

Project Report for

**RE4012 - MACHINE VISION**

Irish Speed-Signs Detection and Classification

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# **Project Team**

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# **Introduction**

Sinogram reconstruction is a common technique used in CT scanners, where one or multiple rotational beams of X-rays pass through an object, generating an image output on a sensing semiconductor. This output, commonly known as a **sinogram**, represents the raw projection data collected from different angles.

The sinogram produced by a CT scanner can be transformed into **2D cross-sectional slices** of the scanned object, revealing its internal structure. This transformation is typically performed using **Filtered Back Projection (FBP)**, a widely used reconstruction algorithm in medical imaging.

This project report focuses on the **Python implementation** of image reconstruction from a given sinogram (CT raw sinogram output) using the **FBP algorithm**. We will first explain the **organizational approach** taken in structuring the implementation, followed by a detailed discussion of the **technical aspects** of the project.

# **Approach**

The project is undertaking by 2 individuals, with attempt of recruit new members made. Unfortunately, we have not yet received a reply from suitable candidates. The project is implemented in 2 phases: Code development and Report writing. Zexin Li has undertaken the main part of the code development, and Qinyuan Liu has taken responsibility for code review and Report writing.

# **Mathematical principles**

Fourier transformation and inverse Fourier Transform are fundamental in Filtered Back Projection (FBP). The Fourier Transform helps in converting the sinogram projections into the frequency domain, allowing us to apply Ramp Filtering, which enhances high-frequency components and reduces blurring effects in the reconstructed image.

Ramp filtering is an essential step in FBP because direct back projection without filtering results in blurry reconstructions. The Ramp Filter acts as a high-pass filter that compensates for the excessive low-frequency components inherent in the projection data.

The following table shows the Mathematical Formula used and it’s associated code:

|  |  |  |
| --- | --- | --- |
| **Step** | Mathematical Formula | Python Code |
| 1D Fourier Transform |  | F = rfft(row\_data) |
| Ramp Filtering |  | k |
| Inverse Fourier Transform |  | recon\_image=iradon(filtered\_sino, theta=theta, filter\_name=None, circle=True) |
| Backprojection |  | recon\_image = iradon(filtered\_sino, theta=theta, filter\_name=None, circle=True) |

Table 1 Formula Table

# **Workflow of the Code**

The workflow of the reconstruction process is as follows:

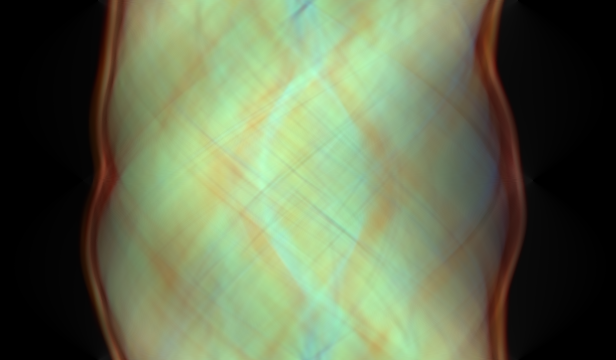
1. Load sinogram
   1. Read the sinogram file (sinogram.png) in RGB format, which usually consists of image projection data and is used for tomography reconstruction.

Table 2 Sinogram.png

A diagram of a crop image

AI-generated content may be incorrect.

Figure 1 Code Workflow

1. Separate color channels
   1. Split the RGB image into three independent channels: red (R), green (G), and blue (B), and process the projection data of each channel separately.
2. Frequency domain stimulation
   1. Apply a ramp filter (implemented in the frequency domain) to each channel. This step requires a Fourier transform (FFT) first, multiplying with the ramp filter (high-frequency compensation), and then converting it back to the spatial domain through an inverse Fourier transform (iFFT) to eliminate projection blur.
3. Backprojection reconstruction
   1. Project the auxiliary projection data into the image space and generate a two-dimensional reconstructed image for each channel by integration.
4. Post-processing
5. Crop region cancellation: remove the black border at the edge of the projected image (cancel region data).
6. Adjust aspect ratio: correct the image ratio to avoid display distortion.
7. Normalize to 8 bits: linearly scale the pixel values ​​to the range of 0-255, equipped with a standard image format.
8. Merge color channels
   1. Restore the brightness of the processed R, G, and B channels to an RGB color image.
9. Save the final reconstructed image (final\_recon\_RGB.png) and display it.

# **Code Implementation:**

import numpy as np

import imageio.v3 as iio

import matplotlib.pyplot as plt

from numpy.fft import rfft, irfft

from skimage.transform import rotate, iradon

from skimage.transform import resize

def ramp\_filter\_1d\_fftrow(row\_data):

    """

    1) rFFT

    2) ramp

    3) iFFT

    """

    N = len(row\_data)

    #rFFT

    F = rfft(row\_data)  # shape: (N//2 + 1,)

    #ramp

    freq = np.arange(len(F))

    F\_filtered = F \* freq

    #irFFT

    filtered\_row = irfft(F\_filtered, n=N)

    return filtered\_row

def hamming\_window\_1d(ffts):

    hamming = np.hamming(ffts.shape[0])

    return ffts \* hamming

def ramp\_filter\_1d\_hamming\_fftrow(row\_data):

    # row\_data must be 1d

    N = len(row\_data)

    F = np.fft.rfft(row\_data)

    print(row\_data.shape)

    freq = np.fft.rfftfreq(N, d=1.0)

    ramp = np.abs(freq)

    F\_filtered = F \* ramp

    F\_filtered = hamming\_window\_1d(F\_filtered)

    filtered\_row = irfft(F\_filtered, n=N)

    return filtered\_row

def ramp\_filter\_1d\_hann\_fftrow(row\_data):

    N = len(row\_data)

    F = rfft(row\_data)

    freq = np.fft.rfftfreq(N, d=1.0)

    ramp = np.abs(freq)

    hann\_win = np.hanning(len(F))

    F\_filtered = F \* ramp \* hann\_win

    filtered\_row = irfft(F\_filtered, n=N)

    return filtered\_row

def apply\_filter\_to\_sinogram(sinogram\_2d, filter\_type='none'):

    """

    use none, ramp, hamming, hann to specify which filter to use

    """

    rows, cols = sinogram\_2d.shape

    output = np.zeros\_like(sinogram\_2d, dtype=np.float64)

    if filter\_type == 'none':

        return sinogram\_2d.astype(np.float64)

    for i in range(rows):

        row\_data = sinogram\_2d[i, :]

        if filter\_type == 'ramp':

            output[i, :] = ramp\_filter\_1d\_fftrow(row\_data)

        elif filter\_type == 'hamming':

            output[i, :] = ramp\_filter\_1d\_hamming\_fftrow(row\_data)

        elif filter\_type == 'hann':

            output[i, :] = ramp\_filter\_1d\_hann\_fftrow(row\_data)

        else:

            output[i, :] = row\_data

    return output

def reconstruct\_from\_sinogram(sinogram\_2d):

    rows, cols = sinogram\_2d.shape

    theta = np.linspace(0., 180., cols, endpoint=False)

    recon\_image = iradon(sinogram\_2d, theta=theta, filter\_name=None, circle=False)

    return recon\_image

def crop\_circle\_region(image, threshold=0.01):

    rows, cols = image.shape

    mask = (image > threshold)

    row\_indices = np.where(np.any(mask, axis=1))[0]

    col\_indices = np.where(np.any(mask, axis=0))[0]

    if len(row\_indices) == 0 or len(col\_indices) == 0:

        return image

    rmin, rmax = row\_indices[0], row\_indices[-1]

    cmin, cmax = col\_indices[0], col\_indices[-1]

    cropped = image[rmin:rmax + 1, cmin:cmax + 1]

    return cropped

def apply\_aspect\_ratio(image, aspect\_ratio\_str):

    if ':' in aspect\_ratio\_str:

        w\_ratio, h\_ratio = aspect\_ratio\_str.split(':')

        w\_ratio = float(w\_ratio)

        h\_ratio = float(h\_ratio)

        ratio = w\_ratio / h\_ratio

    else:

        ratio = 1.0

    height, width = image.shape

    new\_width = int(round(height \* ratio))

    image\_resized = resize(image, (height, new\_width),

                           preserve\_range=True,

                           anti\_aliasing=False)

    return image\_resized

def float\_to\_8bit(image):

    im\_min, im\_max = image.min(), image.max()

    if im\_max == im\_min:

        return np.zeros\_like(image, dtype=np.uint8)

    norm = (image - im\_min) / (im\_max - im\_min)

    out = (norm \* 255.0).astype(np.uint8)

    return out

metadata = iio.immeta("sinogram.png")

aspect\_ratio\_str = metadata.get("AspectRatio", "1:1")

sinogram\_rgb = iio.imread('sinogram.png')

R, G, B = sinogram\_rgb[:, :, 0], sinogram\_rgb[:, :, 1], sinogram\_rgb[:, :, 2]

iio.imwrite('sinogram\_R.png', R)

iio.imwrite('sinogram\_G.png', G)

iio.imwrite('sinogram\_B.png', B)

sinogram\_R = iio.imread("sinogram\_R.png").T  # shape: (W, H)

sinogram\_G = iio.imread("sinogram\_G.png").T

sinogram\_B = iio.imread("sinogram\_B.png").T

# ========== (a) Reconstruction without Filtering ==========

sino\_R\_nofilter = apply\_filter\_to\_sinogram(sinogram\_R, filter\_type='none')

sino\_G\_nofilter = apply\_filter\_to\_sinogram(sinogram\_G, filter\_type='none')

sino\_B\_nofilter = apply\_filter\_to\_sinogram(sinogram\_B, filter\_type='none')

recon\_R\_nofilter = reconstruct\_from\_sinogram(sino\_R\_nofilter)

recon\_G\_nofilter = reconstruct\_from\_sinogram(sino\_G\_nofilter)

recon\_B\_nofilter = reconstruct\_from\_sinogram(sino\_B\_nofilter)

# ========== (b) Reconstruction with Pure Ramp Filtering ==========

sino\_R\_ramp = apply\_filter\_to\_sinogram(sinogram\_R, filter\_type='ramp')

sino\_G\_ramp = apply\_filter\_to\_sinogram(sinogram\_G, filter\_type='ramp')

sino\_B\_ramp = apply\_filter\_to\_sinogram(sinogram\_B, filter\_type='ramp')

recon\_R\_ramp = reconstruct\_from\_sinogram(sino\_R\_ramp)

recon\_G\_ramp = reconstruct\_from\_sinogram(sino\_G\_ramp)

recon\_B\_ramp = reconstruct\_from\_sinogram(sino\_B\_ramp)

# ========== (c) Reconstruction with Ramp Filtering + Hamming Window ==========

sino\_R\_hamming = apply\_filter\_to\_sinogram(sinogram\_R, filter\_type='hamming')

sino\_G\_hamming = apply\_filter\_to\_sinogram(sinogram\_G, filter\_type='hamming')

sino\_B\_hamming = apply\_filter\_to\_sinogram(sinogram\_B, filter\_type='hamming')

recon\_R\_hamming = reconstruct\_from\_sinogram(sino\_R\_hamming)

recon\_G\_hamming = reconstruct\_from\_sinogram(sino\_G\_hamming)

recon\_B\_hamming = reconstruct\_from\_sinogram(sino\_B\_hamming)

# ========== (Optional) Reconstruction with Ramp Filtering + Hann Window ==========

sino\_R\_hann = apply\_filter\_to\_sinogram(sinogram\_R, filter\_type='hann')

sino\_G\_hann = apply\_filter\_to\_sinogram(sinogram\_G, filter\_type='hann')

sino\_B\_hann = apply\_filter\_to\_sinogram(sinogram\_B, filter\_type='hann')

recon\_R\_hann = reconstruct\_from\_sinogram(sino\_R\_hann)

recon\_G\_hann = reconstruct\_from\_sinogram(sino\_G\_hann)

recon\_B\_hann = reconstruct\_from\_sinogram(sino\_B\_hann)

# ========== Post-processing: Crop, Adjust Aspect Ratio, Convert to 8-bit, and Merge into RGB ==========

def postprocess\_and\_merge(r\_img, g\_img, b\_img, aspect\_ratio\_str):

    R\_crop = crop\_circle\_region(r\_img)

    G\_crop = crop\_circle\_region(g\_img)

    B\_crop = crop\_circle\_region(b\_img)

    R\_resized = apply\_aspect\_ratio(R\_crop, aspect\_ratio\_str)

    G\_resized = apply\_aspect\_ratio(G\_crop, aspect\_ratio\_str)

    B\_resized = apply\_aspect\_ratio(B\_crop, aspect\_ratio\_str)

    R\_8bit = float\_to\_8bit(R\_resized)

    G\_8bit = float\_to\_8bit(G\_resized)

    B\_8bit = float\_to\_8bit(B\_resized)

    min\_rows = min(R\_8bit.shape[0], G\_8bit.shape[0], B\_8bit.shape[0])

    min\_cols = min(R\_8bit.shape[1], G\_8bit.shape[1], B\_8bit.shape[1])

    R\_final = R\_8bit[:min\_rows, :min\_cols]

    G\_final = G\_8bit[:min\_rows, :min\_cols]

    B\_final = B\_8bit[:min\_rows, :min\_cols]

    final\_RGB = np.dstack([R\_final, G\_final, B\_final])

    return final\_RGB

# Generate four sets of results (No Filtering / Ramp / Hamming / Hann)

final\_nofilter\_RGB = postprocess\_and\_merge(recon\_R\_nofilter, recon\_G\_nofilter, recon\_B\_nofilter, aspect\_ratio\_str)

final\_ramp\_RGB = postprocess\_and\_merge(recon\_R\_ramp, recon\_G\_ramp, recon\_B\_ramp, aspect\_ratio\_str)

final\_hamming\_RGB = postprocess\_and\_merge(recon\_R\_hamming, recon\_G\_hamming, recon\_B\_hamming, aspect\_ratio\_str)

final\_hann\_RGB = postprocess\_and\_merge(recon\_R\_hann, recon\_G\_hann, recon\_B\_hann, aspect\_ratio\_str)

# Save results

iio.imwrite("final\_recon\_no\_filter.png", final\_nofilter\_RGB)

iio.imwrite("final\_recon\_ramp.png", final\_ramp\_RGB)

iio.imwrite("final\_recon\_hamming.png", final\_hamming\_RGB)

iio.imwrite("final\_recon\_hann.png", final\_hann\_RGB)

# ========== Display ==========

plt.figure(figsize=(12, 8))

plt.subplot(2, 2, 1)

plt.imshow(final\_nofilter\_RGB)

plt.title("No Filter Reconstruction")

plt.axis("off")

plt.subplot(2, 2, 2)

plt.imshow(final\_ramp\_RGB)

plt.title("Ramp Filter Reconstruction")

plt.axis("off")

plt.subplot(2, 2, 3)

plt.imshow(final\_hamming\_RGB)

plt.title("Ramp + Hamming Reconstruction")

plt.axis("off")

plt.subplot(2, 2, 4)

plt.imshow(final\_hann\_RGB)

plt.title("Ramp + Hann Reconstruction")

plt.axis("off")

plt.tight\_layout()

plt.show()

print("Reconstruction results saved. Comparison displayed.")

# **Results**

A collage of images of a brain

AI-generated content may be incorrect.

Table 3 Reconstructed image

# **Conclusion**

The project demonstrates the students understanding of the FBP algorism, and the practical skills of the implementation in python environment.

The no-filter reconstruction illustrate the reconstructed image of sinogram.png, while the different windows (Filters) demonstrate that window function’s capability in digital processing.

Visually, the ramp filter provides the best outcome in terms of brain region distinction, while the Ramp + Hann is best for edge detection.

# **References**

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