Introduction

The following literature review provides insight into the existing works involving the medical imaging and machine learning, dose-related noise in CT and how these have been combined. It begins by providing context in lung functional analysis with both deterministic and data-driven methods. The description, simulation, and removal of noise in X-Ray and Computed Tomography are then discussed. Gaps in this literature are then stated, and the relevant end-to-end architectures are reviewed.

Automatic Lung Functional Analysis

Automatic Lung Functional Analysis is a well-established area of study. With the recent explosion of applied machine learning research, the area has seen significant progress. [3] is an excellent example of this. It analyses a few hundred papers published in 2021, that used machine learning to diagnose COVID-19. The paper [3] focusses on investigating the clinical relevance of the reviewed research papers, finding that none of them were clinically applicable for various reasons. It also provides common pitfalls and recommendations going forward specifically in the realm of automatic lung functional analysis. This is particularly relevant, in terms of how the model designed in this thesis will be developed and assessed. The number of papers reviewed in [3] demonstrates how current the study area is, and thus how important it is to critically investigate the metrics and methods used.

Generally, the approaches to this type of problem can be categorized into 1) deterministic and 2) data-driven methods. The term “deterministic” is used to refer to direct, computational methods such as those in classical computer vision, where a given input image will always provide the same output, while “data-driven” refers to models involving machine-learning-type models built from training data.

Deterministic Methods

Earlier models, such as those described in [4] and [5] provide examples of deterministic methods for lung segmentation and analysis. While [5] is more focused on the segmentation step, [4] demonstrates the effectiveness on the end goal – the task-based accuracy for the classification of lung nodules. Without any machine learning techniques, and a very limited dataset (only 38 scans), the method was quite successful, failing on only 4.9% of the test set. [5] describes the development of an automatic method for the segmentation of 3-Dimensional CT reconstructions. It introduces optimal (dynamic) thresholding and used dynamic programming to identify anterior and posterior junction lines. The paper provides a useful in-depth statistical analysis of the results that will be very useful when informing the assessment of the results of this thesis. Both [4] and [5] were relatively successful, without the use of a data-driven approach. Deterministic methods can thus contribute significantly to the end-to-end system developed here.

Data-driven Models

Modern papers are increasingly focused on the development of data-driven, machine learning models. [2] compares the use of pre-trained deep-learning image models with training from scratch for several medical imaging modalities and datasets. The results showed that the pre-trained models usually outperformed those built from scratch, particularly when the training dataset decreased in size. Deep and shallow fine-tuning was also compared, and overall, the paper shows just how useful pre-trained models can be when combined and trained with task-specific data. [6] is an example of a 3D network architecture used for lung nodule detection, similar to the popular U-net architecture [9]. [6] also discusses and compares other popular machine learning architectures and tools (including the pre-trained models mentioned in [2] used for lung functional analysis. The 3D type of architecture in [6], being popular and current, will be relevantly applied in this study. Furthermore, [6] provides a valuable, robust statistical argument to base our assessment from.

Dose and Image Quality

The dose vs image quality tradeoff is another significant aspect of study in Computed Tomography and Medical Imaging research. As described in [7] and [8], higher doses are linked to higher image quality, but also more risk to the patient, while low doses are better for the patient, but result in much more noise. The ALARA principle (As Low As Reasonably Achievable) describes the goal of gaining as much information as possible with as low radiation dose as possible. [7] details the sources and effects of image quality issues in low dose Computed Tomography as well as the effect of CT exposure on humans. Understanding the physical aspects of this relationship is necessary for the accurate simulation of low dose imaging in this thesis. [8] provides an alternative perspective, providing a more practical description of how CT scanner dose settings (included in the CT DICOM file headers) affect patients medically and the effective dose patients experience as a result. The nuances of CTDI, Effective Dose and Radiation Energy transfer is described, clarifying the concept of “low dose”. Furthermore, [8] details several metrics that are used to describe CT image quality, including Contrast-to-Noise Ratio (CNR) which is not mentioned in [7]. The description and effects of this tradeoff thus justifies the need to improve the modelling of low dose CT images.

**Dose-related Noise and Denoising**

Introduction

There are several ways to categorize the variety of denoising methods that have been researched with CT imaging in mind. In this paper, these have been broadly divided into 1) Projection-domain techniques, 2) Traditional Post-processing techniques and 3) Deep Learning (DL) techniques. Since many publications have investigated denoising methods, three reviews [10, 11, 12] were used to frame the discussion of denoising, with more detail being provided on several important denoising algorithms.

[11] broadly describes four types of noise present in CT scans. These include random noise, statistical noise (also known as quantum noise), electronic noise and roundoff errors. As described in [10], quantum noise results from statistical fluctuations of the X-ray quanta. [11] explains that as more quanta are detected in a measurement, the accuracy of the measurement is increased. To reduce the effects of this, one can increase the X-ray dose, thereby increasing the number of detected X-ray quanta. With dose-related noise in mind, this paper will focus on this statistical noise. The noise distribution present in CT images varies depending on several factors including the type of machine and the reconstruction algorithm used [11] and can be accurately modelled as Poisson or Additive Gaussian white noise (in the case of multi-detector CT scanners). In general, it can be modelled using a Gaussian distribution [10,11,12], thanks to an application of the Central Limit Theorem [14].

[10] provides describes four major requirements of a good denoising algorithm to be the preservation of edges, the maintaining of structural similarity, low complexity (computationally efficient) and not relying too heavily on prior databases. Over time, and for different applications, denoising algorithms achieve these to different degrees. The following section describes some of the most popular and prominent methods.

Projection-domain techniques

As described in [10, 11], CT images are taken by rotating X-ray emitter and detector pairs around a subject. The resulting measurements produce a sinogram consisting of stacked histograms of detected X-ray values for each angle around a patient. The physical process is similar to a radon transform, and through a process called back-projection, the spatial domain image is retrieved with the inverse radon transform. Projection-domain techniques are those that are applied in the Sinogram domain to suppress noise. Without the use of any processing before back-projection is applied, image is often blurry. Filtered Back-projection [15] was the first solution to this, which involved taking the two-dimensional discrete fourier transform of the sinogram and applying a ramp high-pass filter to it to remove the blur. From there, Iterative Reconstruction (IR) methods were developed [16], including Compressed Sensing [10]. IR essentially extends FBP by applying it as an iterative algorithm. IR produces better quality images, particularly in cases with low-dose and/or sparse data.

Traditional Denoising methods (1):

* Mathematical transforms in CT processing (radon transform etc.)
* Linear Filters
* FBP & IR

Traditional Denoising methods (2)

* NLM
* TV
* PWBCD
* BM3D
* Wavelet-based methods

Deep-Learning Denoising methods

* Dictionary learning
* CNNs
* GANs
* Transformers
* Others (VAEs)
* Supervised vs unsupervised

Metrics

* How to think about them:
  + They are useful for getting a good overall idea
  + Limitations
* List and describe them (make a table)

Datasets

* Independence Test
* CTIA, Mayo etc.

Simulation

* XCIST
* Other papers