Image Haze Removal using Dark Channel Prior | Digital Image Processing Project

In hazy weather, outdoor images suffer from poor quality due to the insufficient luminance and noise brought by the atmospheric particles in haze. Haze removal, also known as dehazing, is considered as a significant process as clear, haze-free images are not only favored by human eyes, but also essential for improving the performance of computer vision systems.

In this project, I first implemented the dark channel prior (DCP) haze removal algorithm with MATLAB. Then I improved the algorithm by introducing a depth estimation to adaptively control the level of dehazing in DCP algorithm.

Dark Channel Prior

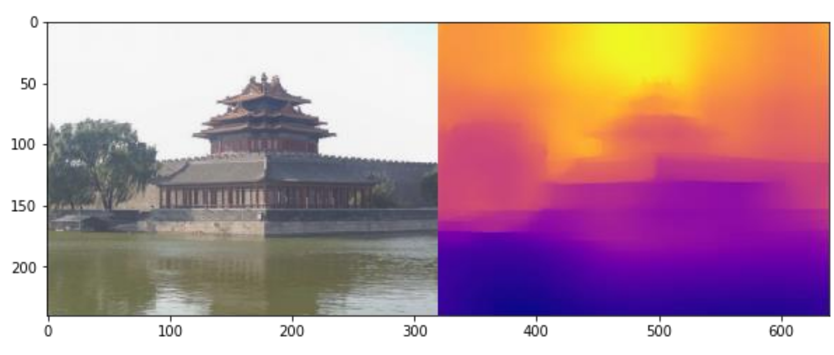
The dark channel is defined as the pixel whose intensity is close to zero for at least one of the color channels within a local image patch. For a haze-free image, the value of dark channel is close to 0 with a high probability, while for a hazy image, the value of dark channel is dramatically greater than 0. The above observation is called dark channel prior (DCP). Based on this observation, we can not only distinguish between hazy image and haze-free image, but also develop a system to remove haze.

The traditional DCP haze removal method has 5 parts: dark channel estimation, atmospheric light estimation, transmission map estimation, transmission map refinement, and image reconstruction, in which transmission map estimation is an essential part, because transmission map records the information about haze density in image.

I first implemented the traditional DCP haze removal method.

Depth Estimation

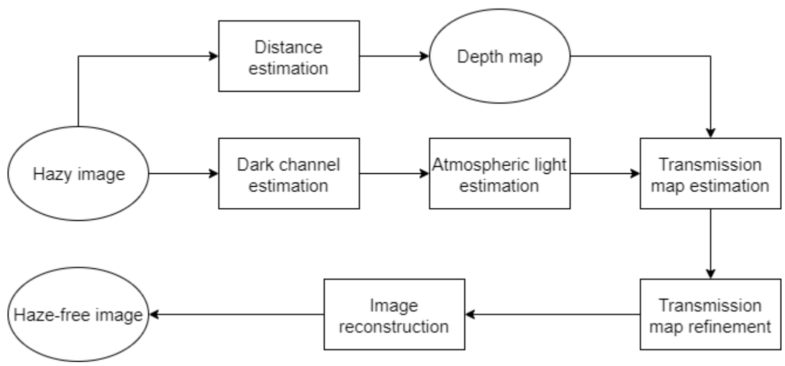
There is a pre-determined global parameter ω in transmission map estimation setting the level of dehazing for the whole image but using a same level of dehazing for ground and



sky would leave strong artifacts in sky region in dehazed image. This is because the human visual system tends to rely on a low level of haze in the sky to preserve aerial perspective. Therefore, instead of using a global value of ω and setting a same level of dehazing for the whole image, I decided to set ω according to the depth, or distance to the camera in the image. For objects in small depth or close to camera, I used large value of ω and stronger dehazing; for objects in deep depth or far from camera (largely sky region), I applied small value of ω and weaker dehazing.

The depth estimation was achieved by using a deep learning neural network called DenseDepth. The image above is an example of depth estimation. In order to combine the DenseDepth with the existed DCP method, I sent the original hazy image into the neural network model, and did a sigmoid normalization on the distance estimation result to ensure that the parameter ω in transmission map estimation had a reasonable range and smooth changing trend.

<u>My Haze Removal Procedure</u>



By introducing the depth estimation into haze removal, the flow chart of my method is shown here. I ran my dehazing program over a dataset called REalistic Single Image DEhazing (RESIDE) because it had ground truth haze-free image with hazy image, providing good reference for the assessment of dehazing effect. I also ran my program over another dataset called CURE-TSD because it was a dataset used largely in image object detection, where image dehazing could be an essential preprocessing part.

Besides the subjective visual assessment, I also ran my program through the RESIDE dataset to calculate an objective assessment criterion called FSIMc. If I only used the traditional DCP haze removal method, the FSIMc was 0.5277. If I used my improved haze removal method, the FSIMc increased to 0.5428.