

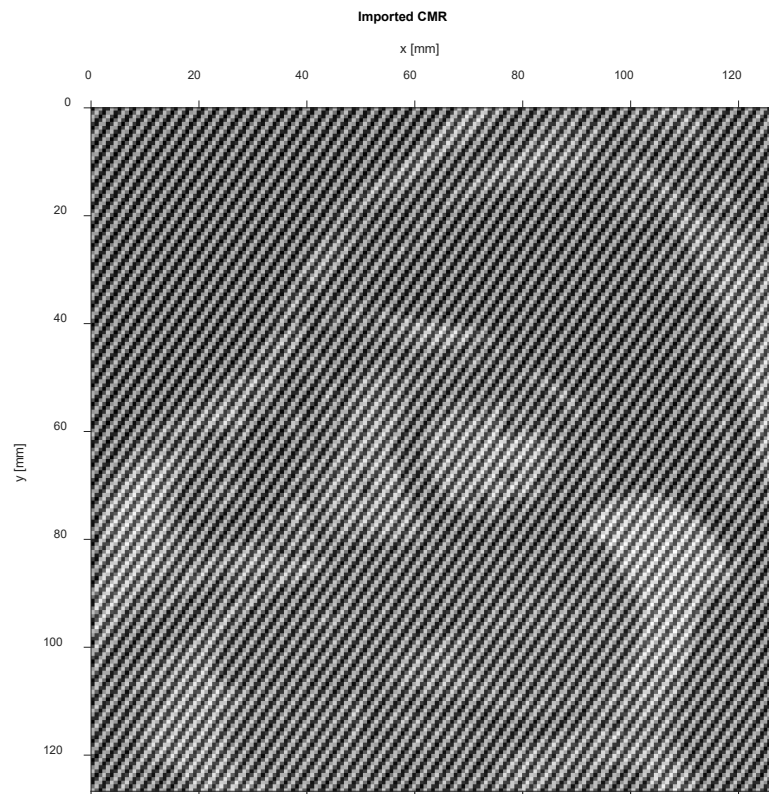
# Report MI Assignment

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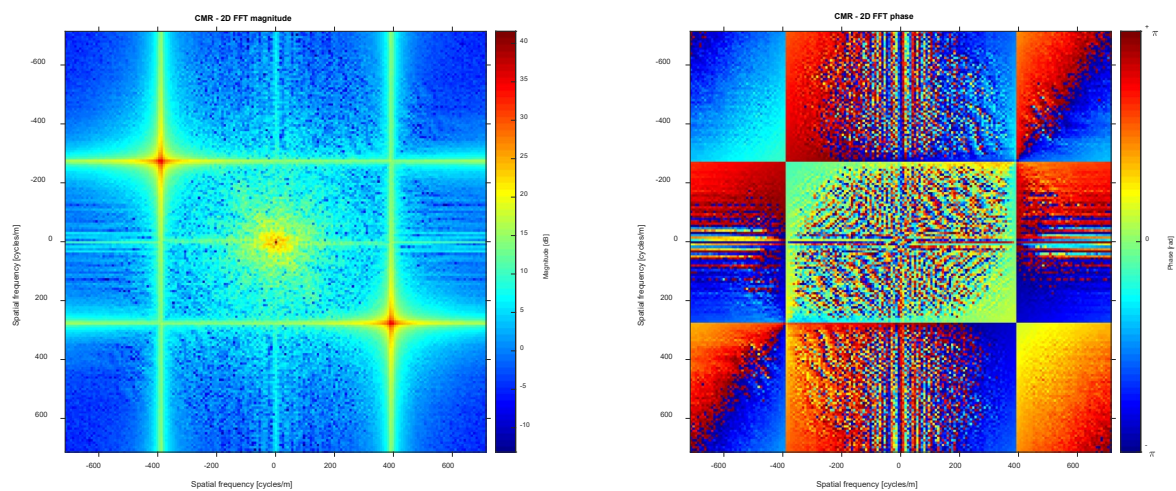
Pozzi Luca 918434

Ratti Alessio 919781

## TASK 1



## TASK 2

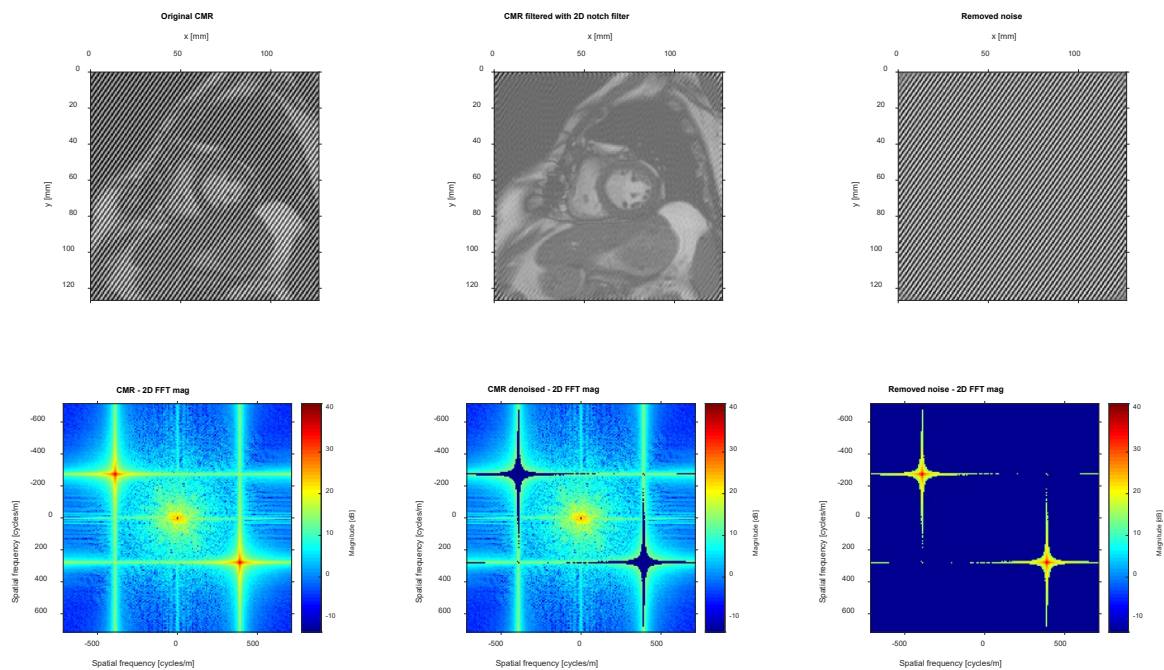


### TASK 3

The original CMR image is affected by the superimposition of a periodic noise characterized by a pattern with repetitive intensity that was added to the original image, consequently, evident spectral peaks in the frequency domain appear when computing the bidimensional Fourier Transform.

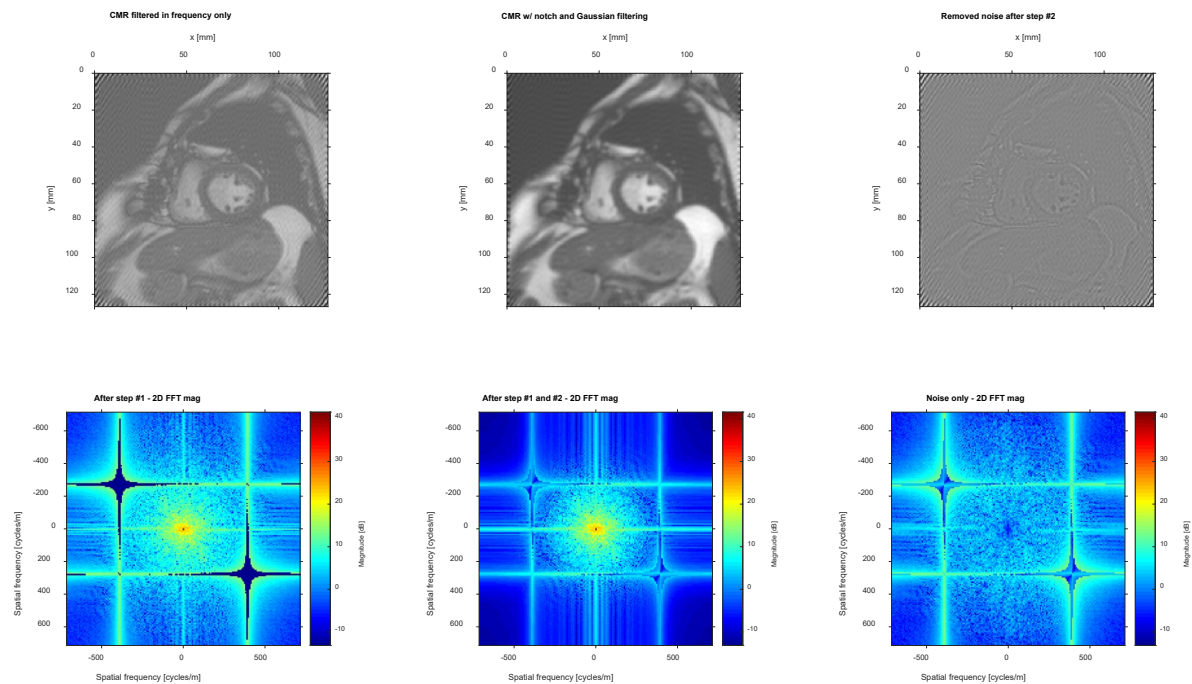
The position of the peaks in the magnitude graph highlights how the sinusoidal noise is characterized by a frequency of about 387 cycles/m in the x-axis direction and around 276 cycles/m in the y-axis direction; In fact, it is trivial to perceive how the angle of the sinusoid with respect to the x-axis is slightly greater than 45 degrees, explaining how the frequency on the x-axis is higher than on the y-axis.

### TASK 4



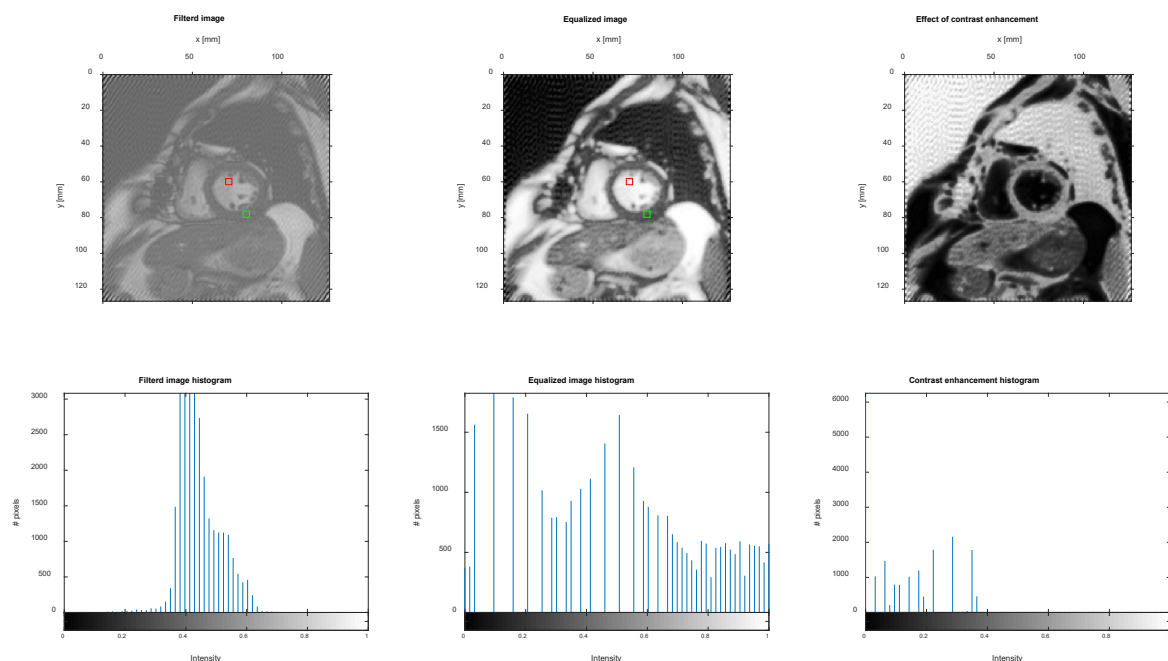
**Filtering approach:** As the image is corrupted by a periodic noise, it can be easily filtered in the frequency domain since the noise is rather separable from the original image. Considering how the noise has a high magnitude and occupies a different position compared to the data relative to the CMR, we first applied an arbitrary experimental threshold that was finely tuned to remove the noise peaks by placing those values to zero; as the image should have been left untouched we also shielded the low frequency components from our threshold-based filtering approach. Once the image was filtered in the frequency domain we applied a bidimensional inverse Fourier Transform to obtain the filtered image in the space domain.

## TASK 5



**Filtering approach:** Although the filtering in the frequency domain is very effective, we can still see some banding in the filtered CMR. In step #2, a spatial filtering was implemented based on a gaussian kernel with variance  $\sigma = 1$ . The resulting image shows less banding, especially along the edges, however, we tuned the variance of the filter in order to preserve the details in the central region of the image as much as possible for the future tasks.

## TASK 6



**Histogram transformation:** In order to increase the contrast, we equalized the filtered CMR image. This operation increased the intensity difference between the light and dark areas highlighting the contours.

**CNR:** To mathematically appreciate the effect of the contrast enhancement we calculated the CNR (contrast to noise ratio) between our region of interest (red square for blood and green square for myocardium) both before and after contrast enhancement. As we were expecting, the difference between the mean value of myocardium and blood increases, however, the variance also increases since the intensity differences between pixels are enhanced.

#### Before

$$\mu_B = 0.5381$$

$$\mu_M = 0.4073$$

$$\sigma_M = 0.0084$$

$$CNR = 15.6261$$

#### After

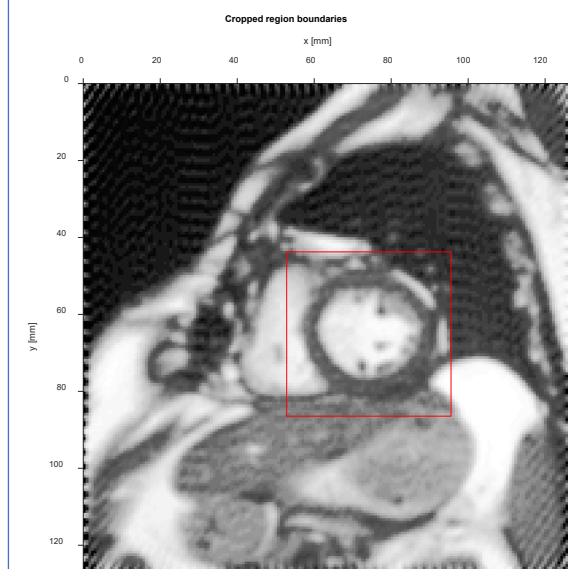
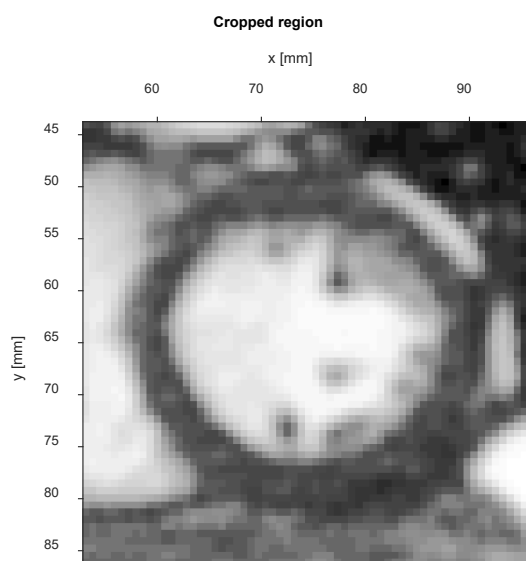
$$\mu_B = 0.9233$$

$$\mu_M = 0.3571$$

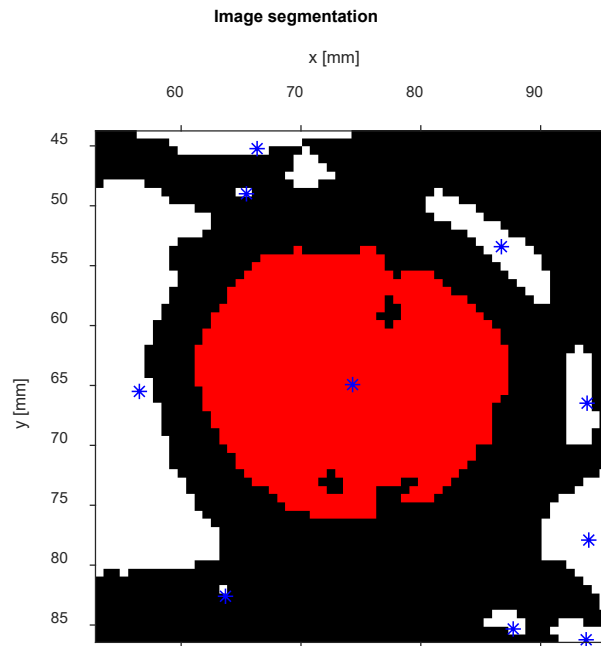
$$\sigma_M = 0.0611$$

$$CNR = 9.2622$$

## TASK 7



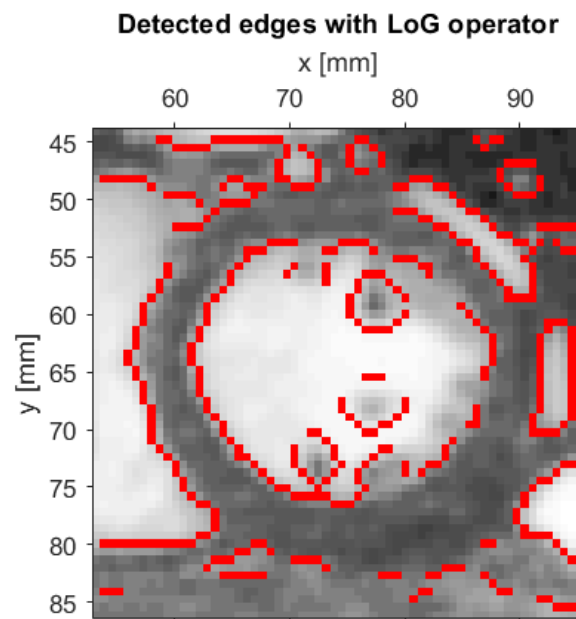
## TASK 8



**Segmentation technique:** To segment the image we first introduce a threshold based on the intensity of the pixels that make up the subregion area; we exploited the Otsu's method, an algorithm which assumes that the image contains two classes of pixels following bi-modal histogram, it then calculates the optimum threshold separating the two classes so that their intra-class variance is minimal. In the image we show the centroids of the segmented areas and the blood section area in red. By applying the function "bwlabel" to the segmented image, we can extract all the pixels that belong to the area of interest and, by multiplying their total sum by the area of each pixel,  $(1/f_s)^2$ , we get the surface occupied by the blood in the left ventricle.

$$A = \sum_{pixel \text{ ROI}} \left( \frac{1}{f_s} \right)^2 = 447.37 \text{ mm}^2$$

## TASK 9



**Edges identification:** Using an automated edge-detection technique we exploited the potential within the Laplacian of Gaussian operator: we convolve the image with a Gaussian filter and then apply the Laplacian to extract the image contours.