CSCE 5222: Feature Engineering

Project Proposal

Project Name : Image De-noising Using Deep Learning

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Idea Description

The problem of image denoising has been in research for decades. Initially filters are used for this denoising, and it worked for the reasonable noise limit, but by using filter techniques results in loss of pixels. Additionally, if the image is sufficiently noisy, the resulting image will be so fuzzy that the majority of the image's important elements will be lost. So, there should be some improved way to deal with this kind of problem.

There must be a more effective approach to handling this issue.We have thus developed a number of deep learning architectures that significantly outperform the conventional denoising filters. In this project, we will demonstrate our method using a case study, going from issue formulation through the use of cutting-edge deep learning models, and then viewing the outcomes.

Goals and Objectives

1. The objective is to use blind noise to denoise the color pictures.

2. The main objective for this project is not to use any traditional methods such as filters on image and with the deep learning architectures we should denoise the image. There is no latency restriction since I want to denoise the photographs as closely as possible to the real world, even if it takes some time.

Motivation

Motivation for building this Image denoising Technique is ‘Loss of Pixels is equal to Loss of Data’. By using traditional methods like filters, we are losing more data where there is no point by following classical techniques like these. In the past, they used to work rather well for pictures with tolerable noise levels. However, applying those effects would result in a subspecialty picture. Furthermore, if the photograph is extremely blurry, much of the item's crucial components will be obscured in the resultant item's fuzziness. So, we are eagerly finding out all the way out of the box to overcome this technique.

Significance

Image denoising is a main feature in a wide range of major applications. Like image restoration, image processing, image segmentation, and image classification. For all these we need to acquire the true image pixels or data for effective performance. So it is important to extract the noise-free image for accurate results in any digital applications.

Literature Survey

The classical de-noising technique used is Spatial Domain Filtering. These are further classified into linear and non-linear filters. In non-linear filters the noise is suppressed using median and weighted-median filtering. Bilateral filtering is also widely used for resulting noise-free images

In linear filtering the disadvantage is they fail to preserve image textures. Thereafter gaussian noise reduction is used but it over-smoothens the images. To overcome this Wiener filtering is brought up, but it results in extremely blur sharp edges.

Objectives

- To acquire noise-free images which are the major inputs for a wide range of applications like image segmentation, visual tracking, image registration etc.,
- To prevent in loss of pixels and loss of data from images
- To avoid fuzzy and blurred textured images after applying filters

Features

Dataset:

As we are doing the supervised machine learning problems, we need the dependent variable and independent variable. For this image De-noisy, we will take the dataset from three sources:

1. **SIDD-Small Dataset:** This dataset contains 160 image pairs (which consists of dependent and independent images or we can say noisy and ground-truth images). Both noisy image and ground-truth image are Gamma corrected which are without tone mapping.
2. **RENOIR:** The photos in the sample include a wide variety of noise levels, making it difficult for a noise removal method to determine the proper hyperparameters for each object.
3. **NIND:** We will take 62 pairs of noisy and ground truth images which have been taken from the Fujifilm X-T1 and XF18-55mm to urge us to submit photos for a broader and varied crowdsourcing project.

Pre- Processing:

First, we will analyze which smartphone has more photos to know the exposure of the images which helps to find the brightness. We will also check the shutter speed of the image to know about the darkness of the image. We will calculate the mean and standard deviation of all three dataset images to know the pixel distribution value of images. We filter the image to denoise using the traditional filtering in the beginning and later on, we will apply the Non-Local means (NLM) algorithm for filtering the images. This algorithm examines a small part of the image, finds additional portions that are comparable, then calculates a weighted sum of those portions.

Model:

We will use deep learning models to denoising images. We will implement three models and compare each other models according to their performance.

1. **REDNet:** Residual Encoder-Decoder Networks is based on Convolution Neural Networks which have the same auto-econder architecture but without connections. We will use 6 layers of each Convolution encoder and Deconvolution decoder respectively.
2. **MWCNN:** Multi-level Wavelet Convolutional Neural Networks have similar architecture as U-Net except down-sampling and up-sampling. Here, we will use Discrete Wavelet Transform (DTW) and Inverse Wavelet Transform (IWT).
3. **PRISNet:** Pyramid Real Image Denoising Network will be the stare of art of deep learning model. We will divide the models into three main modules: first would be Channel Attention Module which will add attention on every channel of the input. Second module is the Multi-Scale Feature Extraction Module which is the main module

of each architecture. This will mean pooling and down-sampling of images. Last module is the Kernel Selecting Module which is similar to the Channel attention module.

Expected outcome:

After implementing these three deep learning models, we will compare and show that our state-of-art model performs better than the remaining two models. We will also compare which models have consumed less time to denoise a single image. For model comparison, we will calculate the Mean Squared Error, Peak Signal to noise ratio and Structural Similarity Index Measure.

References

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