NeRF: Neural Radiance Fields

In this project, we are interested in novel view synthesis: synthesizing how a scene looks like from viewpoints that has not been observed before. Specifically, given a set of images of a scene and their associated camera parameters, the goal is to generate high-fidelity images of the scene for arbitrary* viewpoints of interest. The problem is summarized in Figure 1.

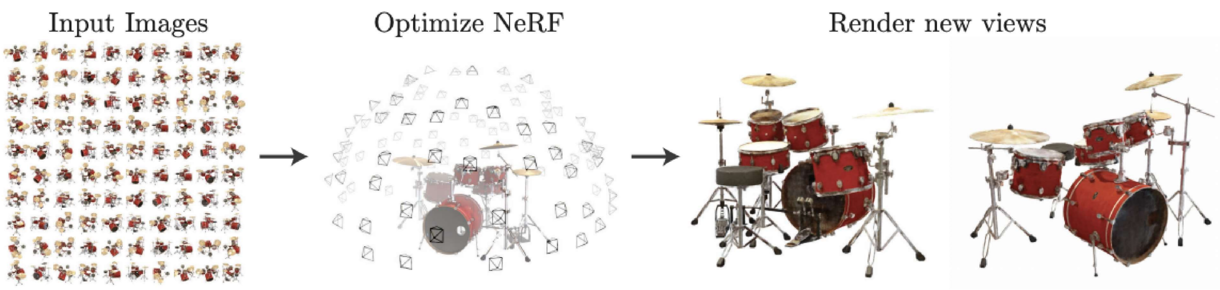

Figure 1: The view synthesis problem [1]. The task is to take as input multiple posed images and synthesize the scene from novel viewpoints.

The recent Neural Radiance Fields (NeRF [1]) is a breakthrough in the field, generating highly photorealistic views of complex scenes. A NeRF learns an implicit representation of a scene, optimizing a neural network mapping from 3D location $\boldsymbol{x} = (x, y, z)$ and 2D viewing direction $\boldsymbol{d} = (\phi, \theta)$ to radiance $\boldsymbol{c} = (r, g, b)$ and volume density σ.

Given this representation, NeRF use classic rendering techniques [2] to render the color of a pixel. To optimize the radiance field, NeRF minimizes the squared loss between the ground truth pixels and the corresponding rendered pixels. The results are shown in Figure 2.

Figure 2: **Click the image to play the video results.** Please visit the official website to check out other stunning demos.

One potential project direction is to implement a NeRF from scratch. There are several implementations online [3, 4] which will be helpful references. Another direction is to make these implementations faster. A core limitation of NeRF is its rendering speed and improving constant factors in the code could make a huge impact.

*Depending on the methods we used, there will be different restrictions on the viewpoints we are capable of synthesizing. You are encourage to play with the systems intensively and figure out when they break respectively.

Other project directions include addressing or improving a limitation of NeRF. One limitation is that NeRF assumes training images have known associated camera parameters. One project direction is to devise a method to train NeRF with noisy, or even unknown, camera parameters [5].

Another limitation is that NeRF is unable to fit to changing scenes and assumes that the training images are of the same scene under the same snapshot in time. One project direction is to train a NeRF on a scene where the training images vary in lighting conditions or times of day [6].

Furthermore, an additional limitation is that NeRF rendering times are slow; it can take several seconds to render a high resolution view. One project direction is to improve the rendering times of NeRF [7, 8, 9].

Besides addressing the limitations of NeRF, another possible direction is to extend NeRF to other domains. For instance, exploiting NeRF to encode the semantics of the scene [10] or combining NeRF with other representations [11].

This is an exciting field and there are a lot things worth exploring, so feel free to pick one you are interested in. Feel free to refer to this survey [12] for a more comprehensive view of potential improvements, extensions, and followup work to NeRF.

References

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