

# Investigation of feature recognition in clinical CT images as a step towards adaptive radiotherapy : Progress Report

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## 1 Aims and objectives of the project

Radiotherapy treatment is based on the destruction of cancerous cells by ionizing radiation. During this process, sane surrounding cells could also be affected by ionizing beam and it is therefore paramount to minimize its effect on those cells. Recent technologies have been devised to modulate the beam intensity in space, allowing a treatment highly adapted to a specific tumour. However, in order to use these techniques to their full potential, the shape and position of the tumour must be precisely known. The process of contouring the cancerous region can be long. The aim of this report is therefore to automate this process on 3-dimensional CT-scans.

## 2 Progress

**Project ownership** The project ought to be written in Python which we had not learned before. Furthermore, a specific file type is used to display and process CT-scans. In order to start this project, we had to learn how to exploit those aspects. To this extent, we first displayed images that were at our disposal. Those images were taken from a 3D scan of a phantom, allowing to display the axial, sagittal and coronal views. We recall here what a phantom is : this is a specially designed object which is scanned to calibrate and evaluate performances of imaging devices like CT-scans. A first display of one slice of the phantom used here can be found in Fig. 1.

**Threshold method** The aim of this method was to detect only the outer boundary. The algorithm here looks for pixels whose intensity crosses a defined threshold. If this is the case, then the pixel is considered as a border. This threshold was obtained after computing the mean intensity of the phantom's interior. This method allowed the detection of the outer boundary and also some of the holes inside the phantom whose intensities crossed the threshold (purple holes inside the phantom on Fig. 1).

**Derivatives peaks** This method relies on the pixel intensity variation (or similarly, its derivative). When moving from one region to another, the intensity should indeed vary greatly. The maxima of this variation therefore give the contours of a region. The directional derivatives of the intensity were computed using central finite differences. Then the already implemented function *findpeaks* was applied on each row and column of the intensity variations returning the maxima of the derivatives. The result obtained were satisfying, however *findpeaks* requires a threshold that defines the minimal height for the peaks considered. Since this value is arbitrarily chosen, the results can be different. To avoid an arbitrary choice, a method based on statistical measures was implemented.

**Statistical method** As above, this method relies on intensity variation. The difference with the previous algorithm is that we use a statistical approach to determine the borders. Here, the intensity average  $\mu_1$  and variance  $\sigma_1$  are computed on a subset of size  $n$ . It is then compared to the mean intensity  $\mu_2$  of the next subset in the following way :

$$\mu_2 > \mu_1 + C\sigma_1 \tag{1}$$

where  $C$  is a known constant.

If this condition is fulfilled, the pixel in the middle of the second subset is considered as a contour. The results obtained with this method were severely affected by noise and did not give conclusive results for the contours inside the phantom.

**Laplacian method** Mathematically speaking, the search for the maxima of the derivatives is equivalent to the search for zero crossings of the Laplacian operator. To find those zeros, the Laplacian was computed at each point of the image using central finite differences. If from one point to another the Laplacian value changes from negative to positive (or the opposite), a zero crossing is found and the pixel is therefore contained in a border. As such, the method also takes into account the background noise. To avoid this, only a small percentage (ca. 10%) of the brightest contours were displayed. The percentage value was once again an arbitrary value but the results were of good standing.

**Canny filter** The Canny edge detector is a standard algorithm used for image treatment. This algorithm relies on the search for the maxima of the intensity gradient. It requires two thresholds, a lower and an upper one. If the norm of the gradient is above the upper threshold, the pixel is considered as a contour. If it is in between the two, it is a contour only if it is connected to a pixel that is already a contour. Finally, if it is below the lower threshold, the pixel is ignored. This process is called edge tracking by hysteresis. In order to remove the noise, the Canny algorithm applies a Gaussian filter beforehand. The results obtained with this method were very conclusive and can be seen in Fig. 2a and 2b. After applying this method on the raw image, we developed an algorithm that fills the different regions with random colours.

### 3 Remaining work

The algorithms developed up to this point work in the particular case of a phantom. Real images will probably not have such well defined regions and their detection might be far more complicated.

Although the different methods developed were applied to 2D images, the final goal of this project is to develop an algorithm for 3D features recognition. A 3D version of the algorithm was tested where the edges were detected (with the Canny filter) on 2D slices of the scan and then grouped together in 3D. However, there seems to be a stack overflow due to deep recursion with the function grouping boundary together. This problem still has to be overcome and it may be resolved by using stackless Python.

Finally, the most recent algorithm used for pattern recognition often use Machine Learning (ML) [1] methods. This is a path we also would like to explore. We are complete beginners in ML so we have to learn the basics of this field first and then apply them to real images.

### 4 New timeline and expected results

The second term will be dedicated to Machine Learning and the final report. As beginners in Machine Learning, the expected results are uncertain, although we hope to surpass the results obtained with standard algorithms. We will have to deepen our knowledge on Machine Learning algorithms in order to implement Neural Networks [2] and Convolutional Neural Networks [2].

# Annex

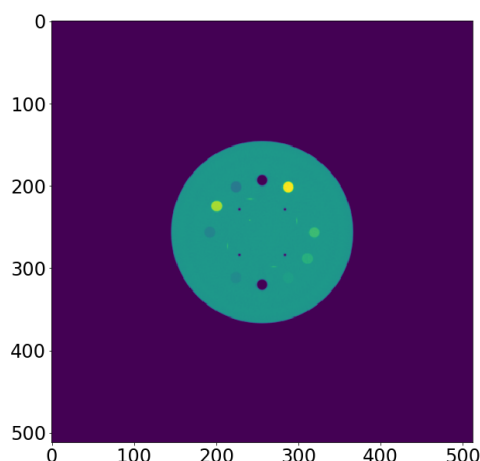
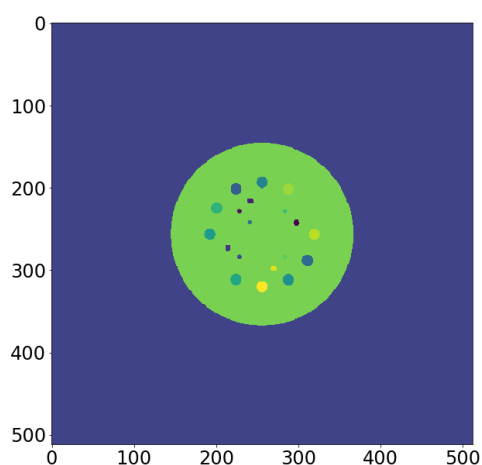
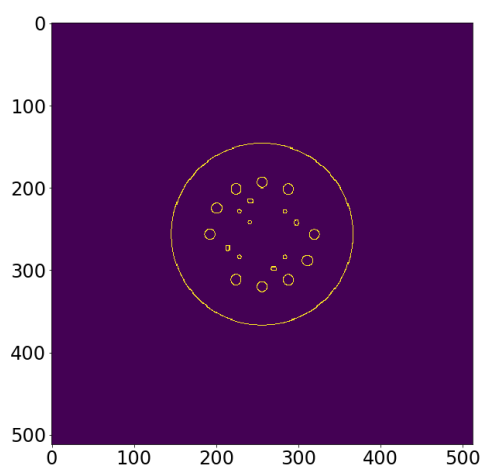


Figure 1 – Image of slice 60 of the phantom without treatments



(a) Image of slice 60 after applying the Canny Filter

(b) Image of slice 60 after filling every regions

Figure 2 – Edge Canny Filter results on slice 60 of the phantom

## Références

- [1] Tseng, HH., Wei, L., Cui, S., Luo, Y., Ten Haken, RK., El Naqa, I. (2018) Machine Learning and Imaging Informatics in Oncology. *Oncology International Journal Cancer Research and Treatment*. 1-19. Available from : doi :10.1159/000493575
- [2] Erickson, B., Korfiatis, P., Akkus, Z., Kline, T. (2017) Machine Learning for Medical Imaging. *RadioGraphics*. 37,505-515. Available from : doi :10.1148/rg.2017160130