

## Introduction

This project serves as pre-project for my master thesis. It deals with heart detection in SPECT images. The images are recorded with two gamma cameras, which moves around the object. Knowing the heart position in "low count" images is useful in many aspects. Firstly it gives the possibility of producing a smaller detector and secondly of taking scouting images in order to plan the actual scan.

In this project two different approaches have been used: *Symmetry Detection* and *Active Contour with Space Carving*.

In order to validate the performance of the two different methods, I have chosen to construct synthetic data. Both methods detect the heart in projection images. To have some global quality measure, which can compare the performance of different algorithms, I decided to use the 3D position of the heart. Since it is desirable to have a fast heart detection, one goal is to use few projection images.

## Method and Theory

### Symmetry detection:

The idea behind using symmetry information is that the heart is the most symmetric shape in these kind of SPECT images. If it is possible to identify the two major symmetry axes of the heart, the intersection of those should give a fair estimate of the center of the heart.

The key idea behind the algorithm that I have used is to look at gradients and their directions. I construct an *orientation histogram* of the angles of the gradients. In this histogram I look for symmetry and simply perform the check by using a sum of squared differences. The minimum is the orientation of the major axis and I project the image onto this axis to find the actual position.

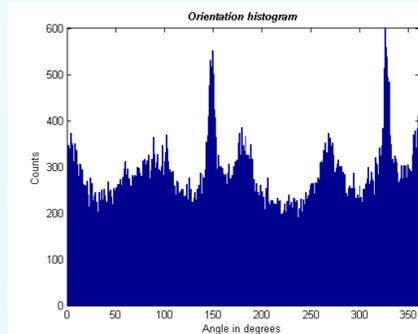


Figure 1: Orientation histogram.

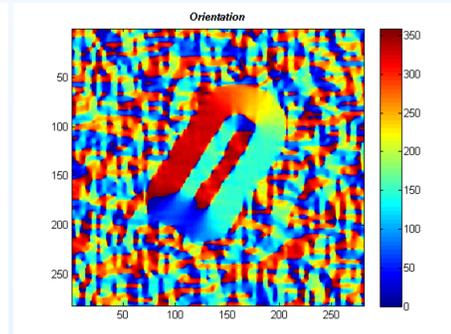


Figure 2: Gradient angles.

### Snakes and Space Carving:

Snakes is an Active Contour method where a parametric shape with a given set of points tries to minimize an energy function given by  $\epsilon(X) = S(X) + P(X)$ . The  $S(X)$  term is the internal energy and deals with the parametric constraints on the snake shape and deformation.

$$S(X) = \frac{1}{2} \int_0^1 \left( \alpha(s) \left| \frac{\partial X}{\partial s} \right|^2 + \beta(s) \left| \frac{\partial^2 X}{\partial s^2} \right|^2 \right) ds$$

The  $P(X)$  term is the potential energy and is calculated from the gradients. It is defined as:

$$P(x, y) = -\omega_c |\nabla [G_\sigma(x, y) * I(x, y)]|^2$$

where  $G_\sigma$  is a Gaussian function,  $I$  is the image and  $\omega_c$  is positive weighting parameter.

The potential energy will force the snake to seek high gradients, while the internal energy pulls the snake towards a desired parametric shape. The method is an iterative process and different parameters need to be tuned for the specific cases. The snake finds the outer edge of the heart.

Space Carving is the concept of having projection images of a given 3D object. The object is found and backprojected into a volume. If this is done for many different angles a rough representation of the actual object is the result, see figure 4 (Right).

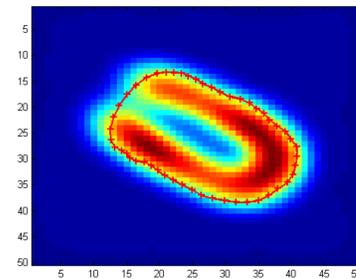


Figure 3: Snake result

Figure 3 displays the result of the iterated snake algorithm. One could suggest to either have two snakes in order to get the inner boundary or a more complex snake, which could find the crevice. But in this project the outer boundary is enough in order to evaluate the position of the heart.

Figure 4 displays the resulting volume, where three snakes are projected into the volume. Three cylindrical shapes appear and their overlapping volume in this case correspond to the actual heart.

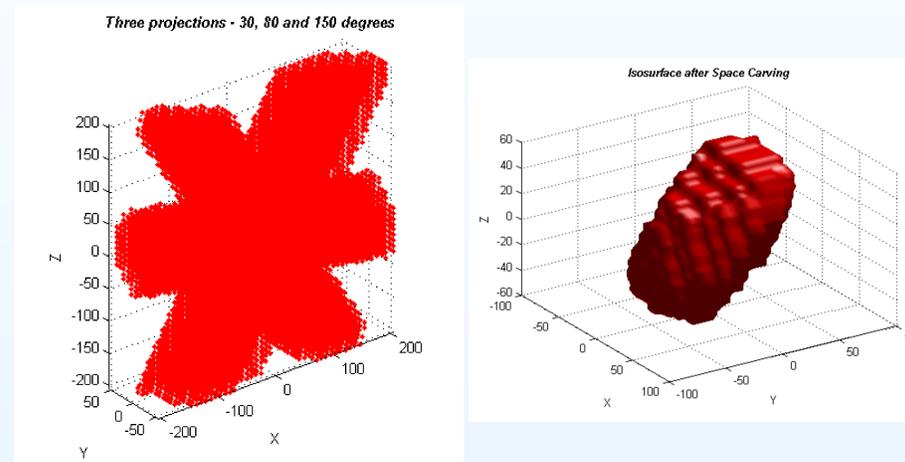


Figure 4: Volume with three backprojected objects (Left). The heart volume extracted (Right).

## Results

The algorithms were tested on synthetic data and one test run on patient data shown in the figure 5 (right). In figure 5 the result of the symmetry detection in a single projection image is shown.

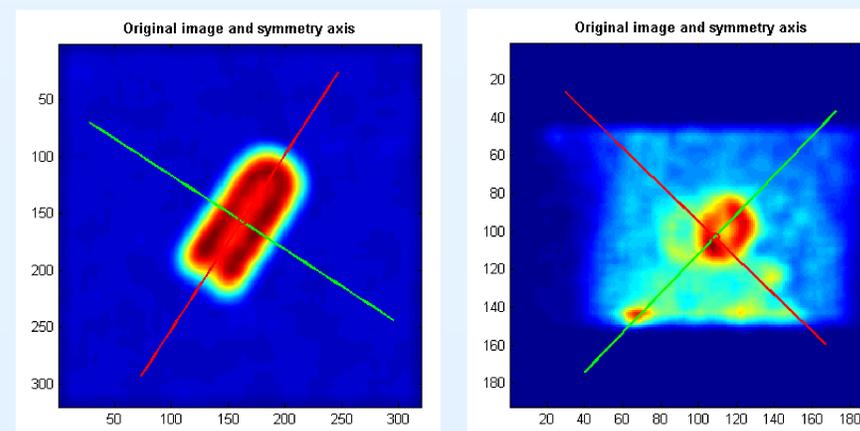


Figure 5: The result of the symmetry detection in one projection image (Left). A single test run on patient data (Right).

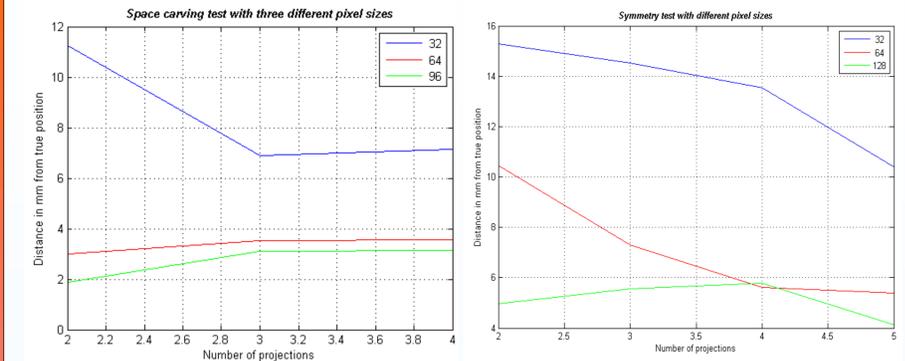


Figure 6: The Space carving algorithm run with different number of pixels and different number of projections. With 32x32: pixel size = 12,8 mm, 64x64: pixel size = 6,4 mm and 128x128 pixel size = 3,2 mm. (Left). The symmetry detection algorithm run with same parameters as the previous plot (Right).

In figure 6 the performance of the two different methods are shown as function of the number of projection images. To investigate their dependency on the pixel size the number of pixels in the projection image also varies in three steps. For both methods the performance increases with both the number of projections and number of pixels for both methods.

Figure 7 shows the investigation of how well the methods deal with background noise.

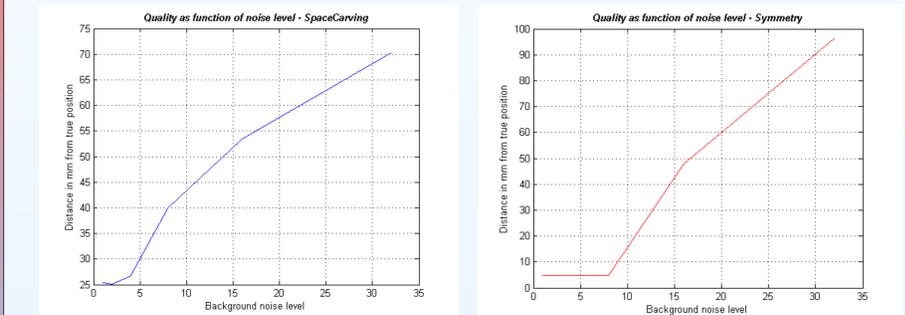


Figure 7: Performance as function of background noise. Result of Space Carving (Left), result of Symmetry Detection (Right).

Of course the performance of the algorithms decreases with the level of background noise. They perform almost equally well.

## Conclusion

The aim of the pre-project was to set up a test environment and test two methods for heart detection. Approximating the shape of the heart as cylinders and hemispheres, has served as an important key for constructing synthetic data. To make realistic images for testing, it is possible to add background noise (poisson) to the images.

I have suggested two different methods for heart detection:

- Active Contour together with Space Carving
- Symmetry Detection

### Further work:

Both algorithms work satisfactorily, but need more fine tuning. The need for preprocessing is high when the algorithms have to deal with noise. The snake parameters need to be optimized and be independent of physical sizes.

In my master thesis I will look into other methods, which are robust with regards to noise and other image characteristics.

## References

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- C. Xu, D.L. Pham, and J.L. Prince. Image segmentation using deformable models. *Handbook of Medical Imaging*, 2:129–174, 2000.