# A2 MEDICAL IMAGING COURSEWORK PRESENTATION

*P. Antonopoulos (pa517@cam.ac.uk)*

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# Introduction

Processing medical images is important because it helps...

- To see inside the body
- Diagnose diseases
- To plan treatments

But it is complex because medical images can be...

- Collected from different devices with different methods
- Affected by noise and artefacts

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# Introduction

A typical procedure to process medical images consists of:

**Image Reconstruction**
- Going from raw data to an interpretable image

**Image Denoising**
- Removing noise and/or artefacts from the image

**Image Segmentation & Classification**
- Segmenting the region of interest and classifying tumours

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# Module 1 – PET-CT Image Reconstruction

**When reconstructing an image, we start with a sinogram**

- This is a collection of x-ray measurements at different angles

**We use the Beer-Lambert equation**

- This describes how radiation is absorbed by tissue

**We can reconstruct the image using different methods**

- Direct methods (FBP)
- Iterative algorithms (SIRT, OS-SART, MLEM, OSEM)

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# Module 1 – Methodology

First clean up sinograms by removing noise

Attenuate correct the PET sinogram

- Trial direct method and iterative algorithms to reconstruct the CT image (tune necessary hyperparameters)
- Resize the CT image and use it to correct the PET sinogram

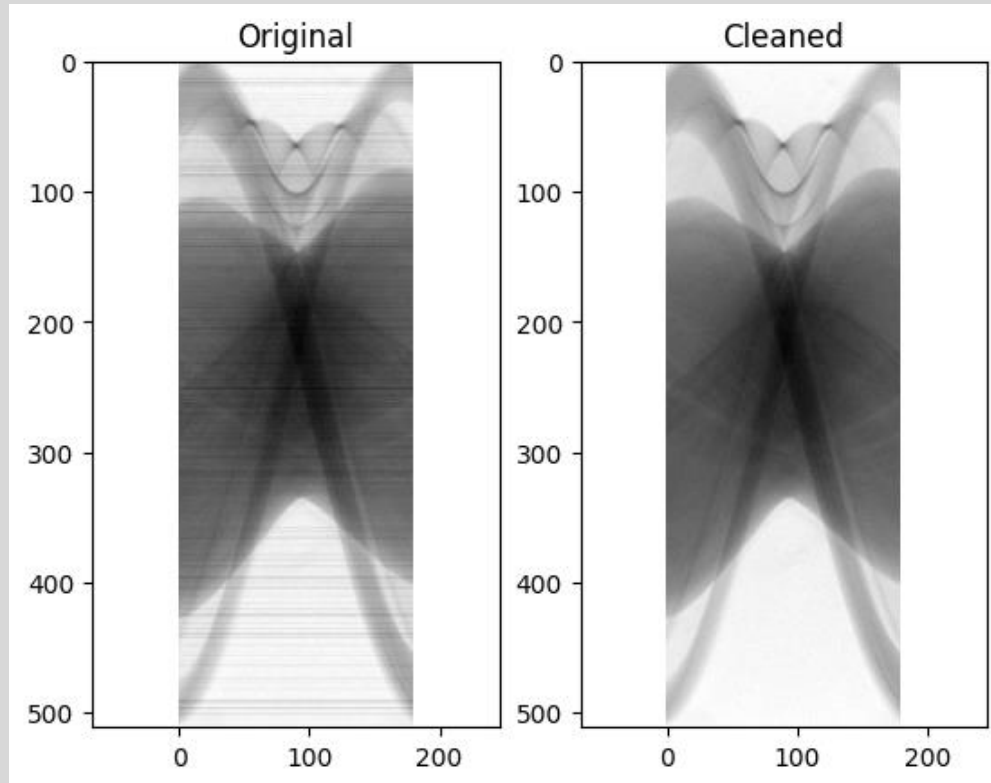Reconstruct the PET image using the corrected sinogram

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# Module 1 – Results I



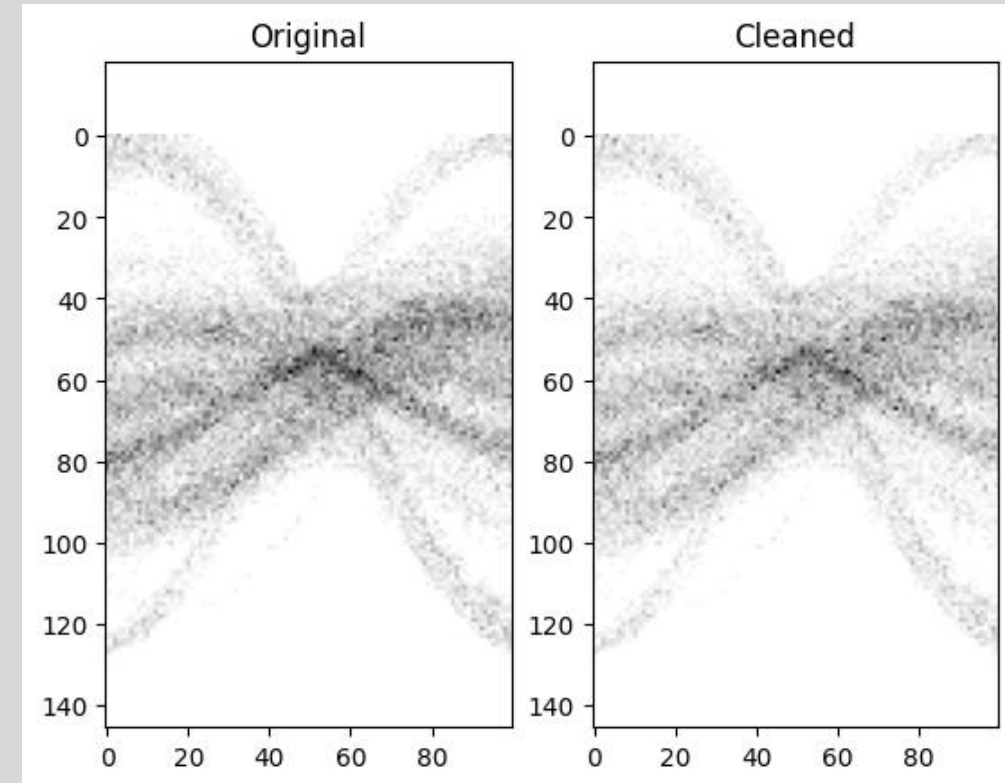Figure 1: Original and cleaned CT sinograms

Figure 2: Original and cleaned PET sinograms
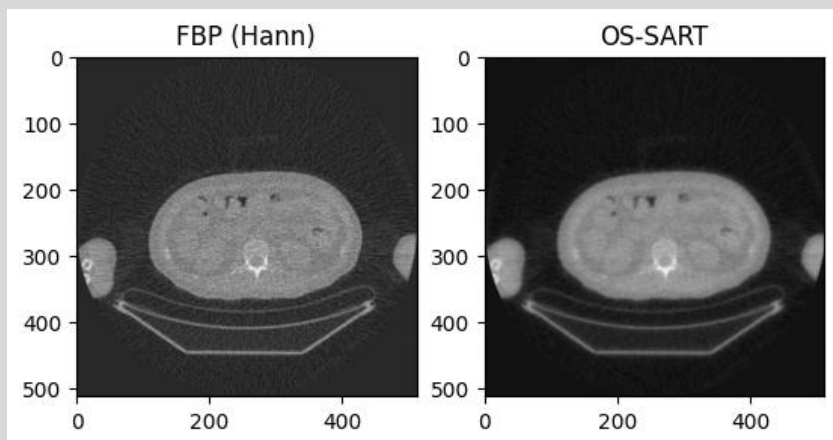
# Module 1 – Results II



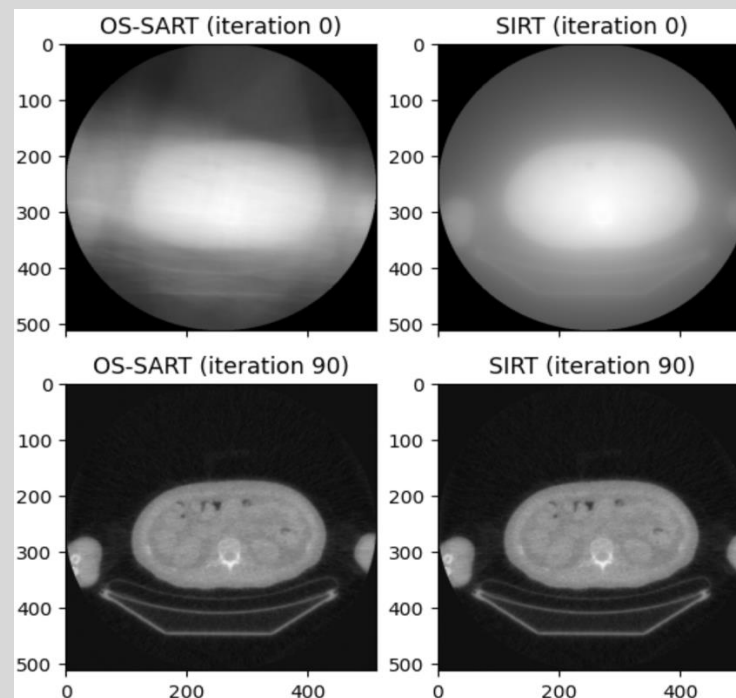Figure 3: Direct method (FBP) vs OS-SART iterative algorithm

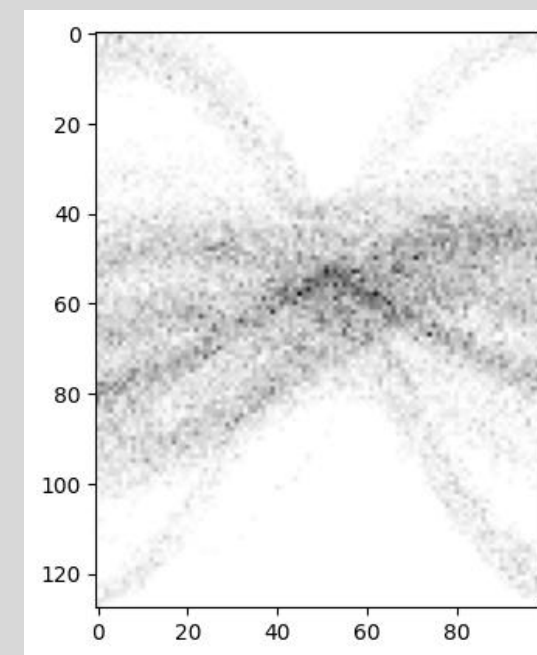Figure 4: OS-SART vs SIRT iterative algorithm

Figure 5: Attenuated corrected PET sinogram
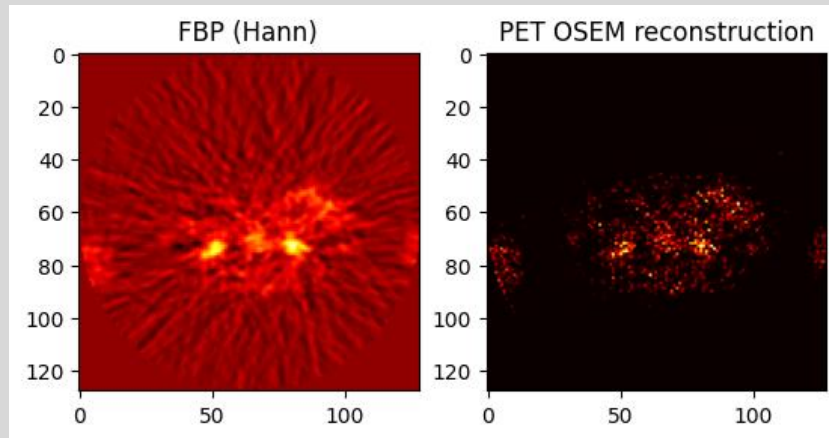
# Module 1 – Results III



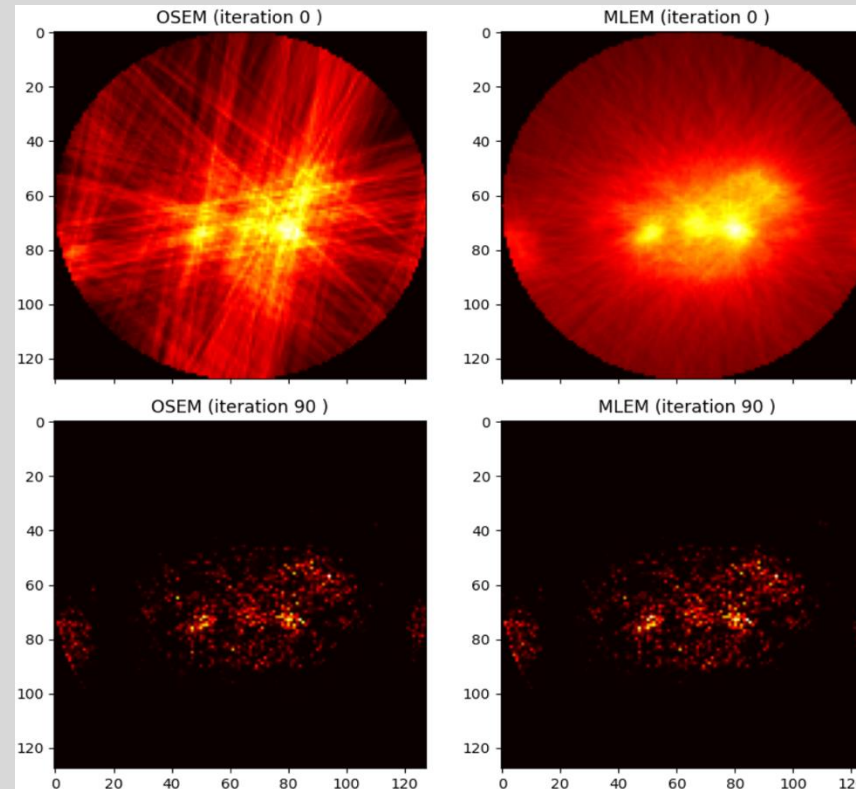Figure 6: FBP vs OSEM iterative algorithm using corrected PET sinogram

Figure 7: OSEM vs MLEM iterative algorithm

# Module 1 – Observations and Conclusions

After tuning hyperparameters, OS-SART could produce a better image than FBP

OS-SART is much faster than SIRT due to it using subsets of angles

For PET images, OSEM is faster than MLEM and both are better than FBP

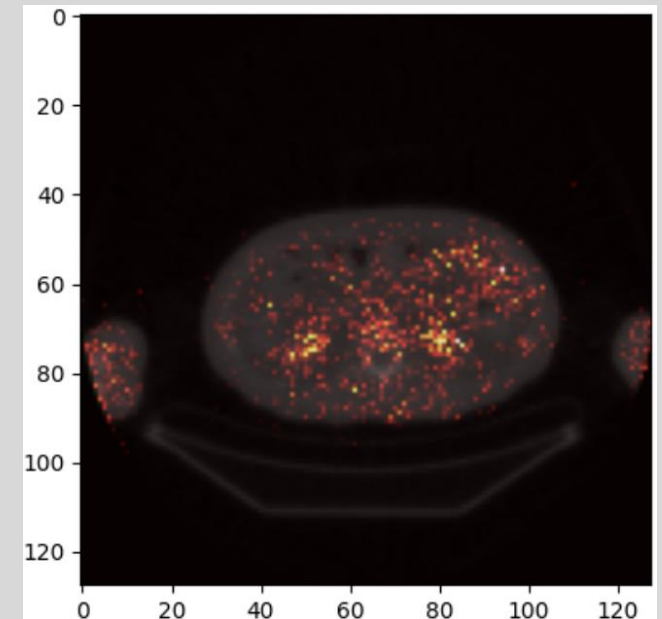Functional (PET) and structural (CT) images can be combined (Figure 8)



*Figure 8: Overlayed PET and CT*

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# Module 2 – MRI Image Denoising

## MRI uses coils to collect data

- Separate data from each coil at different locations
- The different images from each coil must be combined into a single image

## MRI data is complex

- Due to an amplitude and phase component of signal

## Denoise the images using filters

- From the skimage/scipy Python libraries
- Manually defined and used with the convolution theorem

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# Module 2 – Methodology

**Get a combined image from all coils**
- Apply Fourier Transform to the complex data from each coil to get an image
- Combine the images by summing their squared magnitudes

**Denoise the coil images**
- Using the Wavelet, Bilateral, Gaussian and Butterworth filters

**Recreate a new combined image**
- Using the best performing denoising method (Butterworth filter) and the convolution theorem
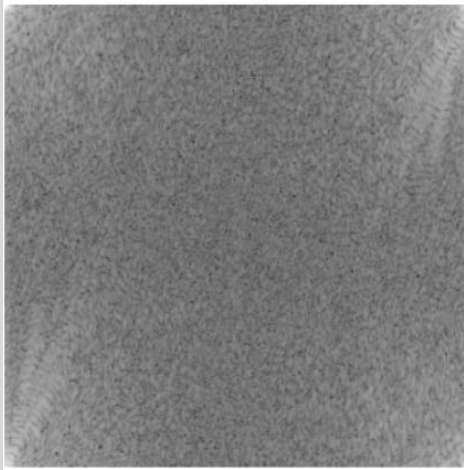
# Module 2 – Results I



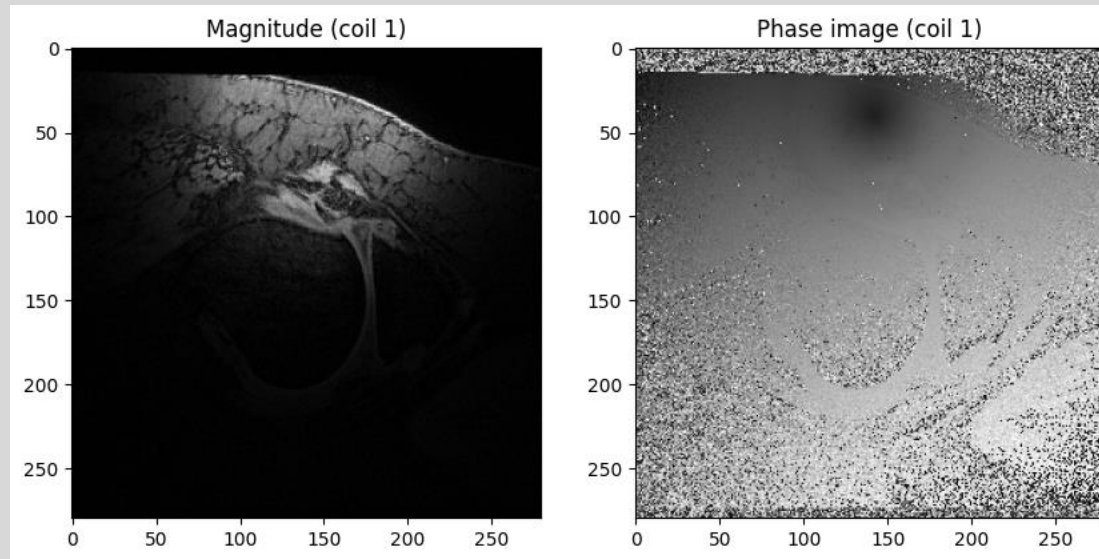*Figure 9: Magnitude of the complex data from the first coil*

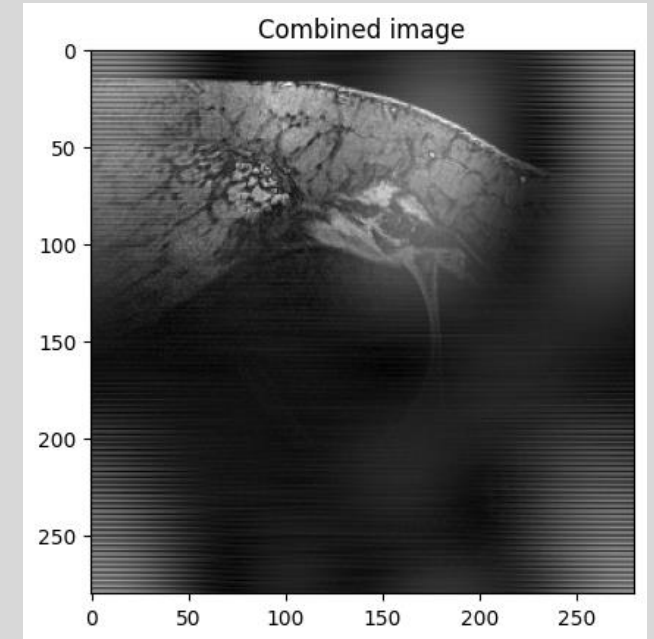*Figure 10: Magnitude and phase of the image space data of the first coil*

*Figure 11: Sum – squared combined magnitude image from all coils*

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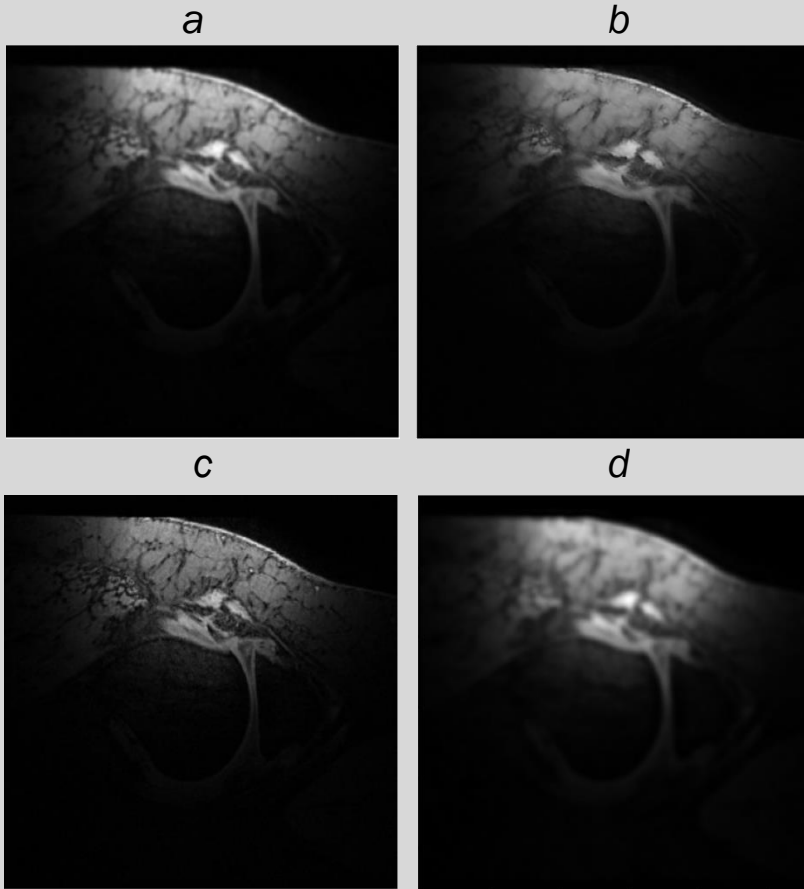
# Module 2 – Results II

a

b



*Figure 12: (a) Gaussian filtered image, (b) Bilateral method, (c) Wavelet method, (d) Butterworth method. All magnitude of image space data from coil 1*
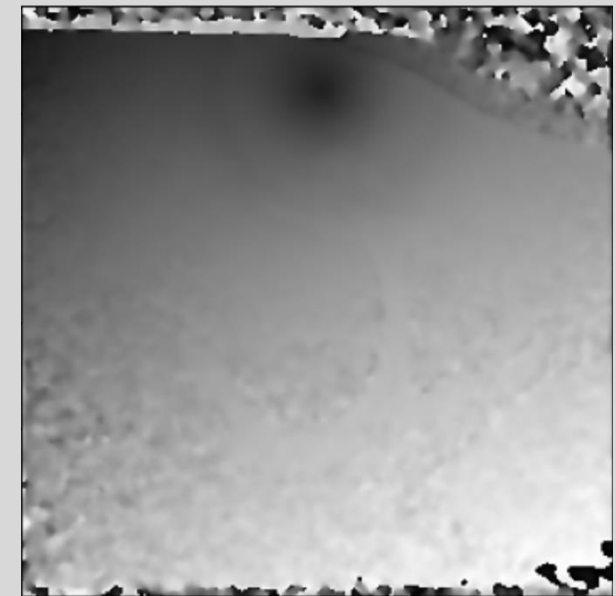
c

d



*Figure 13: Butterworth filtered phase image*
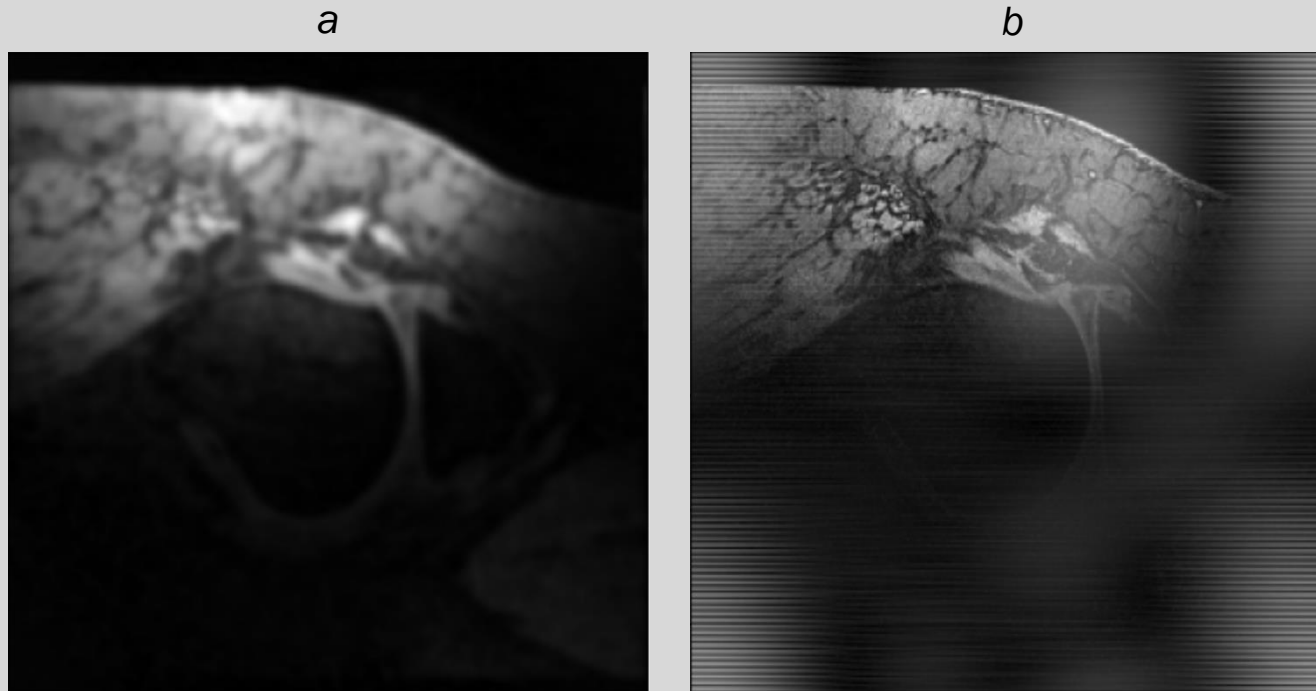
# Module 2 – Results III



*Figure 14: (a) Combined image using the Butterworth filter, (b) Original combined image*

# Module 2 – Observations and Conclusions

Denoising the images using the Butterworth filter appear to improve the combined image

Can tune the Butterworth filter's hyperparameters to further improve image quality

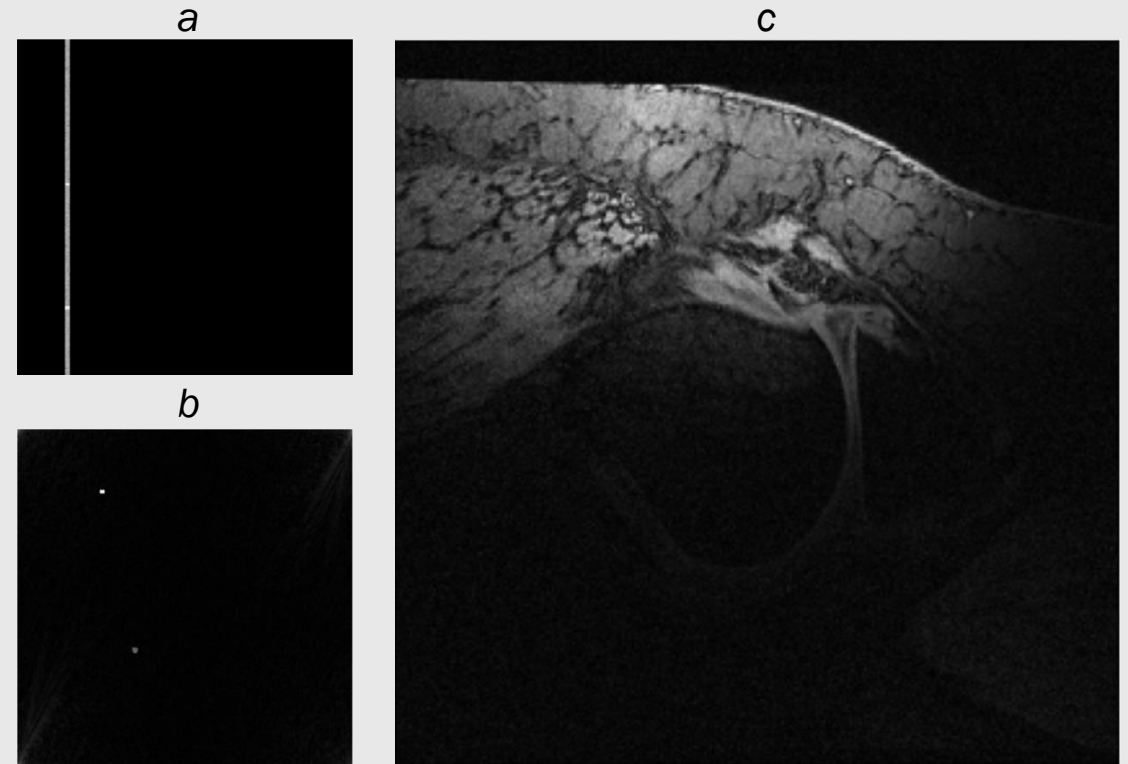Alternatively, excluding seemingly erroneous coils also yields a decent image (Figure 15)



*Figure 15: (a, b) Magnitude of complex data from coil 4 & 6, (c) Combined image excluding these coils*

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# Module 3 – CT Image Segmentation and Classification

## CT scan images were stored as NIfTI files

- Image and true tumour segmentations loaded using Python libraries such as SimpleITK
- Alternative file format for CT images can be used (DICOM)

## Tumours can be segmented in CT scan images

- Using simple methods such as a threshold algorithm based on pixel intensities
- Using more sophisticated methods such as Machine Learning

## Histogram-based radiomic features can be used to classify tumours

- Examples include Energy, Mean Absolute Deviation (MAD), and Uniformity

# Module 3 – Methodology

**Create a sub-volume of each image which contains the tumour**
- Convert the images and true segmentation to numpy arrays
- Use the true segmentations to index the image to obtain the sub-volume

**Segment the sub-volumes using a thresholding algorithm**
- Implement a thresholding algorithm that retains only the pixels whose intensities fall within the min and max intensity values of the tumour region
- Compare the results of this algorithm with the true segmentations

**Classify the malignant and benign tumours**
- Determine the radiomic feature values for each patient's tumour and use these for classification

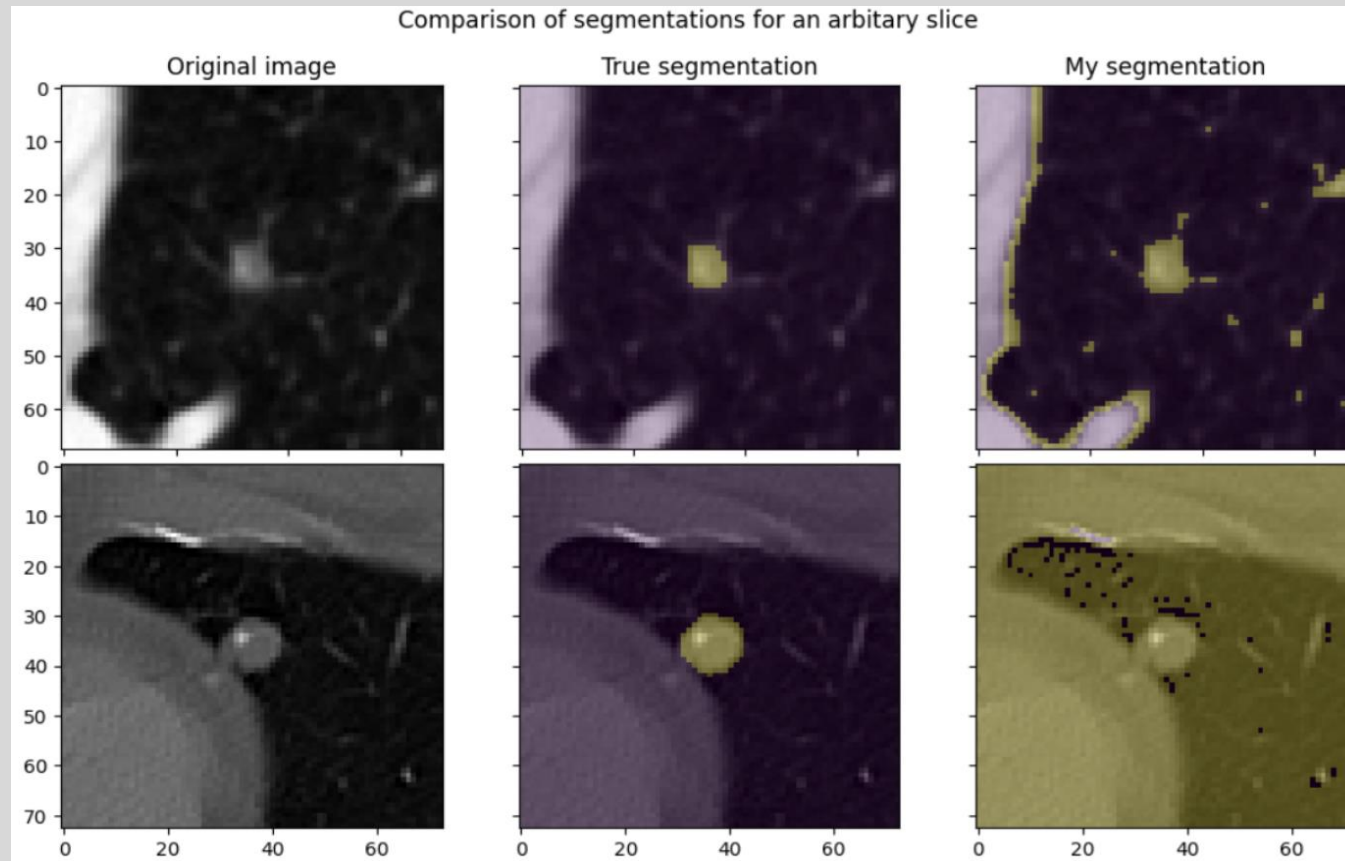DiS MPHIL

# Module 3 – Results I



*Figure 16: A decent (top) and poor (bottom) example of the thresholding algorithm's performance*
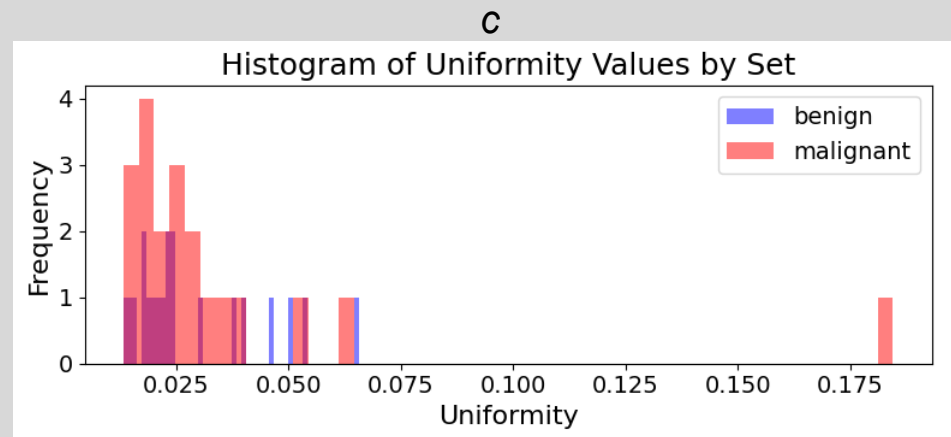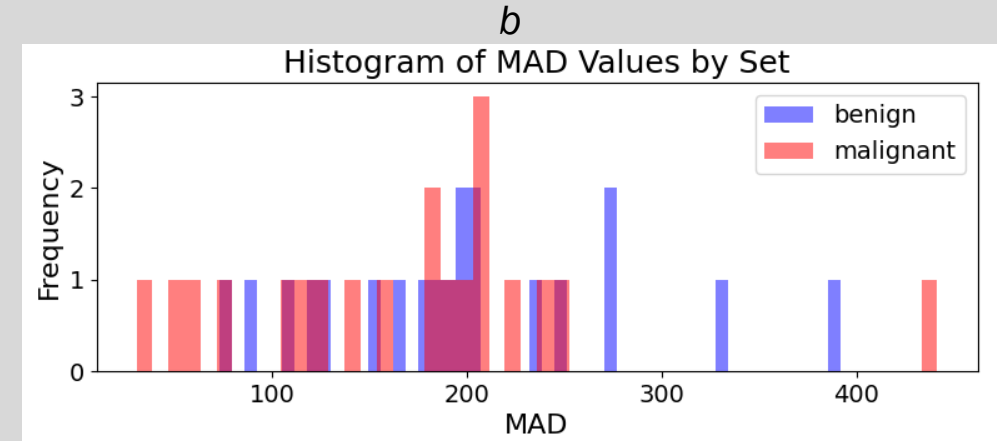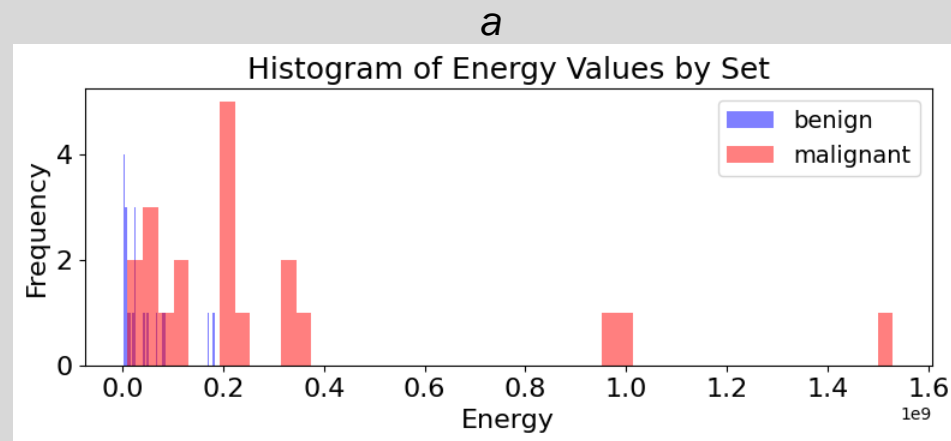
# Module 3 – Results II

*a*



*b*

*c*

Figure 17: (a, b, c) Histograms of the Energy, Mean Absolute Deviation (MAD), and Uniformity radiomic features
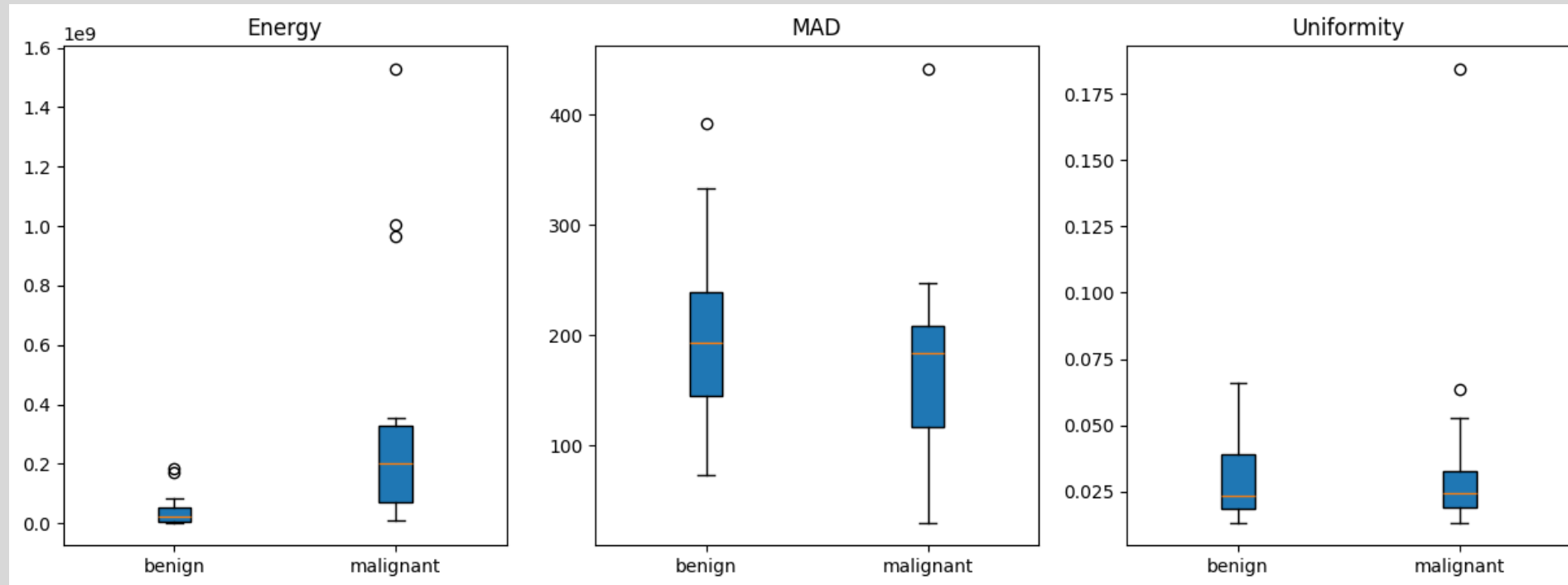
# Module 3 – Results III



*Figure 18: Box-plots of the Energy, Mean Absolute Deviation (MAD), and Uniformity radiomic features*

# Module 3 – Observations and Conclusions

The performance of the thresholding algorithm's segmentations are mixed

- Could be improved using a more sophisticated method such as Machine Learning

The malignant and benign radiomic feature histograms are all relatively overlapped

- No clear separation that can be used for classification

However, the box-plots suggest the Energy feature can be used for classification

- The Energy feature's plot shows a separation between benign and malignant tumours

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# Summary

## We have gone through the main stages of processing medical images

- Reconstruction
- Denoising
- Segmentation and Classification

## We have seen these stages in two different contexts

- (PET)-CT
- MRI

## For further details, please consult the coursework report and GitLab repository

- Thank you for listening!

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