DeblurGAN: Blind Motion Deblurring Using Conditional Adversarial Networks

1 Names and student IDs

- Hao Wang 515021910060
- Zhiwen Qiang 515030910367

2 Problem Statement

In this project, we present DeblurGAN – an approach based on Conditional Generative Adversarial Networks and a multi-component loss function. It can remove motion blur from a single photograph, given no information about kernel or camera movement. We also present a method of generating synthetic motion blurred images and develop a novel way to evaluate the quality of deblurring model.

3 Problem Description

Deblurring is the process of removing blurring artifacts from images, such as blur caused by defocus aberration or motion blur. There are mainly two types of deblurring methods: blind and non-blind deblurring. Many works have been focused on non-blind deblurring in recent years, making an assumption that the blur function is known. Like blur caused by camera shake, etc. Some of these methods improve the estimate of the motion kernel and sharp image on each iteration by using parametric prior models. However, the running time and stopping criterion is too long. Others use assumptions of a local linearity of a blur function and simple heuristics to quickly estimate the unknown kernel. But they work well only only on a small subset of images.

In our approach, we try to recover sharp image given only a blurred image as an input, so no information about the blur kernel is required. To do that, we train a CNN G_{θ_G} as the Generator. For each blurred image it estimates corresponding sharp image. In addition, during the training phase, we introduce critic function D_{θ_D} and train both networks in an adversarial manner.

The benefits of this project is three-fold. First, we provide a state-of-art method, which will help deblur images in a very fast and efficient manner.

Second we provide a method of generating synthetic motion blurred images from the sharp ones. Finally, we present a novel method to evaluate deblurring algorithms based on how they improve object detection results.

4 Project Goals and Objectives/Deliverables

Below are roughly all the goals we try to achieve in our project.

1. Read and fully understand the paper, acquire the dataset and source code for future use.
2. Set up the pytorch working environment.
3. Select a small dataset to train a sample generator to test the algorithm and obtain a rough result.
4. Use a server to train a complete generator to test the performance of proposed method.
5. Go through the source code and try to make some improvements to faster the training process and try to improve the stabilization of the training process.
6. Complete the final report for the project.

5 Project Scope

Our method for image deblurring is based on Conditional Generative Adversarial Networks and a multi-component loss function, we try to make some improvements to faster the training process and improve the stabilization of the training process. So the parts which are outsourced is defined below:

- We will not consider the traditional method, like the classical Lucy-Richardson algorithm, etc.
- We will not attempt to find a blur function for each pixel, which is an ill-posed problem.

6 Success Factors and Benefits

The three main benefits of this project is listed below:

- A state-of-art method, the DeblurGAN, will be presented to help deblur images in a very fast and efficient manner.
- A method of generating synthetic motion blurred images from the sharp ones will be provided.
- A novel method to evaluate deblurring algorithms will be presented.

7 Timeline

- 4.1 – 4.14
  Read and fully understand the paper.
- 4.7 – 4.14
  Set up the pytorch working environment.
- 4.15 – 4.25
  Select a small dataset to train a sample generator to test the algorithm.
- 4.16 – 5.8
  Use a server to train a complete generator to test the performance of proposed method.
- 5.9 – 5.23
  Go through the source code and try to make some improvements to faster the training process and try to improve the stabilization of the training process.
- 5.24 – 5.31
  Write the final report for the project.

8 Assumptions

1. A high performance GPU hardware should be available in order to shorten the training process. Typically, the training process can last for days if the hardware cannot provide with sufficient help.
   Solutions: Find machines that have high performance GPU.
2. Source code should be available and can work if we want to do some improvements based on the original work.
   Solutions: Make sure the source code is available before selecting the paper.
3. Training images should be accessible.
   Solutions: Download the dataset from the link provided by the paper to see if it works well.

9 Limitations/Restrictions

There are a few limitations in this paper. First of all, many blurred images should be accessible in order to train the generator. But sometimes it is not easy to get them. And since the GAN network is not always stable, it is possible that the outcome may perform badly or even fail in some cases.