking every pixel in an image and finding its average intensity over all of them. It then divides this average by the standard deviation of all pixels, which is a way of quantifying how much variation there is from pixel to pixel. This creates a standard deviation value for every pixel, and then it draws a line around the mean of these deviations. The differences between the bottom of the average deviation line and the pixels below it become one cluster, and the same process is repeated with the top of the average deviation line to create another cluster. The clusters are then averaged into a single image that captures those boundaries between sections.

The method is to find the intensity of each pixel, find the average intensity of all of them, then compare the ratio of the average to a threshold (most often 0.5). This is known as Top Hat Thresholding because it gives you a top hat shape if you plot pixels that have an average intensity above 0.5. It's easy to implement, and gives good results if you can take care to avoid noise and other artifacts that might get in the way. An example of a Top Hat Thresholding-based technique for optic disc detection is given by :

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