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Using Artificial Intelligence to Design Next Generation Medical Endoscopes: A Synthetic Approach

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Abstract

Optical Properties of tissue, including the absorption (μ_a) and reduced scattering (μ_s') coefficients, can be useful clinical biomarkers for measuring tubular cancers in a non-invasive manner. Currently, oesophageal and colorectal cancer have a 5-year survival rate of just 20% and 65% respectively [1,2], with the current detection of colorectal and oesophageal cancers typically necessitating a biopsy to make a definite diagnosis. Recent studies show that Spatial Frequency Domain Imaging (SFDI), can improve the detection of cancerous polyps, improving current endoscopic procedures [3,4]. However, SFDI on its own requires 6 images per wavelength at 3 different phases to create a single optical property map and cannot provide these optical property maps in real-time. Although single snapshot imaging of optical properties (SSOP) has reduced the number of images, the method causes image artefacts to arise and requires frequency filtering [5], corrupting the optical property of the image. This project aims to remedy these problems by:

- Using an existing Generative Adversarial Network (GAN) to get fast and accurate optical property maps.
- Training this GAN on simulated tissue to learn the optical properties of images with geometries seen in tubular organs.

Impacts of Synthetic Data and GANs

Versatile – datasets can be generated to meet specific needs or conditions that are not available in existing datasets, improving AI models in not only healthcare but also in the robotics, automotive and finance industries

Fast and Cheap – Real datasets can be expensive and slow to generate. Large synthetic datasets can be generated in seconds

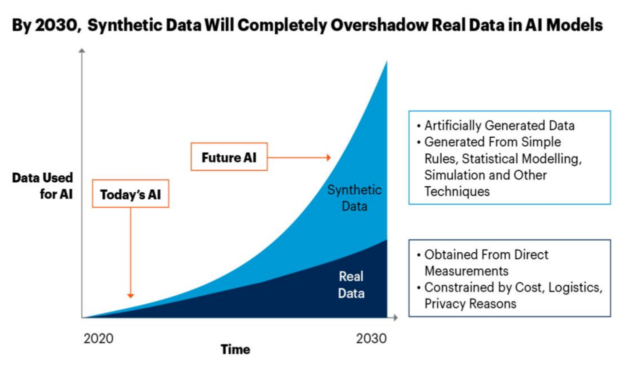

Figure 1: Prediction of type of data used in AI and ML for the next 10 years [6]

Quicker Diagnosis – the 5-year survival rate for colorectal cancer is approximately 90% when it is found at its earliest stages compared to only 15% at the latest stage [2].GANs can recognise cancerous regions quicker hence saving more lives

Data anonymisation – GANs can implicitly map real patient data to synthetic data, allowing sharing of datasets without breaching a patient's PHI

Synthetic Dataset Generation with Blender

Methodology

Blender, an open-sourced 3D rendering software, will be used here as the synthetic dataset generator. Blender will allow us to model the oesophagus, gastrointestinal tract or bowel to a reasonable degree of accuracy, however, due to time constraints we will model these tubular organs as simple cylinders. Additionally, with its raytracing option, it is possible to simulate the physical behaviours of light and consequently simulate the optical property of both cancer and healthy tissue. This is done by three main variables:

Absorption (abs) Factor – controls how much light is absorbed by the material

Scattering (sct) Factor – controls how much light is scattered by the material

Final Factor – Controls the ratio of absorption factor to scattering factor.

For **more** information about the Blender Model, plus how abs and sct fact link to μ_a and μ_s' see [7]

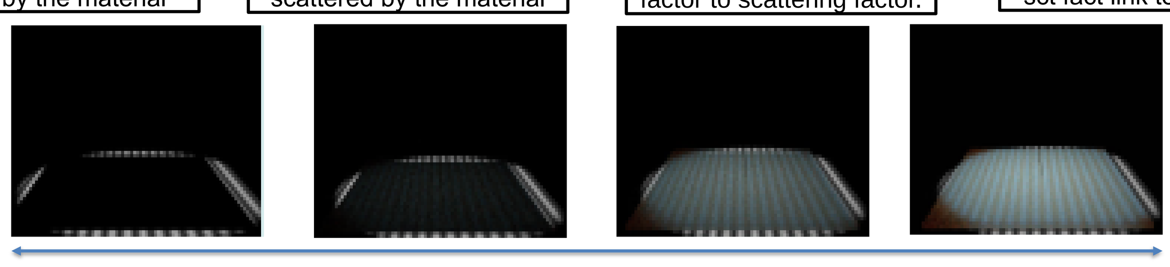
Highly **Absorbing** Material

Figure 2: Varying of optical properties in Blender

Highly **Scattering** Material

Models

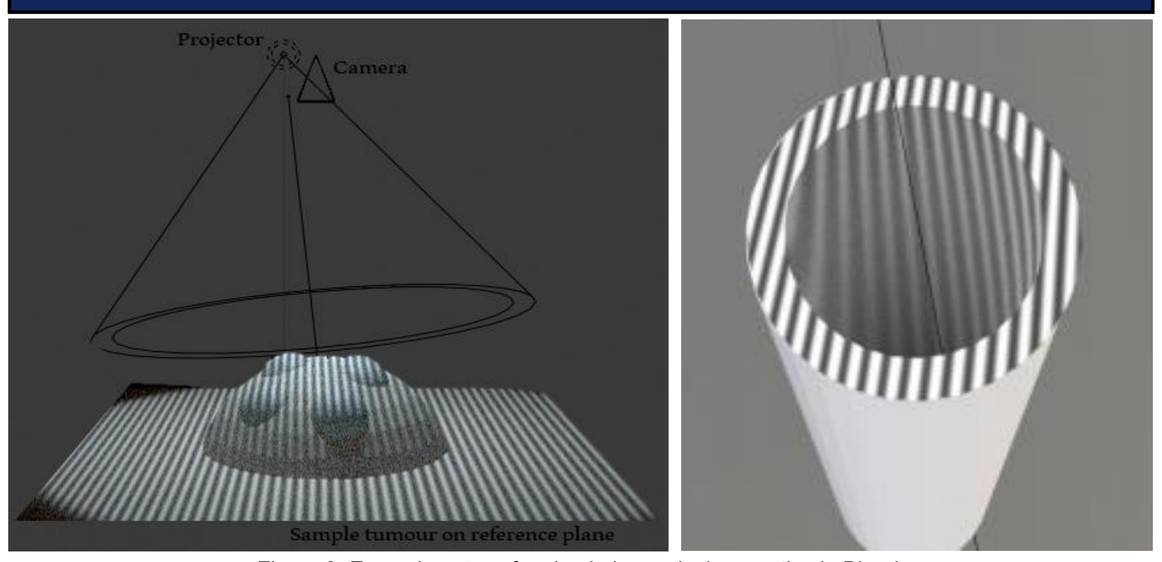

Figure 3: Example setups for simulating optical properties in Blender

A 2D sinusoidal pattern was projected onto two geometries (**rectangular** and **cylindrical**) which would usually be seen under the camera of a capsule endoscope, reproducing SFDI. A tumour was placed on top of a plane (left) and inside the cylinder (right), simulating a polyp sitting on top of a simulated tissue inside the gastrointestinal tract

Results

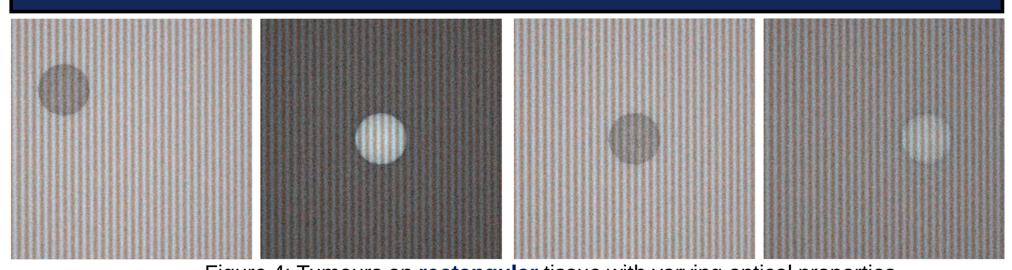
Figure 4: Tumours on **rectangular** tissue with varying optical properties

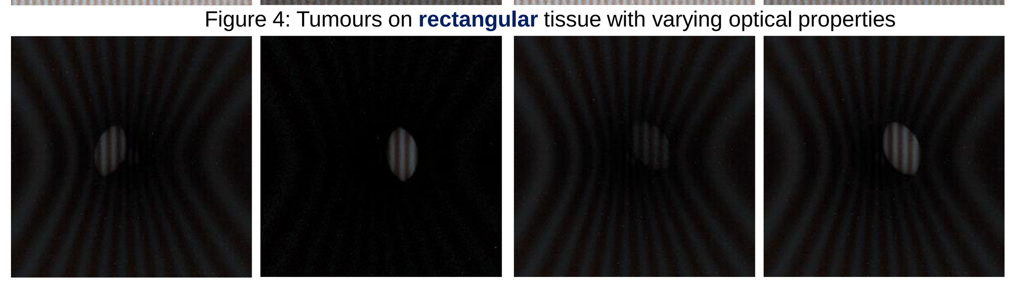
Figure 5: Tumours on **cylindrical** tissue with varying optical properties

Figures 4 and 5 show an example of a typical output image of a capsule endoscope. The 2D sinusoidal pattern can be seen to be straight in the rectangular tissue but bend in cylindrical tissue. This bending of light is what makes it hard to get accurate optical properties maps of tissue, limiting the use of SFDI in new endoscopes. The GAN aims to solve this problem.

AI Processing with GANs

What is a Generative Adversarial Network?

A GAN's purpose is to train a discriminator, an ordinary convolutional neural network (CNN), to distinguish between real and fake data whilst simultaneously training a generator to produce synthetic instances of data that can reliably fool the discriminator. Both neural networks are trained together in a game-like fashion. The generator tries to fool the discriminator by producing hyper-realistic images that match the training dataset. On the other hand, the discriminator tries not to be fooled by trying to correctly distinguish between fake and real data. Once the generator has been trained the discriminator is discarded. This generator could then be fed images from a capsule endoscope and provide the required optical property maps to a radiologist. A recent paper by Mason Chen and his fellows [8] shows a method of using a conditional GAN (coined GANPOP) to obtain optical property maps. By altering their model, it is possible to translate our Blender input images to their respective optical property map, overcoming the problem of refraction of light. Note that the redder the image, the more absorbing the material is and the greener the image, the more scattering the material is.

Structure of System

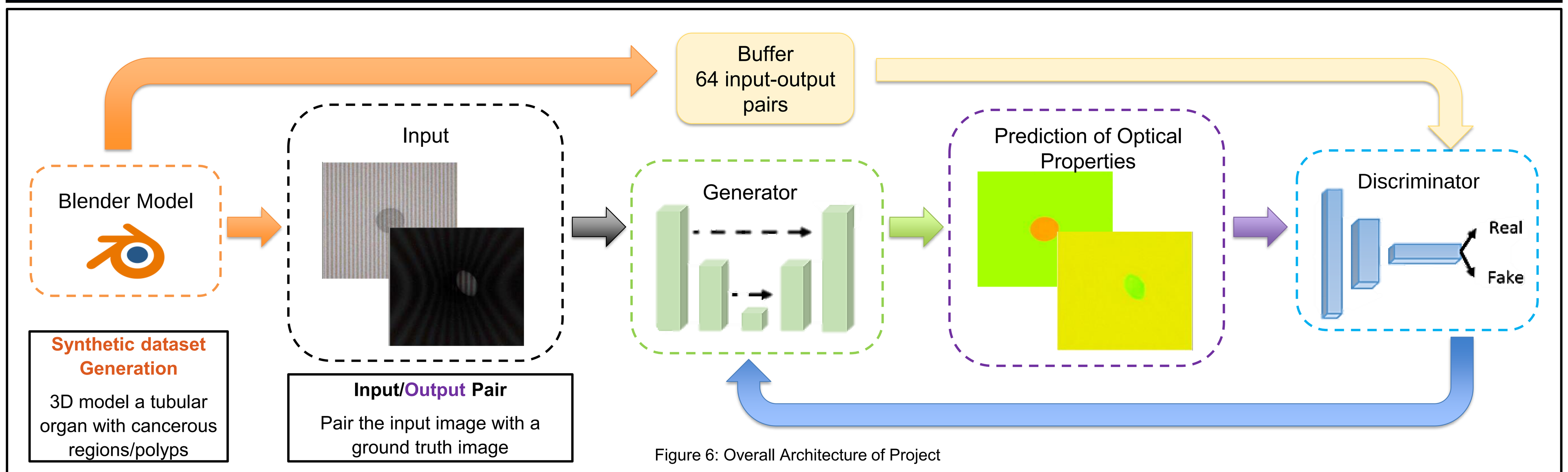

Figure 6: Overall Architecture of Project

Results: Getting the Optical Properties

Discussion

By comparing the fake output of the GAN to the real ground truth, it was found that the average percentage difference per pixel across 75 testing images for a cylindrical dataset was around 1.5% between the real and fake reduced scattering and absorption coefficients. This can be seen more clearly in Figure 7, where one of the testing images is of a polyp inside a simulated gastrointestinal tract. The 'FAKE' image is practically identical to the 'REAL' image, with the difference only truly seen when the image is separated to μ_a and μ_s'. The absorption coefficients for the GAN output and the ground truth were practically identical except for a slight error around the edges of the tumour. Although the reduced scattering coefficients had some small patches where the pixel-to-pixel percentage difference was approximately 3-4%, the GAN still reliably produced a very accurate optical property map. The rectangular dataset performed slightly better, with the average percentage difference per pixel being around 1.2%. For both cases, this number reduced to 0.3% when the separation in optical properties between the tumour and the surrounding tissue was relatively large.

Optical Property Maps

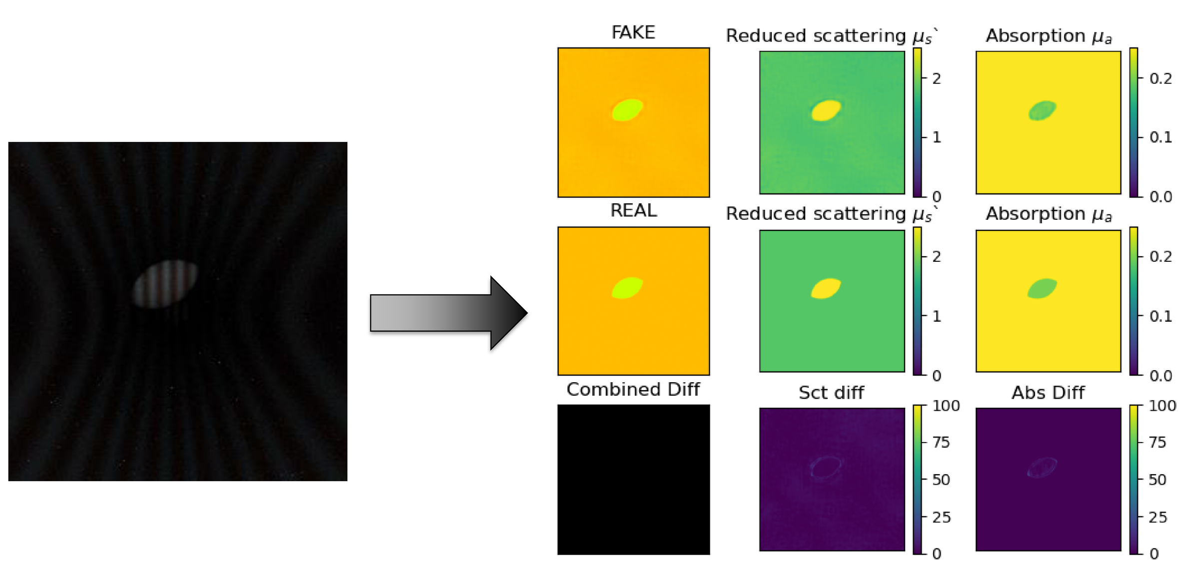

Figure 7: Optical Property map for a polyp in a cylindrical tube.

Limitations

Experience - To truly model tubular organs or any parts of the body in Blender, the person must be an expert in 3D modelling to ensure the tissue looks as realistic as possible

Missing Corner Cases – Real data may have trends, patterns and/or corner cases that may be missed when modelling any organs and cancerous polyps

Virtual environment – Not every single combination of tumour and organ can be modelled by hand. Domain randomisation could solve this problem. A good example of this is Nvidia's Omniverse [9] or open-sourced UnrealROX+ [10].

Conclusion & Future Work

Overall, we have explored the potential of using a combination of synthetic data and generative adversarial networks to create optical property maps from both a rectangular and cylindrical image dataset with varying polyp sizes and positions. In the future, a GAN will be trained on both a combination of real and synthetic data and by cross-referencing with Mason Chen's model, the AI will be able to generalise for all irregular geometries seen in real tubular organs. The optical property maps produced could then be used to help radiologists diagnose cancer at a much earlier stage, in turn saving more lives and improving the quality of life of patients in general.

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