CSC2529 Project Proposal
Low Dose Computed Tomography Denoising Algorithms

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1 Introduction

Computed Tomography (CT) is a widely used medical screening tool. This X-ray technology produces high-quality cross-sectional images and can be used to show bones, muscles, organs, and blood vessels in great detail. In clinical settings, CT scans are commonly used in disease diagnosis and many surgical interventions [1]. One major concern of using CT is its high radiation exposure. When a series of scans are needed to monitor some disease progression or recovery continuously, the cumulative radiation toxicity of CT scans will increase the risk of developing fatal cancer.

Low-dose CT (LDCT) which uses very low dose of radiation was introduced to address this problem [2]. Although LDCT lowers the exposure significantly, it is not a perfect solution. LDCT does not provide image output of similar quality as standard CT in many cases. Lowering the dose would unavoidably increase the data noise. In this project, we propose to review a set of image denoising algorithms that can improve LDCT image quality to support future clinical research.

2 Data

Our data source is the CPI Cancer Imaging Program from the National Institutes of Health (NIH). The dataset is Low Dose CT Image and Projection Data (LDCT-and-Projection-data) [3]. It is a library of CT patient projection data in an open format DICOM-CT-PD. We will choose a subset of 100 paired abdominal CT images in our project. We also include clinical data for performance analysis, such as patient age, gender, and pathology annotation.

3 Methods

Image denoising has been widely investigated in the past. Some of the early works utilize linear and nonlinear filters to remove noise in the spatial domain. Examples include mean filtering, Wiener filtering and bilateral filtering. Spatial filtering can eliminate noise considerably. However, image blurring is often observed in their results. In addition to spatial domain filtering, transformation techniques have also been developed to explore noise in different domains. Examples include Fourier transform, wavelet transform, and cosine transform.

Non-quadratic regularization models are later studied to address the blurring issue. Total variation based regularization model and non-local regularization models have shown promising result, and great success has been achieved by a combined model in [4]. The limitation of this method is the loss of structural information. Thus, visual image quality is still not ideal.

To further improve denoising performance, model based optimization methods and convolutional neural network(CNN) based methods are proposed. Model based optimization involves iterative inference optimization upon the image prior, popular methods include Adam and Alternating Direction Method of Multipliers (ADMM). Long running time is the major concern when using model based methods on large datasets.

In contrast, CNN based methods minimize a loss function through training on a set of degraded-truth image pairs. With less running time, time complexity needs to be resolved with those methods.

Different neural network structures are designed for different purposes. Zhang et al. proposed CNN based model DnCNN that learnt the residual distribution, which can handle Gaussian denoising with unknown noise level [5]. Yang et al. proposed a Generative Adversarial Network (GANs) based denoising algorithm using Wasserstein distance and perceptual similarity (WGAN) [6]. Generator G generates an FDCT image given LDCT as input. Discriminator D compares the generated FDCT image with the true FDCT image. WGAN algorithm can reduce noise and increase contrast for improved lesion detection.

Above NN-based methods heavily rely on paired datasets. However, it is hard to find well-prepared datasets in many real-world clinical studies, which can be a restriction in fitting denoising models. CycleGAN is a newly proposed GAN structure that can transfer image from domain to domain, such as between horse and zebra [7]. We only need unpaired data to train a CycleGAN to obtain a

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robust denoising model [8]. Main components of CycleGAN contain two GANs models, one generates LDCT to FDCT, the other one generates FDCT to LDCT. The bidirectional image transfer pipeline can capture more information and correlations between data spaces.

4 Evaluation

To benchmark different denoise approaches, we first split the dataset into training (80%) set and testing (20%) set. In each model based denoising approach, we fit model on the training set and validate the model performance on the testing set. In rule based denoising approaches, we will only process the testing LDCT images.

In the testing set, there are paired LDCT and FDCT images. FDCT images will serve as the reference (truth), and we will compare the denoised LDCT images to the FDCT images. The performance evaluations are in three aspects: reference based metrics, visualization, and downstream analysis results [9].

We will provide reference based image quality metrics such as Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR).

In addition, we will visualize and compare denoised LDCT images and FDCT images.

Image denoising can help downstream research analysis. We propose to show how image quality impacts diagnosis by validating lesion classification performance on the original LDCT image, denoised LDCT image and FDCT image [10].

5 Conclusion

In this project, we propose to review denoising methods: filters, DnCNN, WGAN, and CycleGAN and validate the performance on real-world data set LDCT data. We expect neural network based methods can perform better than rule based denoising methods since neural networks can fit complex unknown noise distributions, which are more robust. Improving LDCT image quality through a good computational denoising algorithm will be helpful for future medical research to provide better clinical evidence in disease diagnosis.

Acknowledgments

We acknowledge Dr. David Lindell and his TA teams Parsa, Shayan, Robin, and Mian for providing us with endless support in learning computational images and designing this project.

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