CSC 2529 Project Proposal
Imaging denoising using ResNet and UNet

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Motivation

Image denoising is an important problem in the area of low-level image processing. Traditional model-based methods such as non-local means (NLM)[1], block-batching and 3-D filtering (BM3D)[2], weighted nuclear norm minimization (WNNM)[3] rely on image prior modeling, and their optimization algorithms are time-consuming. In recent years, we have witnessed a dramatic upsurge of exploiting convolutional neural networks (CNNs) toward solving image denoising[4] and the U-Net[9] model is one of them. The U-Net model's architecture consists of a contracting (encoder) path to capture context and a symmetric expanding path (decoder) to estimate the segmentation. This architecture has recently been used for image denoising and is able to obtain good results. In Homework 5, we used a UNet model to remove Gaussian noise and we got significant results. In lecture, the Residual Network[10] (ResNet) model was also introduced as one of the most popular and successful neural networks with skip connections. We are interested in combining these two remarkable networks : Unet and ResNet, to further improve our denoising results.

Related work

Image denoising is one of the significant problems in computer vision, and many different neural network methods have been proposed in this field. Jain and Seung[8] proposed a convolutional neural network(CNN) on image denoising. Zhang et al. [5]proposed a deep convolutional neural network for image denoising (DnCNN). This model improves the denoising performance by stacking multiple blocks of convolutional layers, batch normalization and rectified linear unit (ReLU) activations. Gurprem Singh[6] and his team members proposed a deep convolutional neural network with added benefits of residual learning for denoising. The network is composed of convolution layers and ResNet blocks along with rectified linear unit activation function, and it is capable of learning end-to-end mappings from noise distorted images to restored cleaner versions. With a single end-to-end model, this model can tackle different levels of Gaussian noise efficiently. Another work from Javier Gurrola [7] uses a residual dense U-net neural network for image denoising. In this work, they present a residual dense neural network (RDUNet) for image denoising based on the densely connected hierarchical network. The encoding and decoding layers of the RDUNet consist of densely connected convolutional layers to reuse the feature maps and local residual learning to avoid the vanishing gradient problem and speed up the learning process. Moreover, global residual learning is adopted such that, instead of directly predicting the denoised image, the model predicts the residual noise of the corrupted image. The algorithm was trained for the case of additive white Gaussian noise and using a wide range of noise levels.

Project overview (what exactly your project is about and what the final goals are)

We will propose a network that combines the structure of UNet and ResNet. Intuitively, we will replace each encoder and decoder block of a residual block. This model will learn how to remove the noise of the image. The input of the model is the noisy image and the output is the denoised image.

Denote the original image as x, the denoised image as x', the ground truth image as y, the width of image as W and the height of image as H.

We will use MSE loss ($L_{MSE} = \frac{||y-x'||^2}{WH}$) or cross-entropy loss function to train this model.

Even though the UNet-ResNet can reduce a majority of noise, we would like to add another loss function — a perceptual loss to capture more edge information from the residual noise in order to further reduce noise and improve the image quality. The denoise images from UNet-ResNet model and the ground truth images will be both sent to a pre-trained SegNet. We will grab the $\varphi(x')$ and $\varphi(y)$ from one of the convolutional layer to calculate the perceptual loss ($L_{per} = \frac{||\varphi(y)-\varphi(x')||^2}{W*H}$). Thus, the new loss function will be $L_{loss} = L_{MSE} + L_{per}$, which will be used to train our UNet-ResNet model.

We are planning to run our model on the BSDS300 dataset, which is the dataset that we use in Homework 5 task 3. We will compare our results qualitatively and quantitatively (by PSNR) with results trained by pure UNet, which is the model used by Homework 5 task 3.

Milestones

Week1: Select dataset and preliminary implementate the model
Week2: Train and adjust the model. Tune the hyperparameter
Week3: Make experiments and compare them with other methods.
Week4: Write the report and make a poster.

Bibliography (APA)

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