Probabilistic Chan-Vese

Group 8: S183796 Christine Ibæk Topp Lindenhoff, S212693 Simon Jakob Köhn, S183810 Nicklas Czyfczynski Rasmussen, S222962 Jonathan Mikler

Technical University of Denmark, Kgs. Lyngby, Denmark

1 Introduction

The aim of this project is to implement the Chan-Vese algorithm with a probabilistic curve evolution to segment images based on the article by Dahl and Dahl.[1] The original approach with Chan-Vese segments an image based on mean pixel intensities, whereas the new approach takes the distribution of intensities into account, extended with a patch-based approach based on k-means.

2 Method

The probabilistic Chan-Vese curve evolution is driven in the direction of the external force that minimizes the energy. This is given as:

$$F_{ext} = -\nabla E = (P_{in} - P_{out}) \cdot N \qquad (1)$$

where N are the normals of the snake, P_{in} and P_{out} are the probabilities of the inside and outside region, given as:

$$P_{in/out} = \mathbf{B} \mathbf{p}_{in/out} = \mathbf{B} \cdot \frac{\mathbf{f}_{in/out}}{\mathbf{f}_{in} + \mathbf{f}_{out}} \qquad (2)$$

where f are the frequencies of the pixels being inside or outside the mask, given as:

$$f_{in/out} = \frac{\mathbf{B} \cdot c_{in/out}}{A_{in/out}}$$

$\mathbf{B}$ is a binary matrix of size k x n, where k are the discrete intensities or number of clusters and n is the total amount of pixels. The $\mathbf{B}$-matrix has a 1 where the n^{th} pixel is equal to the k^{th} intensity.

A step-guide for implementing the center-pixel patched based approach is:

- Extract M x M - patches from image, I
- Perform k-means clustering on patches
- Collect dictionary of cluster centers
- Create image, S, with patch centers linked to their cluster center
- Create matrix $\mathbf{B}$ of size $nr_{clusters}$ x n, equal to 1 where the n^{th} pixel corresponds to the dictionary element
- Find dictionary probabilities

The dictionary probabilities. reshaped to the image, are then used in equation 2 to update the snake.

To add robustness in the curve evolution, regularization terms are used that minimize the internal energy E_{int}, moving the snake in the direction of the internal forces F_{int}:

$$\mathbf{B}^{new}_{int} = (\mathbf{I} - \alpha \mathbf{A} - \beta \mathbf{B})^{-1} \mathbf{B}_{int} \qquad (3)$$

where α and β are the weighting terms minimizing the length and the curvature of the snake.

To analyze the segmentation abilities of the snake, the recall, precision, accuracy and F-measure are found by comparing a ground truth (drawn by hand) with the snake in 5 different images.

3 Results

The non-patched based probabilistic Chan-Vese algorithm is implemented :

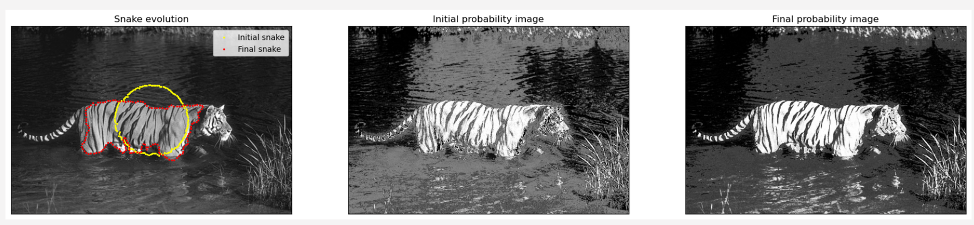

Figure 1: Inital and final snake (left), probability image with initial (center) and final snake (right). Implemented with 200 iterations and a stepsize of 3.

The patched based probabilitic Chan-Vese algotithm:

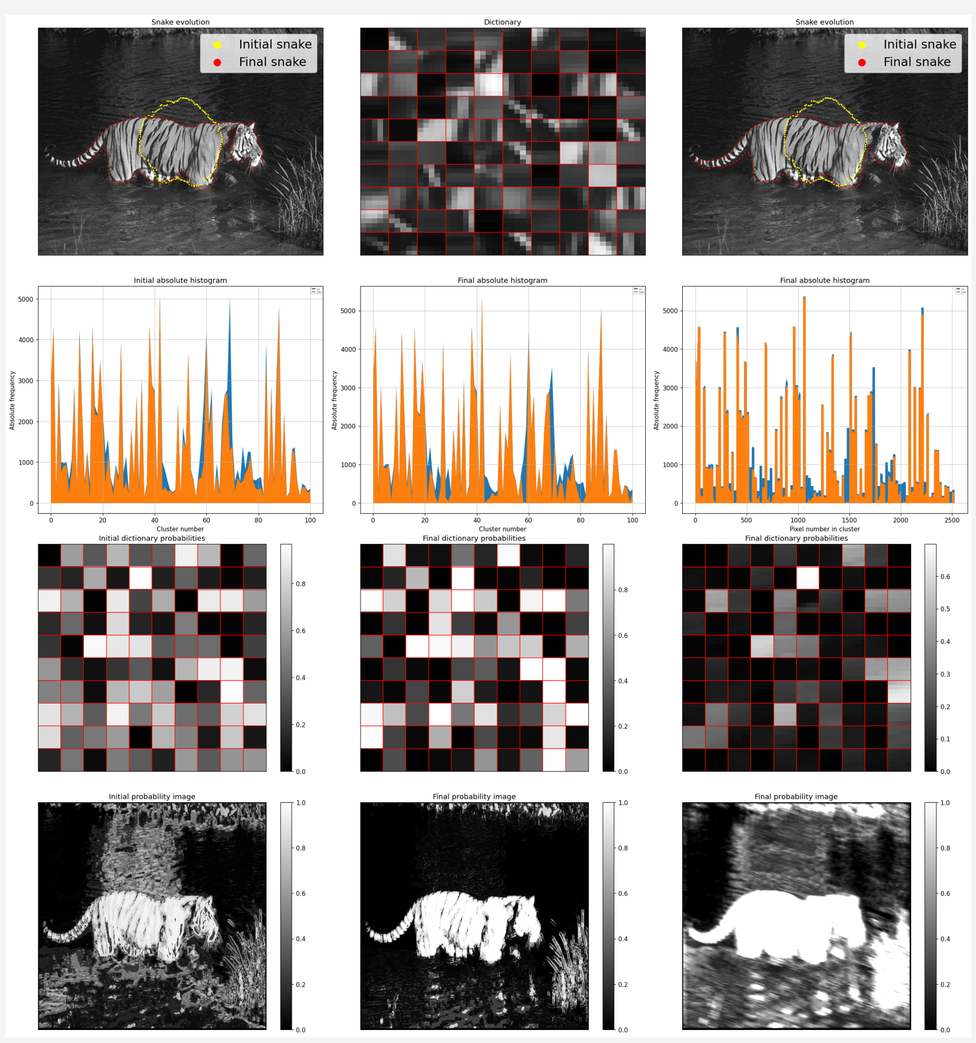

Figure 2: Left & middle: center pixel patch aproach with 200 iterations, right: individual pixel patch approach with 75 iterations. Both have 100 clusters, patchsize of 5x5, and a stepsize of 3.

An example is shown of the ground truth and snake estimate, drawn on an image of two flowers, in figure 3:

Figure 3: Flower (upper left), true mask (upper right), segmentation with standard parameters (patch size = 7x7, amount of iterations = 200, alpha = 0.01, beta = 0.1, and stepsize = 3) (lower left), and segmentation using more customized parameters (patch size = 5x5, amount of iterations = 250, alpha = 0.01, beta = 0.1, and stepsize = 10) (lower right)

The snake segmentation abilities for 5 different images is summarized in table 1:

	Recall	Precision	Accuracy	F-measure
Tiger	0.91	0.94	0.98	0.92
Flowers	0.79	0.36	0.78	0.50
Flowers*	0.84	0.91	0.89	0.87
Seafish	0.44	0.32	0.79	0.37
Leopard	0.88	0.51	0.86	0.64
Moray Eel	0.60	0.37	0.80	0.46

Table 1: Performance metrics of the patch-based algorithm with standard parameters for different images, and for an image with more suitable parameters (*)

4 Discussion

- Convergence of the center-pixel patched based method depends on the distribution of pixel intensities in the foreground
- More iterations are needed to include entire foreground when the object is larger
- The center-pixel patch based approach shows poor performance when the foreground has a multi-modal distribution (e.g. the flower image)
- We note a blurring effect in the pixel-wise patch-based method probability images. This is presumably due to an implementation error.
- Segmentation converges faster for the pixel-wise patched based method compared to the center-pixel patched based method

5 Conclusion

The main conclusion points are:

- The patched based method appears to perform better than the non-patched method
- The highest accuracy is obtained for image foregrounds with uni-modal pixel distributions
- The pixel-wise patch approach showed poorer results in the posterior probability image than the center-pixel patch approach. The snake however fits better for the pixel-wise case.

Bibliography

[1] Vedrana Andersen Dahl. *A Probabilistic Framework for Curve Evolution*. Ed. by Anders Bjorholm Dahl.

DTU Space
National Space Institute
DTU Space
National Space Institute
DTU Space
National Space Institute