IMAGE DENOISING USING BAYESIAN METHODS

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1 INTRODUCTION

A major component in the process of image processing is the denoising of images which essentially is the process of removing noise from an image to restore the true image in order to minimize information loss from the image due to noise. Image denoising plays an important role in various tasks such as image classification, image restoration and image segmentation. For our project, we will focus on denoising images from the medical MNIST dataset.

In our project, we aim to estimate a denoised image for a given noisy image. Since our original data is a collection of pre-processed clean images (without noise), we create noisy images by adding Gaussian noise to them. We select suitable distribution for the parameters of the noisy image distribution and even model the hyperparameters of these distributions leading to a hierarchical model. We ultimately aim to estimate the denoised image distribution using sampling methods.

2 DATA DESCRIPTION

The data set comprises of simple MNIST-style medical images[apo17] with a 64 X 64 dimension. This data set has 58,954 medical images divided into 6 classes namely Abdomen, BreastMRI, CXR, ChestCT, Hand, HeadCT

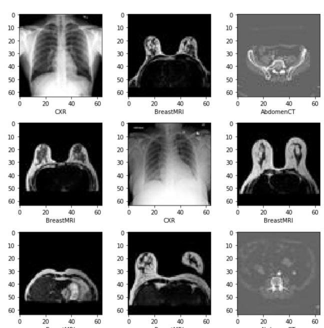

Figure 1: Sample Medical Images

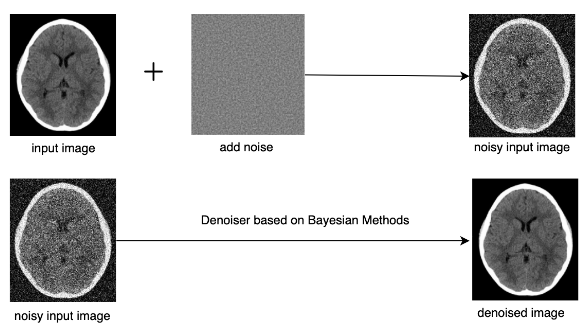

Figure 2: Method Overview

3 METHODOLOGY

3.1 PERFORM EXPLORATORY DATA ANALYSIS

To begin with, we will summarize and visualize the dataset which includes understanding the pixel distributions etc.

3.2 DEFINE THE LIKELIHOOD FUNCTION

We will define the likelihood function of the noisy image which follows a Gaussian distribution with x and expected value and σ^2 as some variance. Here x is the pixel-valued matrix of the original image.

$$f(y|x, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2}\left(\frac{||y-x||}{\sigma}\right)^2\right)$$

3.3 Choose parameter priors

Since our noisy image distribution follows a Normal distribution, we have two parameters namely the expected value and variance.

3.3.1 Choose image priors

The distribution of the original image x(its pixel-valued matrix) is one prior.

The images in our data have very few non-zero pixels. Therefore, selecting a prior distribution that mimics sparsity for the pixel values would be suitable. We would experiment with appropriate continuous distributions for non-negative values such as exponential distribution(with only a positive side), and gamma and beta distributions.

3.3.2 Choose noise variance priors

We adopt a conjugate inverse-Gamma distribution as the prior distribution for the noise variance as it would significantly reduce the computational complexity for Bayesian inference.

3.4 Choose hyperparameters prior

We will model the hyperparameters of the two prior distributions mentioned above. We will build a hierarchical model and the distribution of hyperparameters of the prior distribution above can be either informative or non-informative. Upon selecting suitable priors, we will be able to model their hyperparameters' distributions.

3.5 Estimate Posterior distribution using Sampling Techniques

We will compute the (joint) posterior distribution of the parameters of the noisy image. Since the computation of the posterior distribution involves a complex integral as the normalizing constant, we resort to MCMC sampling techniques such as Gibbs sampling or Metropolis-Hastings sampling[DHT09].

3.6 Estimate Original Image Distribution (Marginal Distribution of x)

We will then estimate the marginal distribution of the x parameter which gives us the distribution of the denoised images.

3.7 Evaluating the closeness of the computed denoised image & original image

The closeness between the denoised images and the original images will define the goodness of our applied Bayesian methods. We plan to evaluate the performance by experimenting with different metrics such as KL Divergence between the distribution of denoised images and original images. Metrics such as the L_1 and L_2 norms of the distance between the pixel values of the denoised and original images could be other alternatives.

References

[apo17] apolanco3225. *Medical MNIST Classification*. `https://www.kaggle.com/datasets/andrewmvd/medical-mnist`. 2017.

[DHT09] Nicolas Dobigeon, Alfred O Hero, and Jean-Yves Tourneret. "Bayesian sparse image reconstruction for MRFM". In: *2009 IEEE International Conference on Acoustics, Speech and Signal Processing*. IEEE. 2009, pp. 2933–2936.