Rapport TP

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1 Visualisation of images

1.1 Abdominal CT

Starting with the manual segmentation, we can see in the various images of kidneys several tumors, each of them of different sizes and most likely at different stages :

1. One kidney, and one tumor

Figure 1 – First image

2. Two kidneys, and no tumor

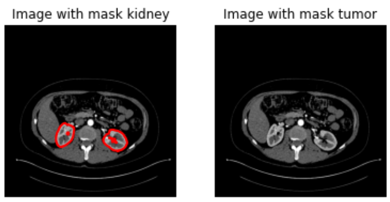


Figure 2 – Second image

3. One kidney, and one tumor

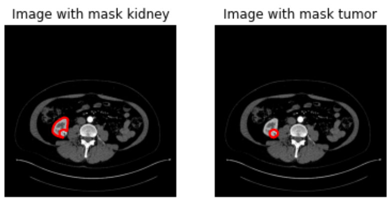


Figure 3 – Third image

4. Two kidneys and no tumors

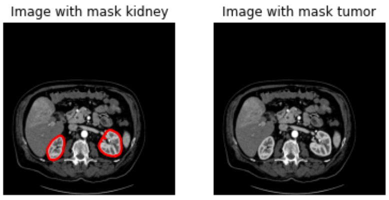


FIGURE 4 – Fourth image

5. Two kidneys and one tumor, one kidney is very "sick"

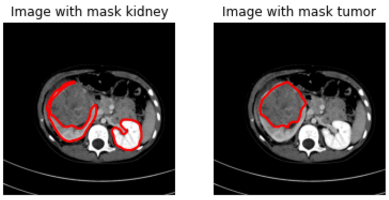


FIGURE 5 – Fifth image

6. Two kidneys and one tumor, one kidney is very "sick"

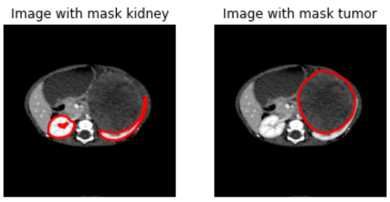


FIGURE 6 – Sixth image

1.2 Brain MRI

Manual segmentations of the corpus callosum on some brain MRI images :

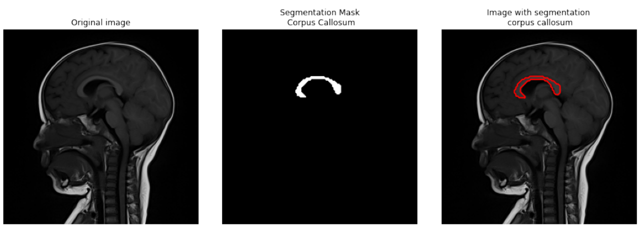


FIGURE 7 – MRI 1

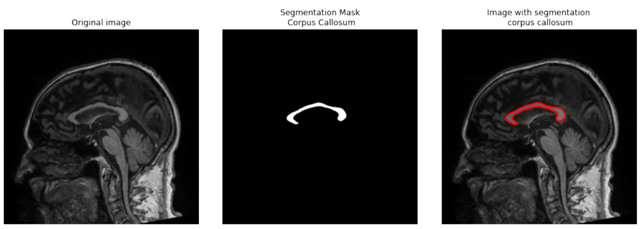


FIGURE 8 – MRI 2

1.3 Skin lesions

Manual segmentations of skin lesions (nevi and melanoma) :

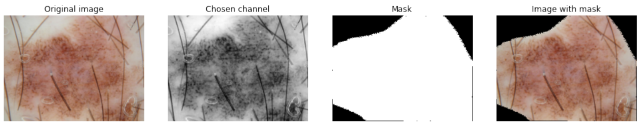


FIGURE 9 – MRI 1

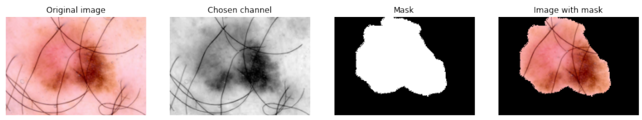


FIGURE 10 – MRI 2

1.4 MRI heart : Segmentation of the left ventricle

Here we can see a slice of heart MRI, we have landmarks of the segmentation of the left ventricle, we will try to make a binary segmentation mask. For that we first compute binary mask with integer values of landmark set in white, then we apply a closing on it to get the final segmentation mask.

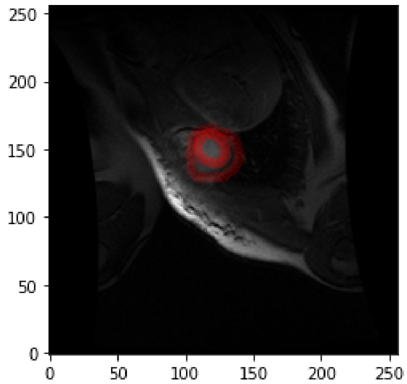


FIGURE 11 – Original image with landmarks

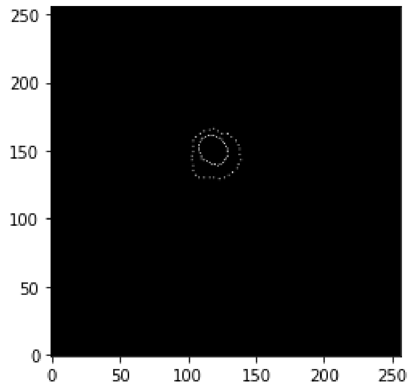


FIGURE 12 – Binary integer mask

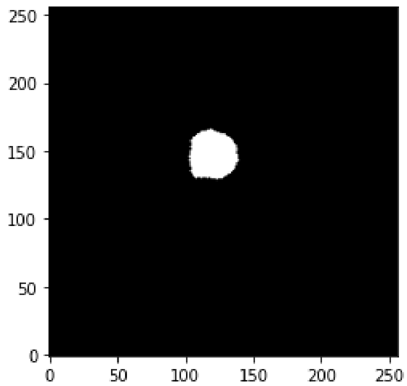


FIGURE 13 – Mask

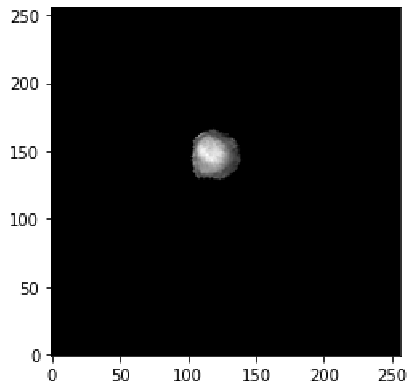


FIGURE 14 – Visualisation of the segmentation

2 Segmentation using thresholding

Compare the histograms of images of the same modality. Are the conclusions the same on CT images and on MRI images ? CT and MRI are acquisition methods that enable to get anatomical information (fMRI functional). Since a CT scanner and MRI machine use completely different methods for generating internal images of the body, they are often used to diagnose specific problems.
By comparing histograms of images acquired with CT and MRI, we can notice that the histogram for MRI images is much more spread out than the one for CT images that is mainly a pic in the black area, indeed the image of CT are less nuanced than MRI. The pic depend on the main color on the image, in this case is the black color but this depend on the image. In any case MRI are more detailed, more contrasted images, so they have more nuances, that is more levels of gray.
Here are the plot of the histogram for different images and different type of acquisition CT and MRI. For the heart MRI we have to normalize and multiply values by 255 to have the same representation.

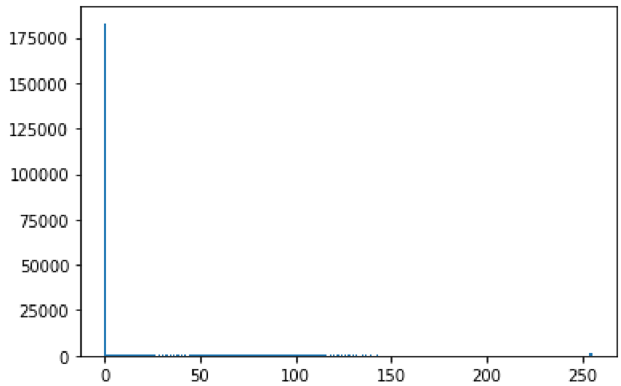


Figure 15 – CT 1

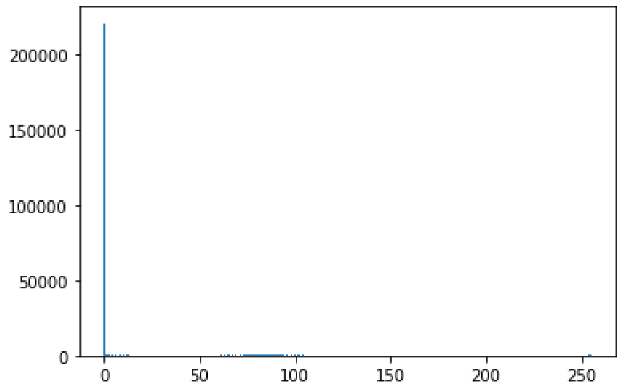


Figure 16 – CT 2

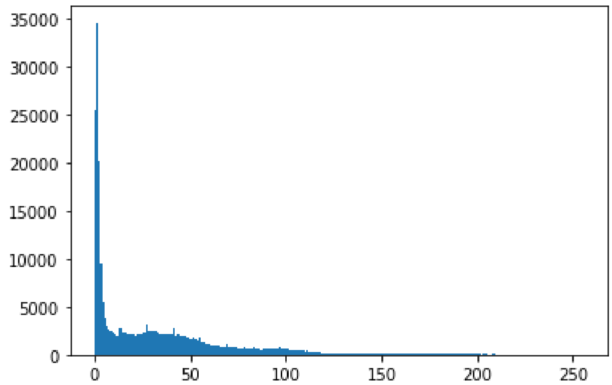


Figure 17 – Brain IRM

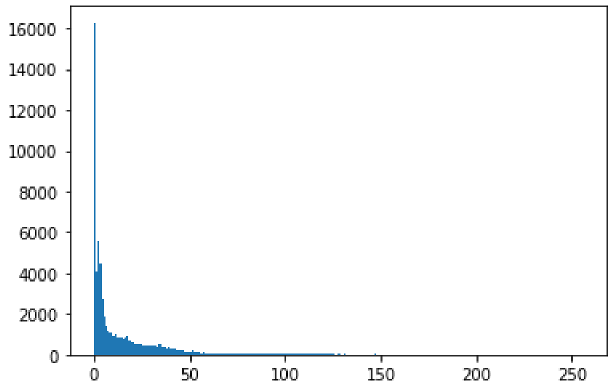


Figure 18 – Heart IRM

Consequences on manual thresholding ? The consequences on manual thresholding is that the threshold must be adapted for different modalities. The adaptation by hand will not necessarily be optimized since the threshold is a human choice. For these reasons, automated threshold

may be relevant. However, manual threshold may be relevant for CT acquisitions. Indeed, the gray levels of a CT image are designed to fit the value of the attenuation coefficient of a specific tissue. As a consequence, each gray level can be connected to a specific tissue. Knowing this connection allows an efficient manual thresholding.
We can see below that the choice of the threshold enable to get different modalities.

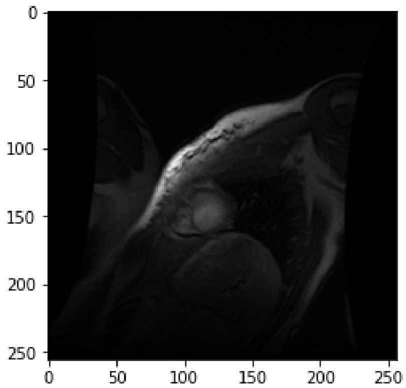


FIGURE 19 – Original image

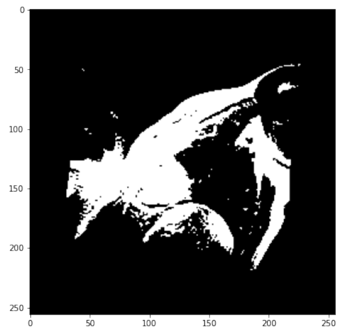


FIGURE 20 – T=120

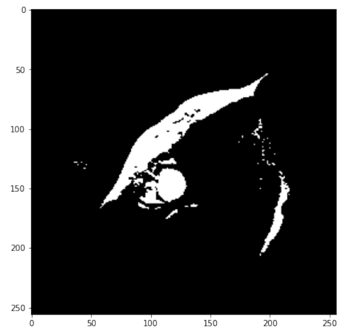


FIGURE 21 – T=220

Test the automatic Otsu's thresholding method. Conclusions ? The automatic method Otsu tends to separate the image to minimize the variance on each side of the two chosen regions, it allows to have a binary segmentation of the image depending on the automatic threshold found. However it is not adapted to solve all of our problems. For MRI image of the heart, if our goal is to segment the left ventricle, we can notice that more than that is detected (as shown in Fig22), since other parts of the image are as light as the ventricle. In Fig.23 we can also notice that without any pre-processing all the hair are detected as part of the lesion. Otsu is a useful method in cases where one would need to minimize this variance, usually, it produces appropriate results for bimodal images.

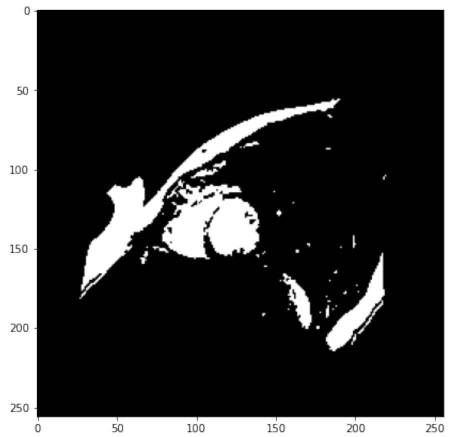


FIGURE 22 – MRI image of heart - Ostu segmentation

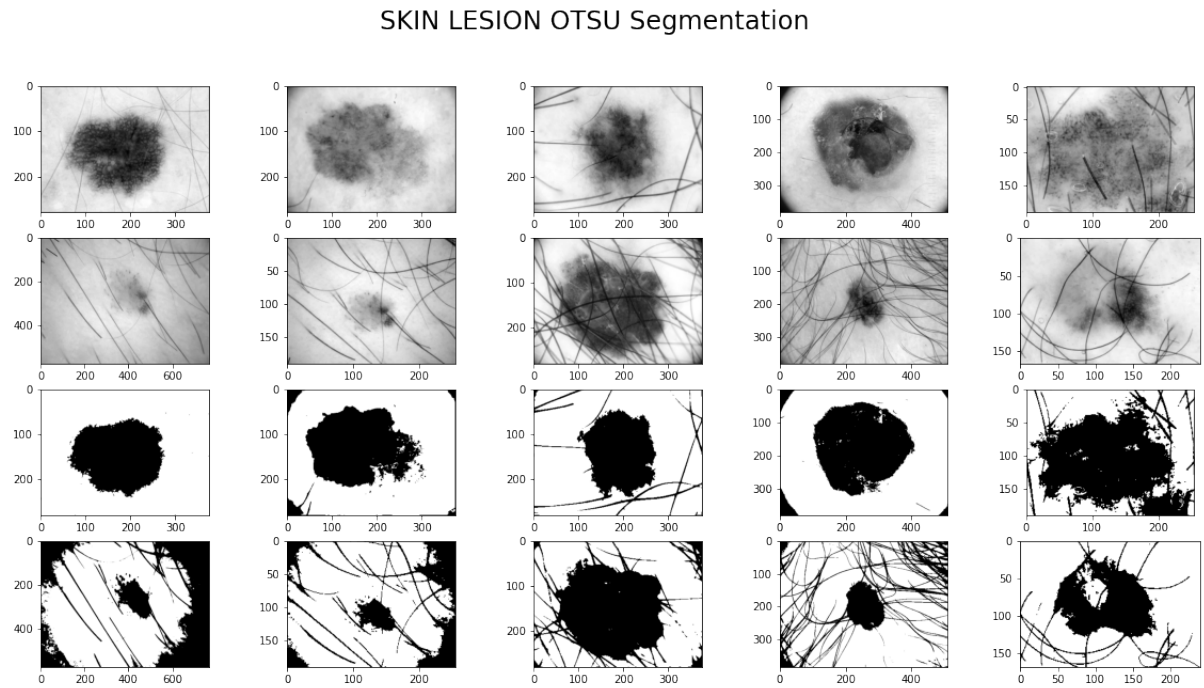


FIGURE 23 – Optical image of the skin - Ostu segmentation

Test the automatic k-means method (2 classes or more). Conclusions ? The k-means method allows to have a segmentation of the image a bit more detailed than the Ostu or manual thresholding methods, with nuanced grey levels. It tends to reduce as much as possible the variability of each cluster of the image, corresponding to a grey level. The number of clusters can be chosen by the user. The figure below was computed with the k-means method with 3 and 6 clusters.

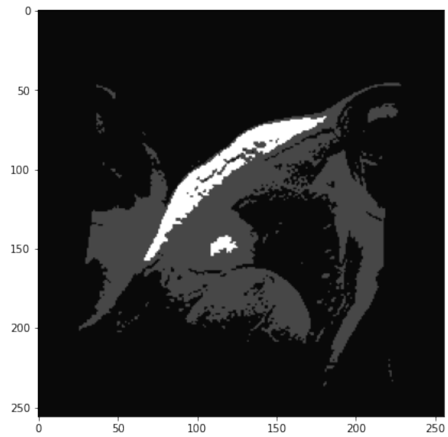


FIGURE 24 – MRI image of heart - k-means segmentation, k=3

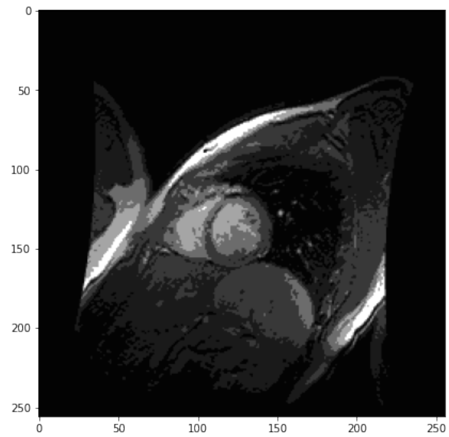


FIGURE 25 – MRI image of heart - k-means segmentation, k=6

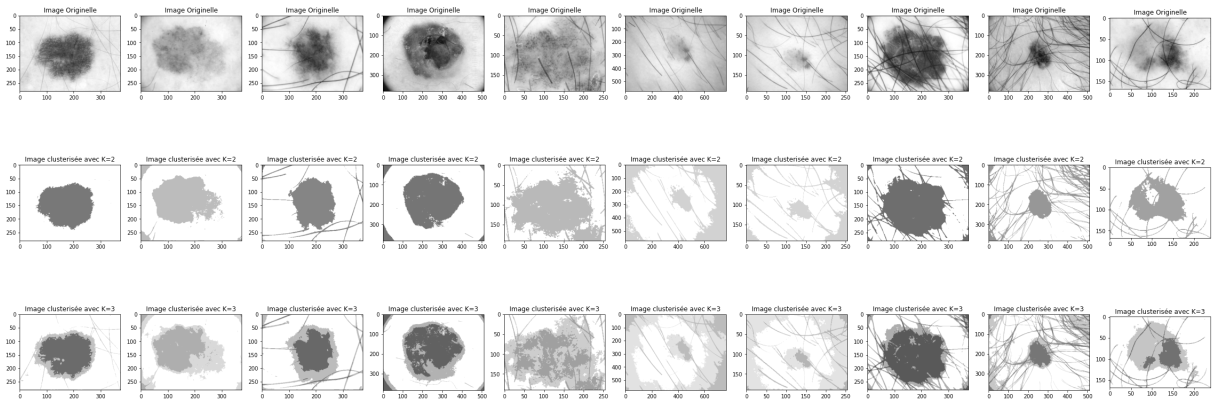


FIGURE 26 – Optical image of the skin - k-means segmentation

The segmentation method to use depends on the problem to be solved.

3 Initialize a segmentation by region growing, watersheds or deformable models from the previous results (the method can vary according to the images and the subsequent segmentation method), and try to improve this initialization using pre- and post-processing (filtering, etc.)

We can use the region growing algorithm with initialisation point manually placed :

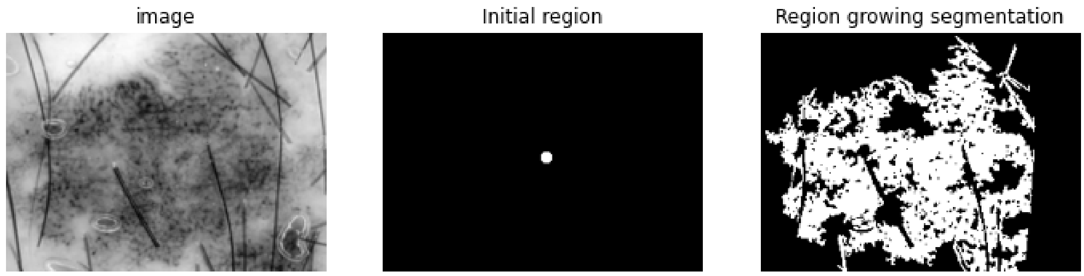


FIGURE 27 – Original image

We can also use previous segmentation results to create an initialization, by making a segmentation of the object and peak random point in the object :

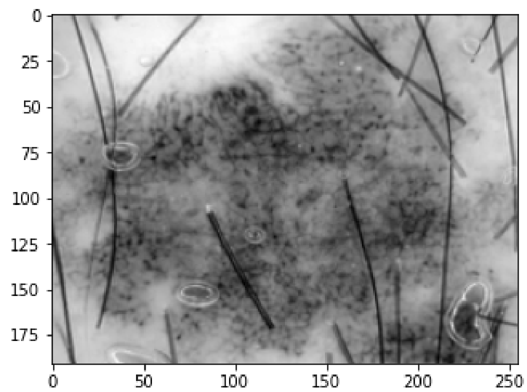


FIGURE 28 – Original image

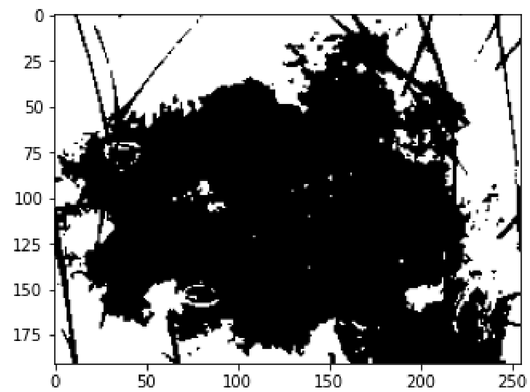


FIGURE 29 – Otsu thresholding

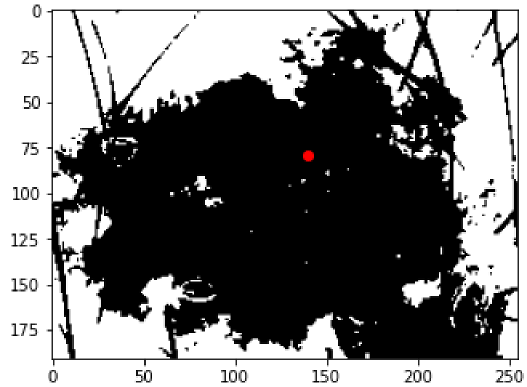


FIGURE 30 – Random marker 1

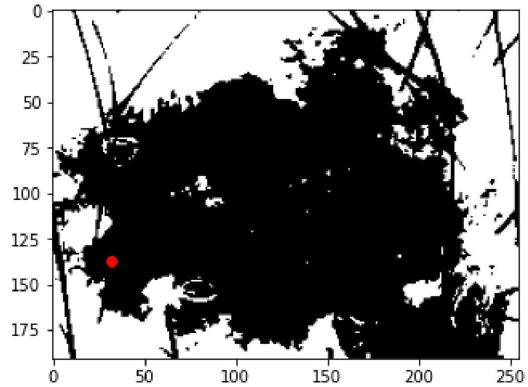


FIGURE 31 – Random marker 2

We can also think about adding a pre processing step to the thresholding before taking a point, for example we can use a reconstruction by dilatation to remove small white spot and then chose a random point in the object :

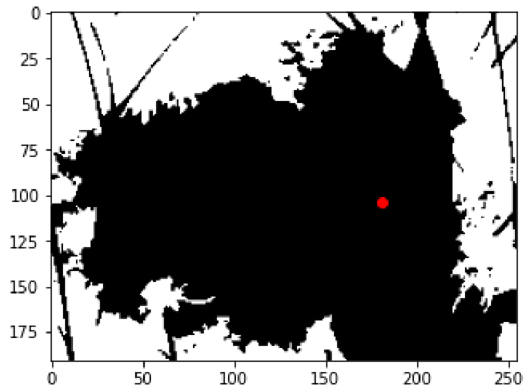


FIGURE 32 – Original Image

We can also do a kmeans and then apply a threshold to get an initialisation with certains region of the object :

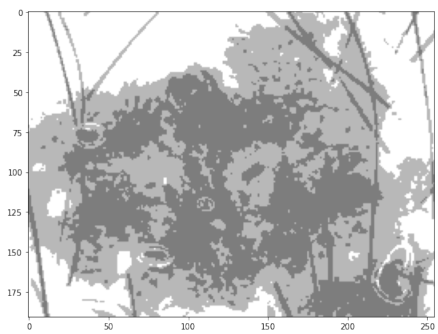


FIGURE 33 – Kmeans

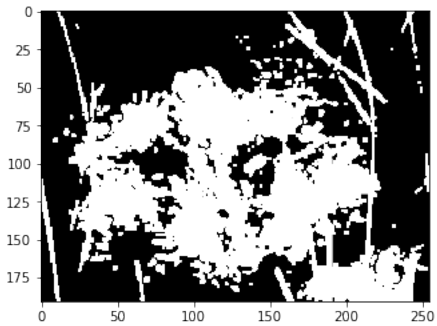


FIGURE 34 – thresholded Kmeans

A lot of others method of initialisation are also possible.

3.1 Segmentation by region growing

Test of region growing with 1 points as manual initial region :

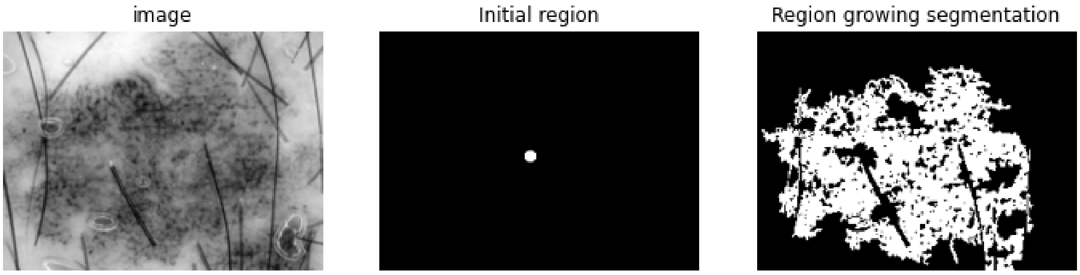


FIGURE 35 – Growth of regions

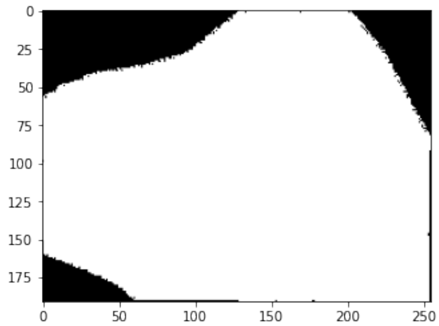


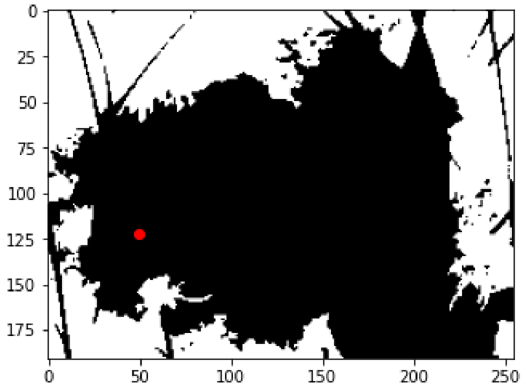
FIGURE 36 – Manual segmentation

Dice index between manual segmentation and mask from our restults : 0.6211376109833672

The initial region must be in the object as we can see below :

FIGURE 37 – Bad segmentation

We can experiment the region growing with automatic initial region, with for example a random point in the object :



3pts

FIGURE 38 – Marker

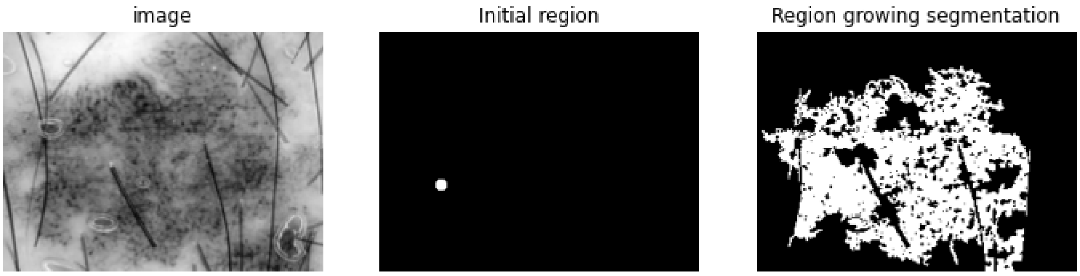


FIGURE 39 – Growth of regions

Dice index between manual segmentation and mask from our restults : 0.5735123026966955
In this case we may need to make the image smoother in order to get a better segmentation with a pre-processing step.

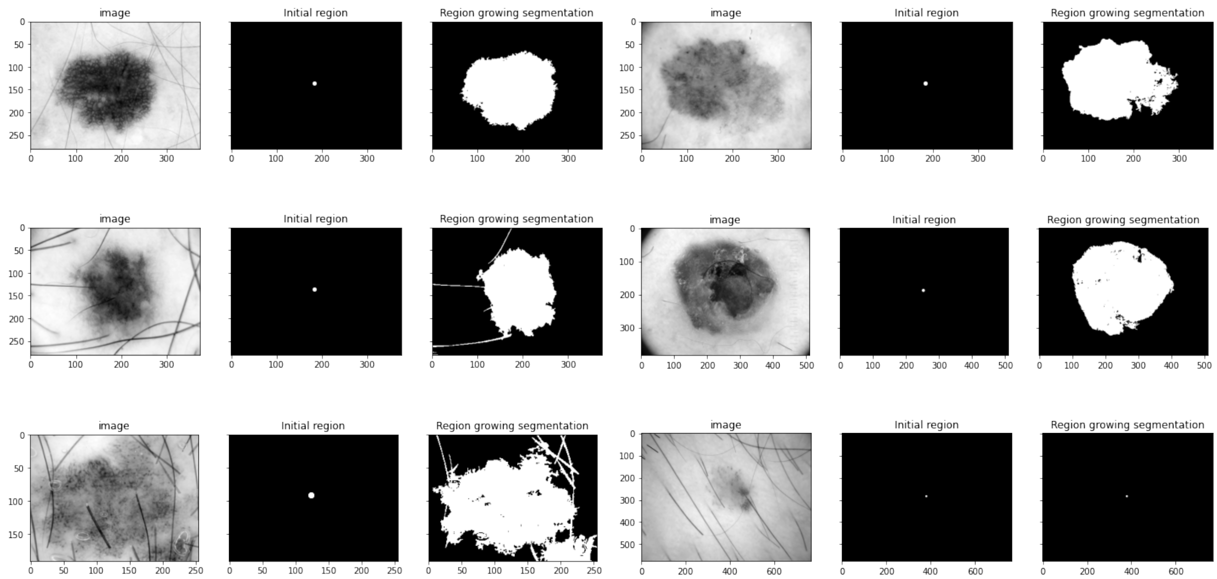


FIGURE 40 – Region Growing

3.2 Segmentation with watershed

We can test watershed with initial marker in the object, to be consistant on our test we choose a manual point at $x = 130, y = 100$

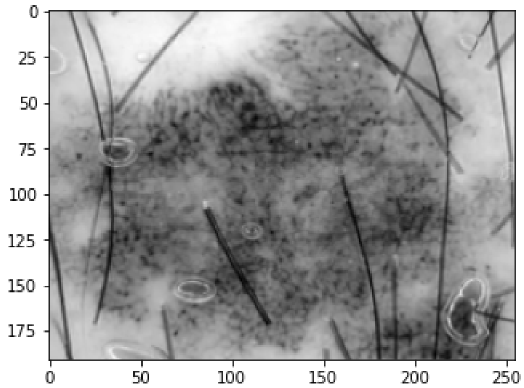


FIGURE 41 – Original image

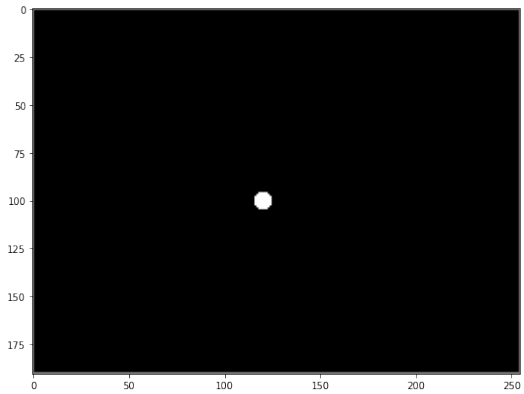


FIGURE 42 – Markers

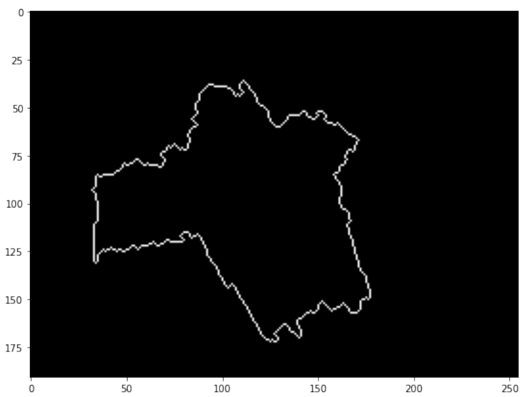


FIGURE 43 – Segmentation

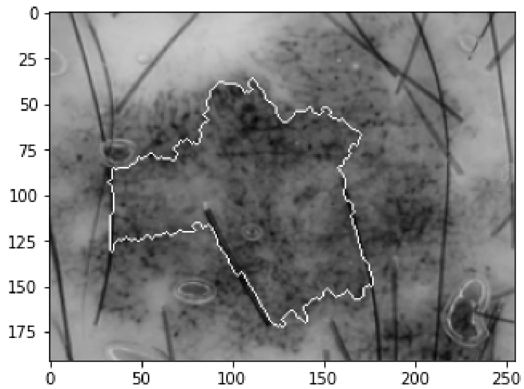


FIGURE 44 – Visualisation of the segmentation

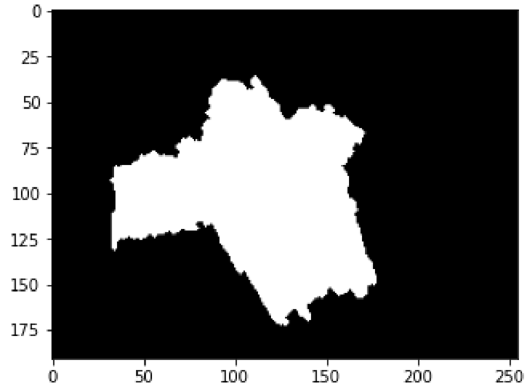


FIGURE 45 – Segmentation mask from our results

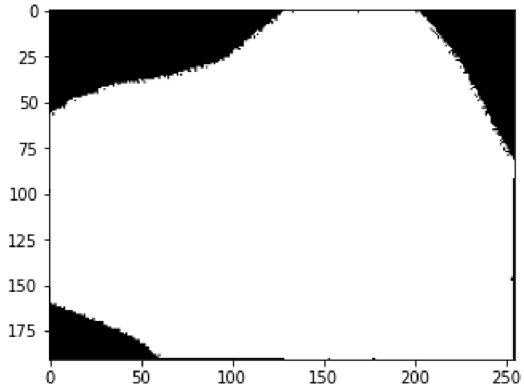


FIGURE 46 – Manual segmentation

Dice index between manual segmentation and mask from our restults : 0.42094538743968785

The results is pretty bad because of hair that block the watershed segmentation. So, we tried some pre-processing on the original image before the computation of the morphological gradient on which watershed is computed :

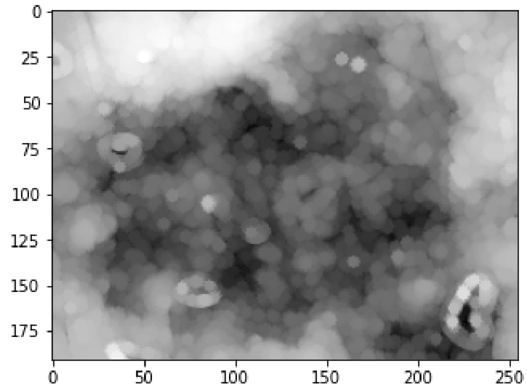


FIGURE 47 – Image dilated by size 3 disk structuring element

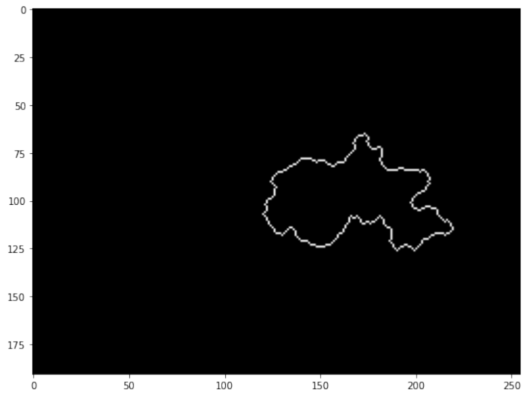


FIGURE 48 – Segmentation

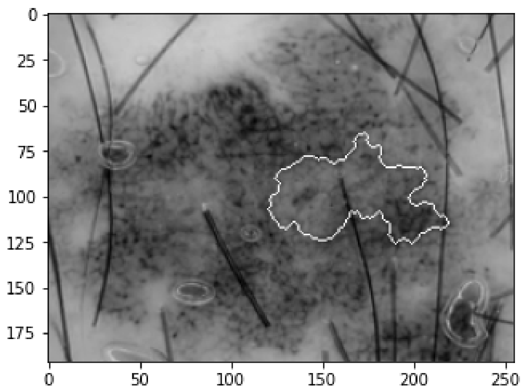


FIGURE 49 – Visualisation of the segmentation

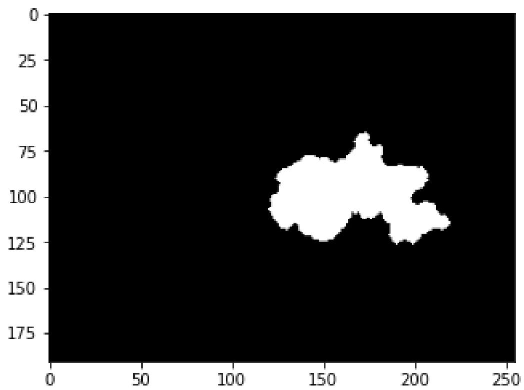


FIGURE 50 – Segmentation mask from our results

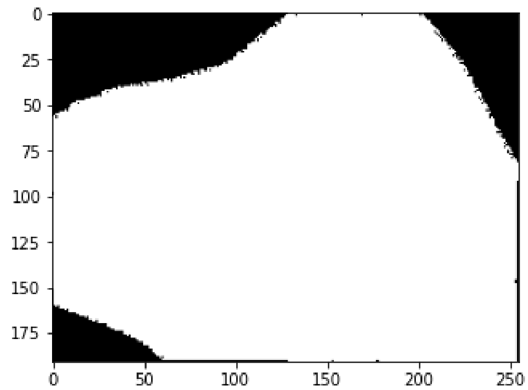


FIGURE 51 – Manual segmentation

Dice index between manual segmentation and mask from our restults : 0.1508261672144433

We have even worse result here, indeed our image lost all edges informations with the dilation, and as the watershed is based on the filling of the catchment basins (corresponding to the markers) on the image of the morphological gradient, it is important to have well defined contours. For that we will apply an ASF filtering to get more homogeneous region and therefore more defined contours :

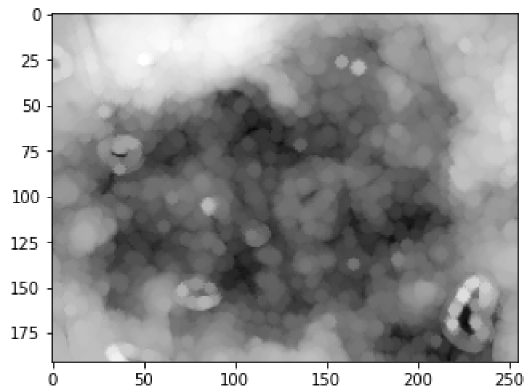
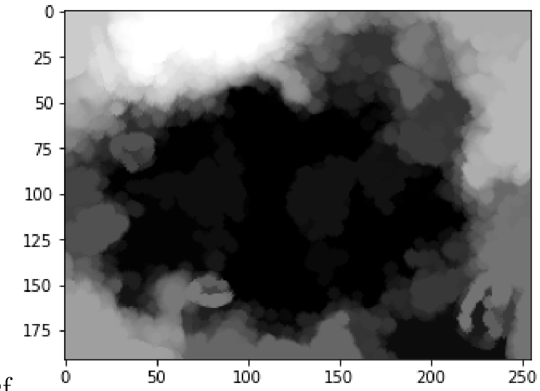


FIGURE 52 – Image dilated by size 3 disk structuring element



4asf

FIGURE 53 – ASF on dilated image, N=20

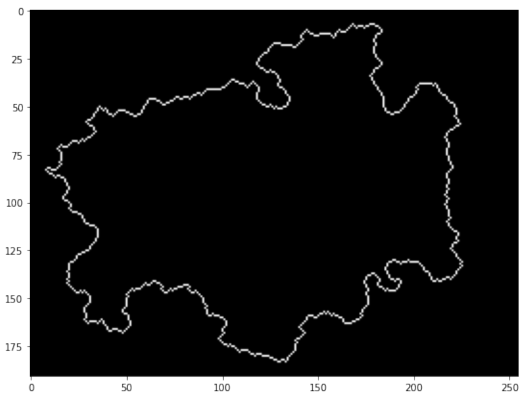


FIGURE 54 – Segmentation edges

FIGURE 55 – Segmentation mask

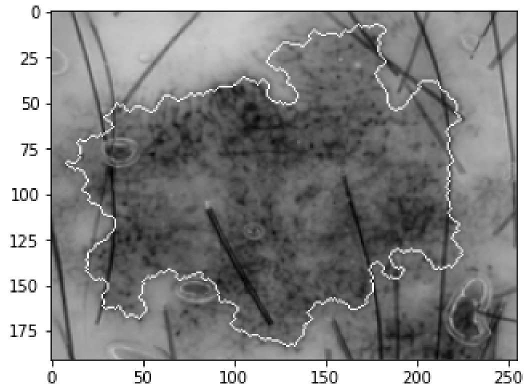


FIGURE 56 – Visualisation of the segmentation

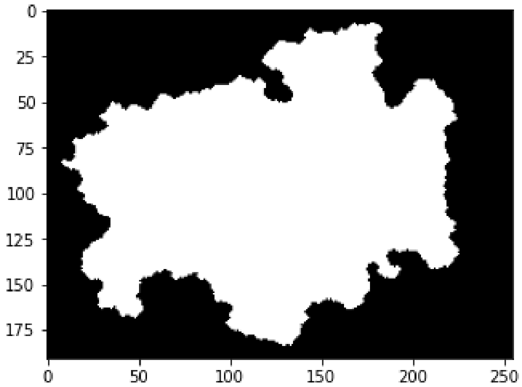


FIGURE 57 – Segmentation mask from our results

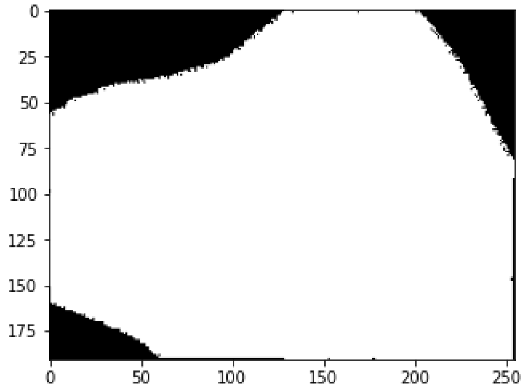


FIGURE 58 – Manual segmentation

Dice index between manual segmentation and mask from our restults : 0.7301705081234832
With this preprocessing we have good result.
Now we can try to get an random initialisation point :

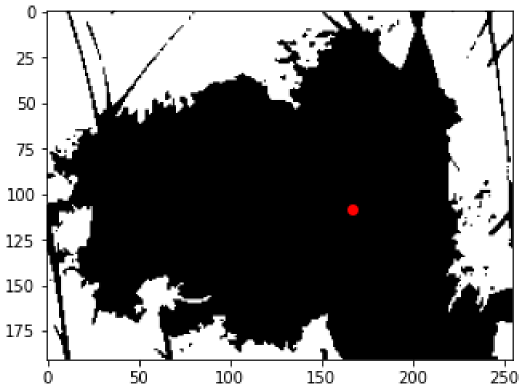


FIGURE 59 – Random initialisation point

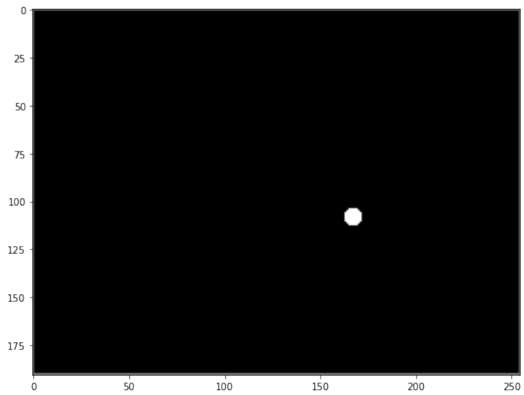


FIGURE 60 – markers

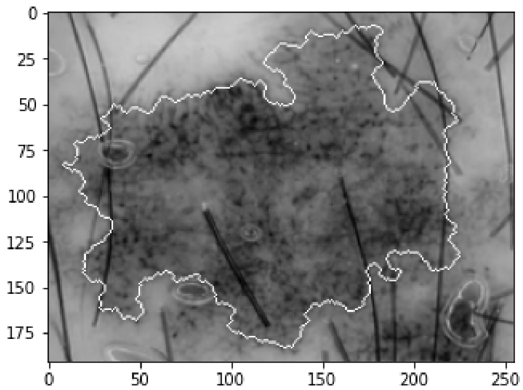


FIGURE 61 – Segmentation visualisation

Dice index between manual segmentation and mask from our restults : 0.7301705081234832

3.3 Segmentation using deformable models

3.3.1 Active contour

Image :

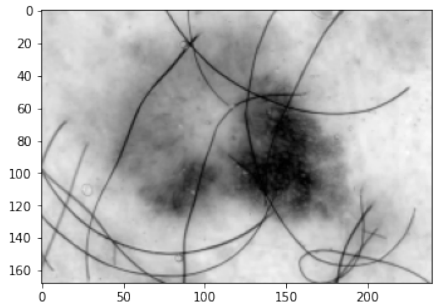


FIGURE 62 – Original image

We will need to do a pre-processing step to remove hair, in order that the hair not interfere with the contours of the lesion :

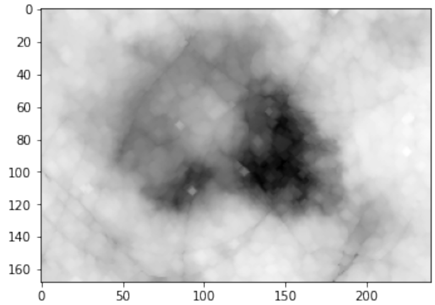


FIGURE 63 – Image dilated

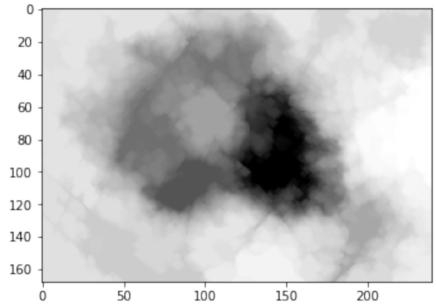


FIGURE 64 – ASF on dilated image N=10

Results with active contour :

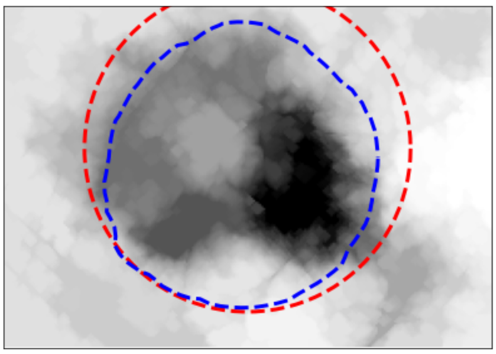


FIGURE 65 – Results with $\alpha = 1, \beta = 1, w\_edge = -100, w\_line = -10, \gamma = 0.002$

Mask :

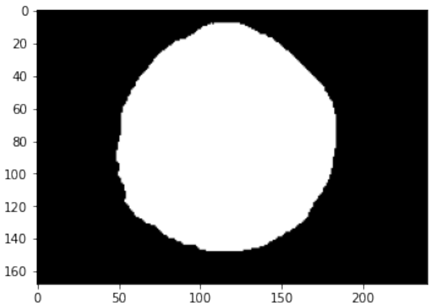


FIGURE 66 – Mask

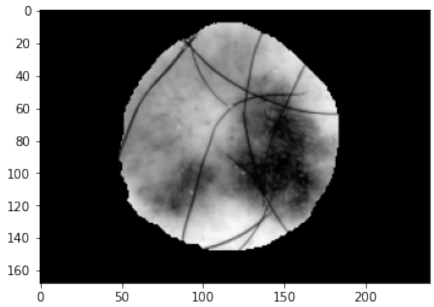


FIGURE 67 – Segmentation Visualisation

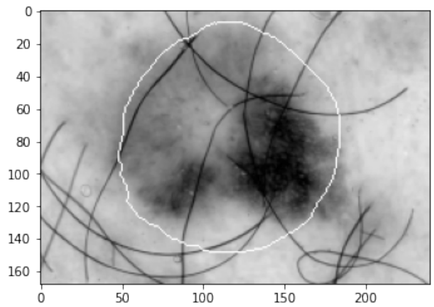


FIGURE 68 – Visualisation of mask

Dice index between manual segmentation and mask from our restults : 0.8367908192713815
We have good result but the initialisation need to be good.

3.3.2 Chan Vese

Without pre-precessing, Chan Vese method can already give good results, as shown below with $\lambda 1$ being equal to 5 and λ_2 being equal to 1.

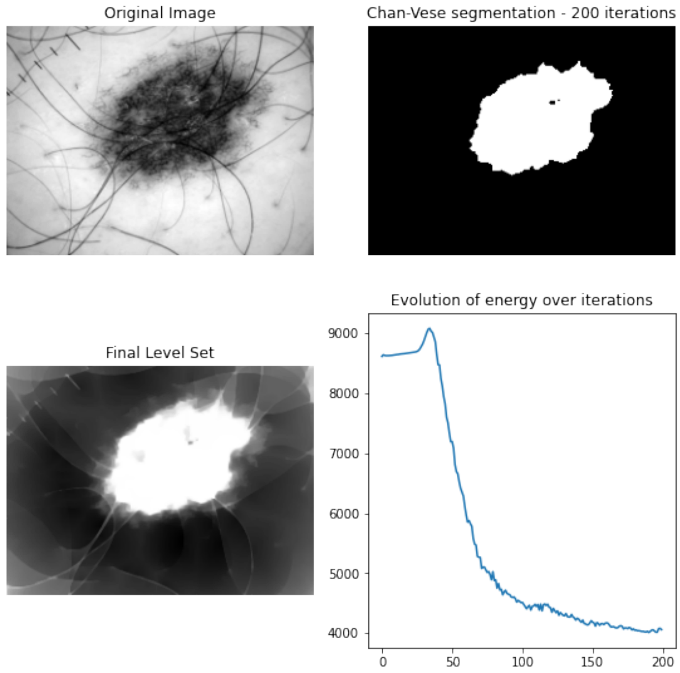


FIGURE 69 – Results with $\lambda_1 = 5, \lambda_2 = 1$

Even is chan_vese can be more robust to imperfection in the image if the imperfections have slightly differents values to the object to be segmented. However in the previous case, the hair can be easily confused with the lesion, it will be better to remove the hair to avoid any problems, we use the same pre processing as before :

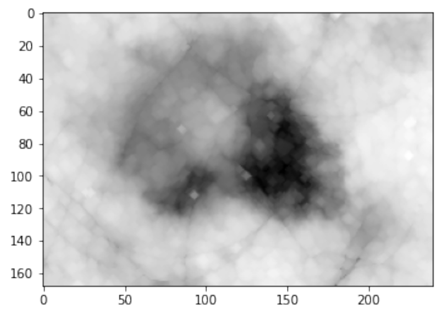


FIGURE 70 – Image dilated, disk, size=2

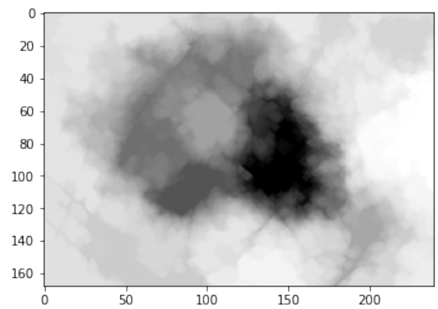


FIGURE 71 – ASF on dilated image N=10

We can also chose a manual point as initialization level set :

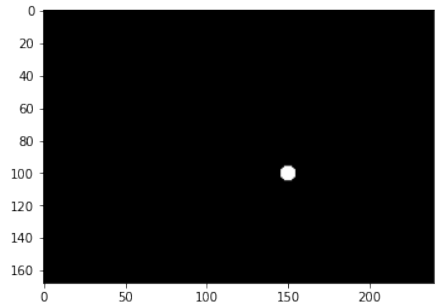


Figure 72 – Initialisation level set

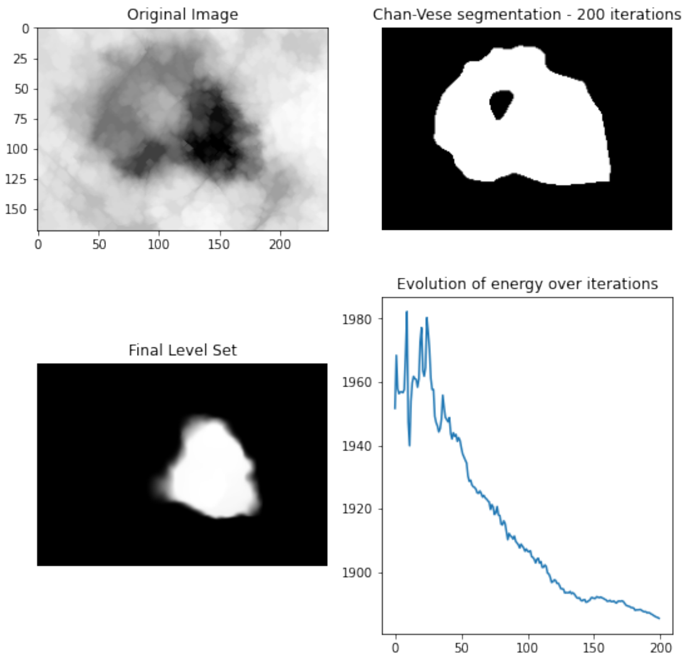


Figure 73 – Result with : $\mu = 0.2, \lambda 1 = 1, \lambda 2 = 1, tol = 1e - 3, max\_iter = 200, dt = 0.5$

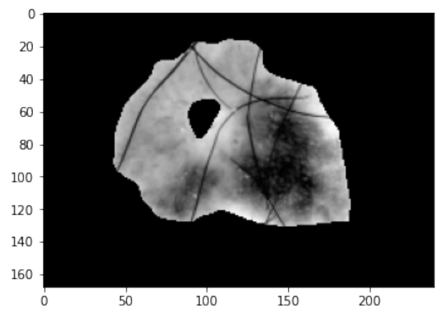


Figure 74 – Result of Segmentation

Dice index between manual segmentation and mask from our restults : 0.8692979857819905
We can try with automatic level set initialization, for exemple with a simple threshold on the dilated image :

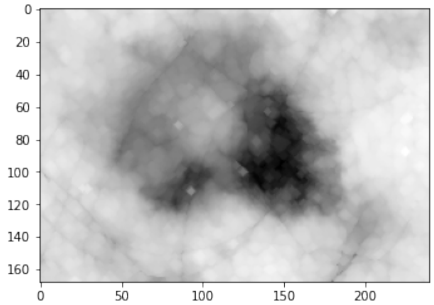


FIGURE 75 – Dilated image, disk, size=2

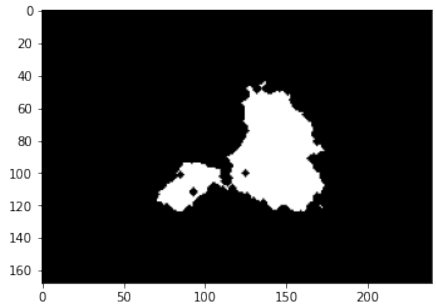


FIGURE 76 – Initialization level set, dilated image < 100

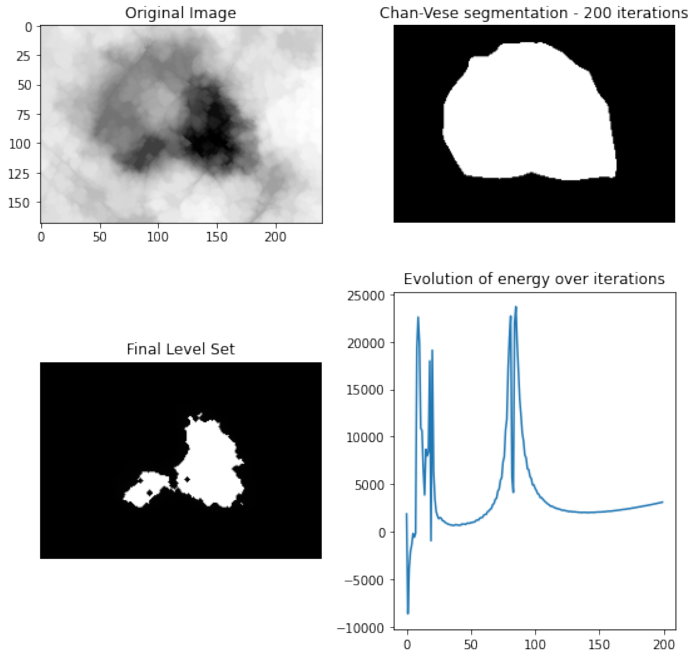


FIGURE 77 – Result with : $\mu = 0.2, \lambda1 = 1, \lambda2 = 1, tol = 1e-3, max\_iter = 200, dt = 0.5$

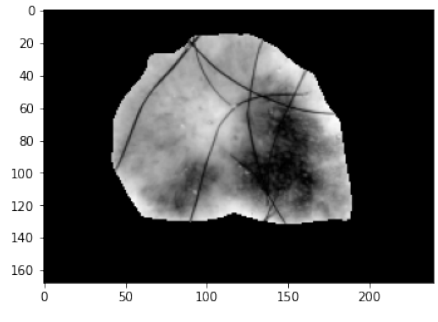


FIGURE 78 – Result of segmentation

Dice index between manual segmentation and mask from our restults : 0.9238440616500453.
We have good visual and quantitative result. We can notice that the initialisation with chan_vese is easier than with active_contour and the parameters easier to tune.

4 Segmentation of an image sequence

We want to use the result of segmentation on the previous frame of a slice to guide the segmentation of the next frame.

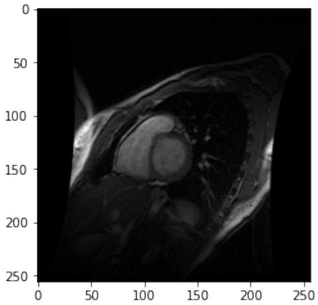


FIGURE 79 – Frame 0

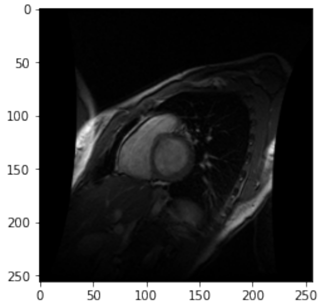


FIGURE 80 – Frame 1

First segmentation with watershed :

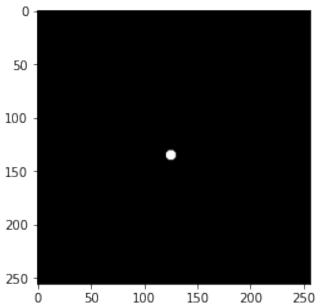


FIGURE 81 – Frame 0 : Markers $x = 125, y = 135$ + borders

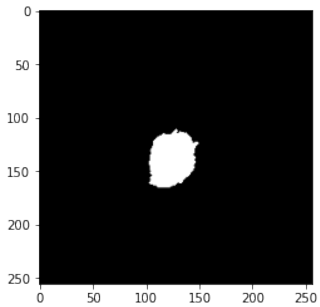


FIGURE 82 – Frame 0 : Mask

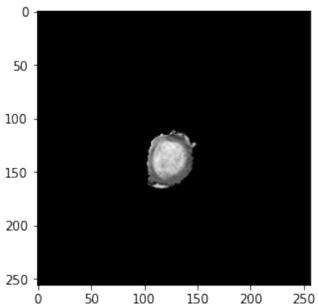


FIGURE 83 – Frame 0 : visualisation

Second segmentation with watershed. We can use as makers an eroded version of the previous segmentation result in order to guide the segmentation on the next frame :

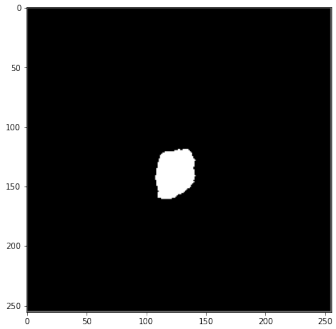


FIGURE 84 – Frame 1 : Markers = previous mask + white borders

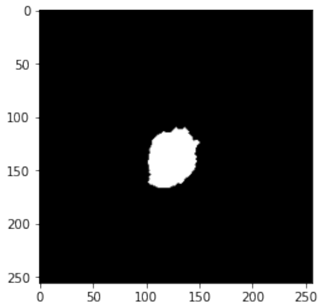


FIGURE 85 – Frame 1 : Mask

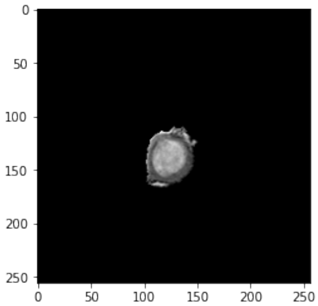


FIGURE 86 – Frame 1 : visualization

In order to segment the left ventricule with watershed over for a slice of the heart for all frames, we will iterate over the 20 frames and use the previous segmentation mask for the new markers. For this exemple of heart mouvement, the contraction of the left ventricule can be huge, therefore we will add an erosion with big structural element of size 9 :

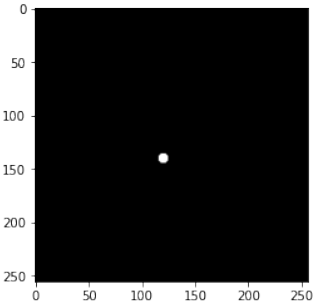


FIGURE 87 – Iter 0 : markers

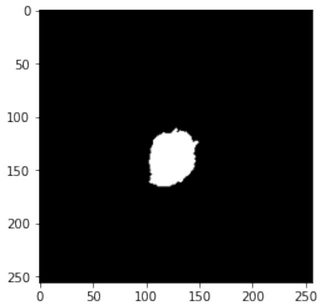


FIGURE 88 – Iter 0 : segmentation mask

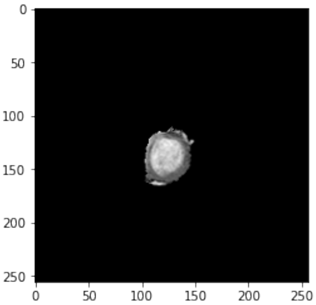


FIGURE 89 – Iter 0 : visualisation of segmentation

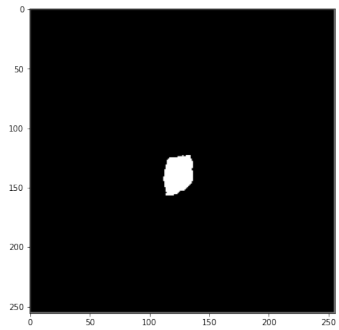


FIGURE 90 – Iter 1 : markers

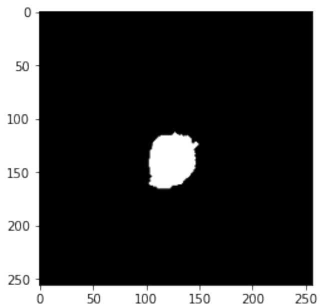


FIGURE 91 – Iter 1 : mask

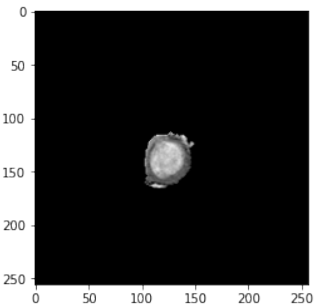


FIGURE 92 – Iter 1 : visualisation of segmentation

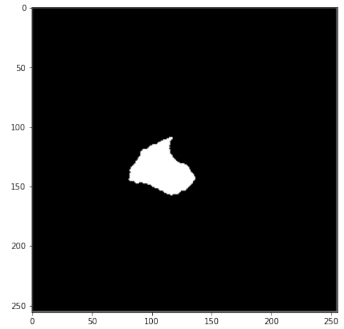


FIGURE 93 – Last iter : marker

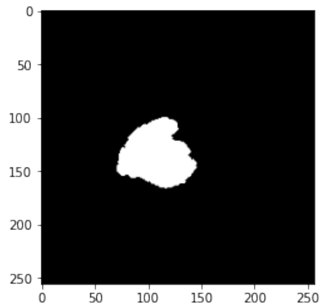


FIGURE 94 – Last iter : mask

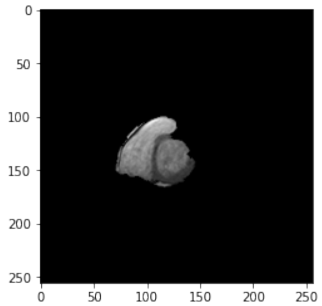


FIGURE 95 – Last iter : visualisation of segmentation

We can see that along the iteration, the segmentation will be of both ventricule and no more the left. It's because of a step where the contraction is too important, it's can be difficult to guide the entire segmentation frame by frame with unicly this process if the contraction/mouvement are important. It will be necessary to reajust makers at a certain frame.
We choose to erode with an element size of 9 because with lower values, the new marker overflow the object to be segmented caused to the strong contraction of the heart. The contraction in this case is so strong that the object to be segmented undergoes too much change to have a good result with using uniquely previous segmentation as new markers, even with erosion.
Visual evaluation :

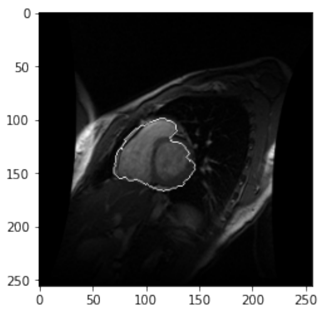


FIGURE 96 – Visualisation of segmentation

Quantitative evaluation :

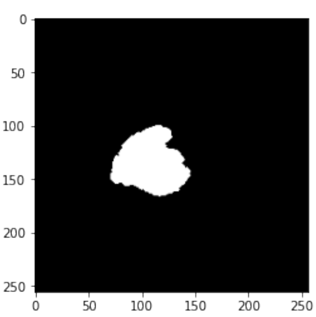


Figure 97 – Segmentation with active contour

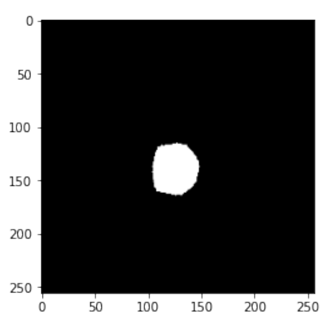


Figure 98 – Manual segmentation (landmarks to mask)

Dice index between manual segmentation and mask from our restults : 0.5764869703600557

We can also use the segmentation information to guide the new segmentation with active contour model. We start from manual markers at frame 0 and for the markers of the next frame 1 we create new markers corresponding to the contour of the segmentation in frame 0 and so on. As previous we can also erode a little the segmentation if necessary.

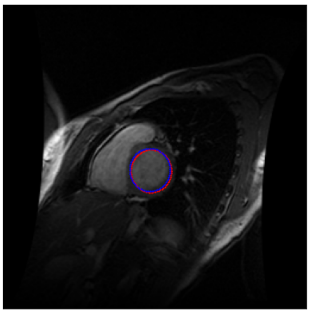


FIGURE 99 – First iter : manual markers in red and segmentation in blue

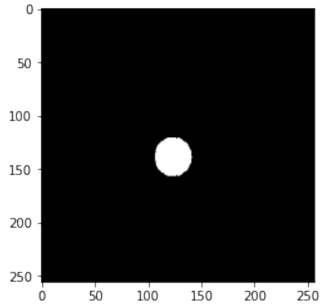


FIGURE 100 – First iter : mask

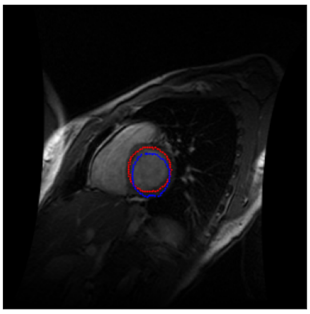


FIGURE 101 – Iter 2 : Marker from contours of previous segmentation

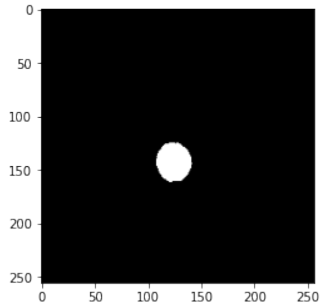


FIGURE 102 – Iter 2 : mask

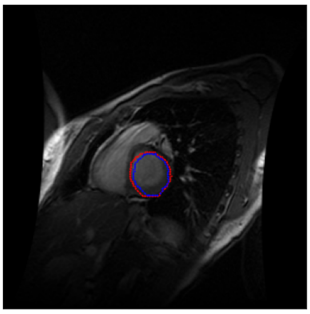


FIGURE 103 – Iter N

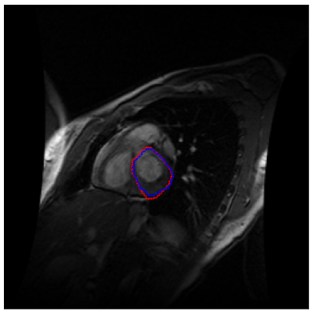


FIGURE 104 – Iter N1

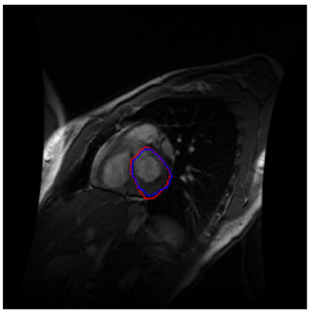


FIGURE 105 – Iter N2

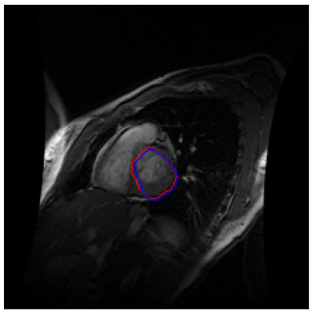


FIGURE 106 – Iter N3

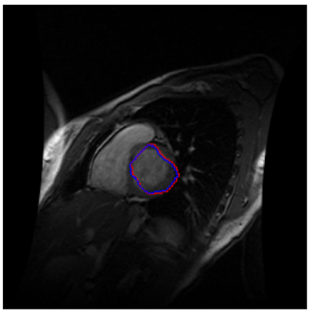


FIGURE 107 – Last iter : marker + segmentation

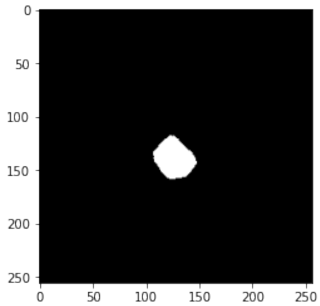


FIGURE 108 – Last iter : mask

Visual evaluation :

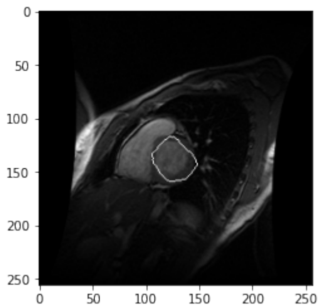


FIGURE 109 – Visualisation of segmentation

Quantitative evaluation :

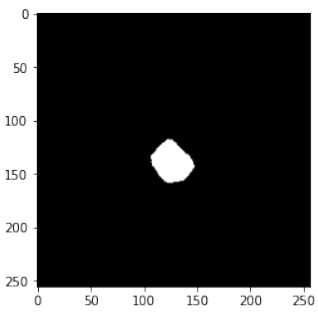


FIGURE 110 – Segmentation with active contour

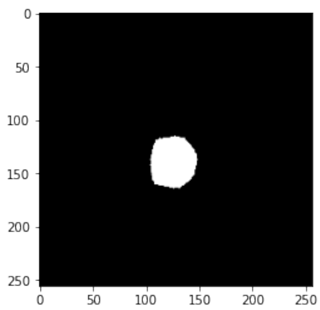


FIGURE 111 – Manual segmentation (landmarks to mask)

Dice index between manual segmentation and mask from our restults : 0.7801966292134831
We have better result with active contour method in this case.
It can be useful to use previous segmentation in order to create new markers for the next frame, that enable to avoid manual initialisation. However we have to be careful on the evolution of the segmentation that can diverge easily.