Medical Sensors Project

Implementation of the article:
Dual optimization based prostate zonal segmentation in 3D MR images

Master in Medical Imaging and Applications

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Based on the original work by:
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1 Introduction

Prostate cancer is the most common non-skin cancer in men, with one in six men affected during their lifetime [2]. This is why the development of new techniques for early detection and accurate diagnosis have been taken importance in recent years.
The accurate and efficient segmentation of the prostate into its respective regions (show in Figure 1) is an essential role for prostate cancer diagnosis due to the fact that the malignity of the cancer is dependent on its zonal location.

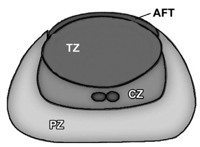


Figure 1: Regions of the prostate

Efficient and accurate segmentation of the prostate and two of its clinically meaningful sub-regions: the central gland (CG) and peripheral zone (PZ), from MR images, is of great interest in image guided prostate interventions and diagnosis of prostate cancer [1].

2 Objectives

The aim of this project is to reproduce the implementation of the article, *Dual optimization based prostate zonal segmentation in 3D MR image* by Wu Qiu, Jing Yuan, Eranga Ukwatta, Yue Sun, Martin Rajchl,Aaron Fenser. The article presents a novel Continous Max Flow Method for segmenting the prostate and its two major sub-regions.

This report will contain:

- A brief summary of the main points of the article.
- An explanation of how we implemented the main steps on Matlab.
- A comparison of results obtained by the proposed implementation versus the results of the original article.

3 Diagram Flow

The following figure illustrate the steps following in order to reproduce this approach, each section will be described in the next sections.

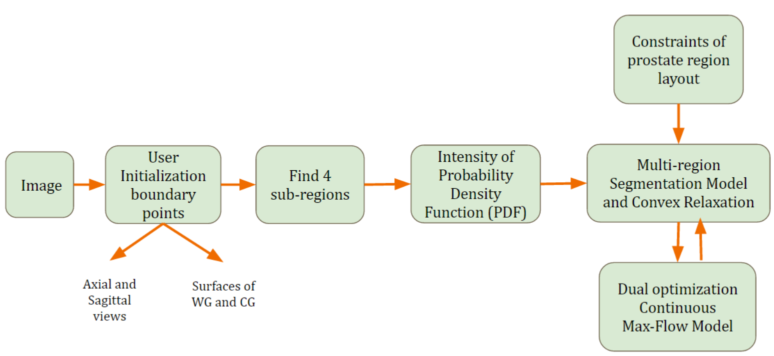
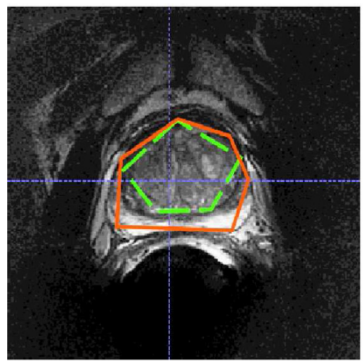


Figure 2: Diagram Flow

3.1 User Initialization

The described approach is semi-automatic, thus it is required that the user initializes the program by setting 10 to 12 points that delimit (1) the Whole Gland and (2) the Central Zone. The rest of the regions can be calculated from this two initialized regions.

In the original article sagittal and axial views were used to obtain the Whole Gland and the Peripheral Zone boundaries as they were performing a 3D segmentation of the image. However, as we did not have 3D data, in the proposed implementation a 2D segmentation is done. For that reason, the boundaries are initialized using only images of axial views. Figure 3 illustrates the user initialization performed for the original article. The boundary of the Whole Gland is showed in orange, while the boundary for the Central Gland is in green.



(a) User initialization in original article

(b) User initialization in proposed implementation

Figure 3: Comparison of the initialization from the article and from the proposed implementation

In the implemented Matlab program, the initialization can be performed by running the file called 'InteractiveProstateSegmentation2D.m'. This program will open a first window, to allow the user to select points along the boundaries of the whole gland. After the selection process is finished, a second window will appear for the user to collocate points that will delimit the Peripheral Zone. Figure 4 illustrates the user initialization performed in our proposed implementation by calling the roipoly function in matlab.

Once the user has manually initialized this points, the rest of the regions are computed and stored in variables that will later be used to perform the Probability Density Functions. In the Matlab program, the selected regions are saved in the variable "scribbles" and are then exported as a .mat file called "ProstateLabels.mat" for further segmentation in the "MaxFlowProstateSegmentation2D".m file.

3.2 Sub-Regions

After the user initializes and thus defines the first 2 regions (Whole Gland and Central Gland), the rest of the sub-regions can be obtained by performing the following equations:

$$Background = ImageI(x) - WB$$

$$PeripheralGland = WholeGland - CentralGland$$

This will give us a total of 4 regions in which the prostate should be segmented:

1. Whole Gland (WG)
2. Central Gland (CG)
3. Peripheral Zone (PZ)
4. Background (BG)

3.3 Regions consistency constraint

The most appropiate way to define this regions is to use the anatomical region prior, which can be essentially represented by:

$$\Omega = R_{WG} \cup R_B, \quad R_{WG} \cap R_B = 0 \tag{1}$$

where R_B denotes the background region and R_{WG} denotes the Whole Gland region. And the two spatially disjoint sub-regions R_{CG} and R_{PZ} constitute the whole gland region R_{WG}

$$R_{WG} = R_{CG} \cup R_{PZ};\ R_{CG} \cap R_{PZ} = 0 \tag{2}$$

3.4 Probability Density Function

Next step is to compute the intensity Probability Density Function (PDF) of each one of the regions of the image, this can be represented as $\pi_i(I(x)), \quad i\epsilon\{CG, PZ\}$, where $I(x)$ is the original image. Thess PDF models will provide the global statistical descriptor of the sections of interest. Figure 5 shows an example of the PDFs from the article. While Figure 6 shows the PDFs obtained from our Matlab implementation.

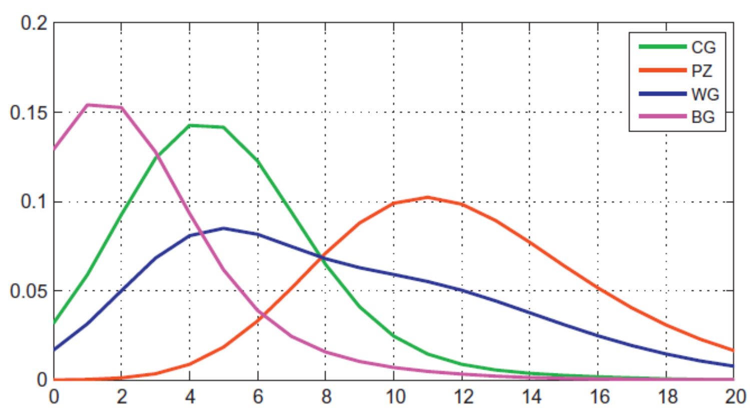


Figure 4: Typical intensity probability density function (PDF) models of the respective regions.

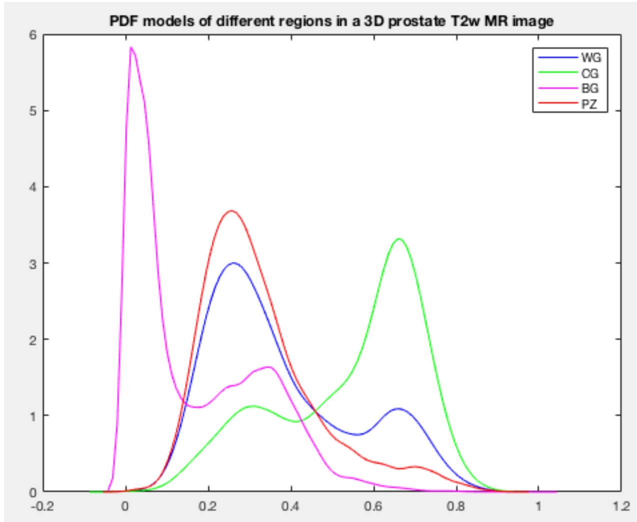


Figure 5: PDF models in proposed implementation

Once we have the insensity PDFs, we need to define the cost function of labelling any pixel $x \epsilon \Omega$ to be in the one of the prostate sub-regions by applying the log-likelihood of the respective PDF.

$$D_i(x) = -log(\pi_i(I(x))),\ i\epsilon L(:= CG, PZ, B)$$

Consequently, the total labeling cost of segmenting the input prostate image into the regions $R_{WG} \cup R_B := R_{CG} \cap R_{PZ} \cup R_B$ can be formulate by:

$$\sum_{i\epsilon L} \int_{R_i} D_i(x)dx \tag{3}$$

In our implementation, the Cost functions (Ct) for each of the labels (or regions) are allocated in the Matlab file "MaxFlowProstateSegmentation2D".m. This Matlab function receives as input the "scribbles" file that was created after the manual initialization and the computed automatic constraints of the regions. The Ct functions are initialized according to the number of regions that we want to segment the image, therefore for segmenting the prostate we will have a total of 4 Cost Functions.

Once this functions are defined, we proceed to compute the log likelihood of the respective PDFs. For this purpose, we created a special Matlab function called 'ComputeLogLikelihood' which computes the log likelihood from any pixel to correspond to a certain predefined label or region of the image. It returns 0 when the pixel does not correspond to the PDF of the region and 1 when the pixel is inside the PDF of the region.

3.5 Multi-region segmentation model and convex relaxation

In this part, the authors propose to partition the given image $I(x)$ by achieving the minimun total labelling cost (3) along with the minimun total area of all the segmented regions (subject to the constraints of (1) and (2):

$$\min_{R_{WG}, R_B, R_{CG}, R_{PZ}} = \sum_{i\epsilon L} \int_{R_i} D_i(x)dx + \sum_{i\epsilon WG \cap L} \int_{\partial R_i} ds \tag{4}$$

Now, as as the authors declare that typically, the minimization of total area of the segmented regions is a problem of geodesic computation in a Riemannian space, so a minimizer will be obtained when the contour is on the boundary of the object. For implement this we need to modify the equations. Let $u_i(x)\epsilon\{0,1\},\ \ i\epsilon\{WG, CG, PZ, B\}$

be the indicator or labeling function of the corresponding region R_i, such that

$$u_i(x) := \begin{cases} 1, \text{ where } x \text{ is inside } R_i \\ 0, \text{ otherwise} \end{cases}$$

Then, we need to rewrite the regions of constraint:

$$u_{WG}(x) + u_B(x) = 1, \quad \forall x \epsilon \Omega \tag{5}$$

$$u_{CG}(x) + u_{PZ}(x) = u_{WG}(x), \quad \forall x \epsilon \Omega \tag{6}$$

Correspondingly, the optimization problem (4) can be reformulated in terms of the defined labeling functions $u_i(x) \epsilon \{0, 1\}, \quad i \epsilon \{WG, CG, PZ, B\}$, as follows

$$\min_{u(x)\epsilon\{0,1\}} \sum_{i \epsilon L} (u_i.D_i) + \sum_{i \epsilon WG \cup L} \int_{\Omega} g_i(x) |\nabla u_i(x)| dx \tag{7}$$

subject to the labeling constraints (5) and (6), where $g_i(x) \geq 0$ gives the non-negative edge weight function and each weight total-variation function of (7) measures the weighted area of the surface $\partial R_i . i \epsilon WG \cup L$

The proposed solution to the challenging combinatioral optimization problem (7) is through the convex relaxation:

$$\min_{u(x)\epsilon\{0,1\}} \sum_{i \epsilon L} (u_i.D_i) + \sum_{i \epsilon WG \cup L} \int_{\Omega} g_i(x) |\nabla u_i(x)| dx \tag{8}$$

subject to the linear equality constraints (5) and (6). Given the convex energy of (8) and the linear equality constraints (5) and (6), the challenging combinatorial optimization problem (7) is then reduced to its convex optimization version (8) which is much simpler to be optimized.

3.6 Dual optimization model

In order to solve the proposed *convex relaxed multi-region segmentation problem* (8) with the constrainst (5) and (6), the authors introduce a new continuous max-flow approach.
First, the spatially continuous flow settings are introudeced (Figure 6).

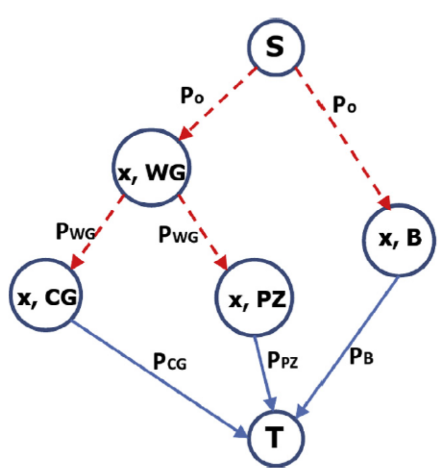


Figure 6: Flow settings for the proposed continuous flow-maximization scheme.

The flow settings are integrated by two terminals: S, the source of flows, and T, the sink of flows. It will pass from S through T creating image copies according to the sub-regions. A detailed explanation of the flow settings can be found on the article, section 2.5.
Based upon the settings described above, the novel continuous max-flow model, which maximizes the total flow streaming from the source S to the sink t can be formulated as:

$$\max_{p.q} \int_{\Omega} p_o(x) dx \tag{9}$$

As defined above, the source flow function $p_o(x)$ and the prostate flow function $p_t(x)$ are both free of constraints.

At the end the authors could proof that the continuous max-flow model (8) and the convex relaxed optimization model (9) are dual equivalent to each other. And as the continuous max flow is easier to implement and faster to compute, the authors decide to perform the segmentation using the Max-flow model. For more details of how the convex optimization and the max flow model are dual equivalent, please refer to the Appendix B of the article.

In our Matlab code, we created a function called "Potts2D", which was obtained from a previous implementation by Yuan, J. et al [2]. The Potts2D function performs a 2D multi region image segmentation problem (Potts Model), based on the fast continuous max flow method (CMF). This function is called in the file "MaxFlowProstateSegmentation2D".m after computing the cost log likelihood. The results of the Potts function will return a variable called "u" which contains the final results u(x) in [0,1]. The u variable is use to generate the images for each of the segments of interest.

4 Results

The algorithm described in the article was successfully implemented in Matlab to segment 2D T2w MR images of axial views. The following figures show our results:

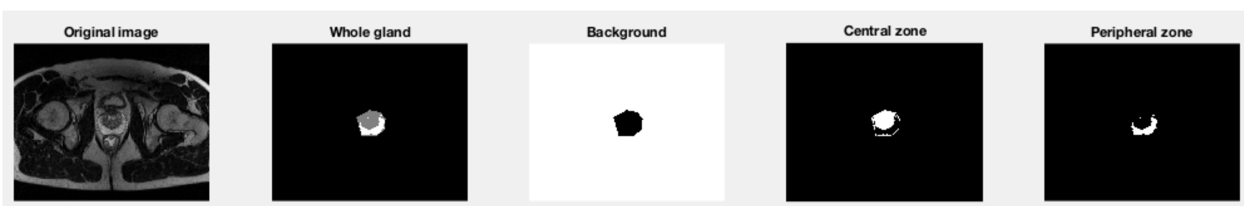


Figure 7: Result 1, Data taken from random patient.

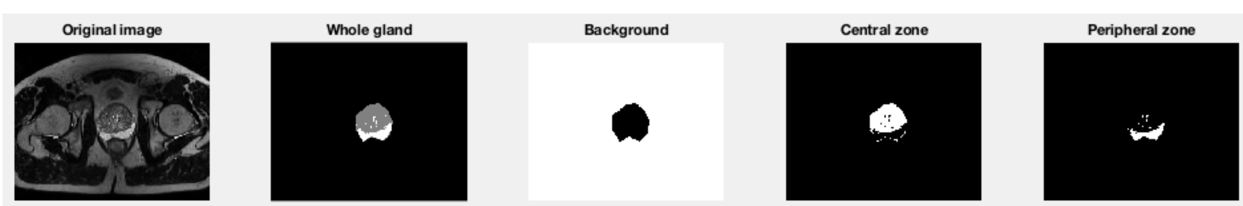


Figure 8: Result 2, Data taken from random patient.

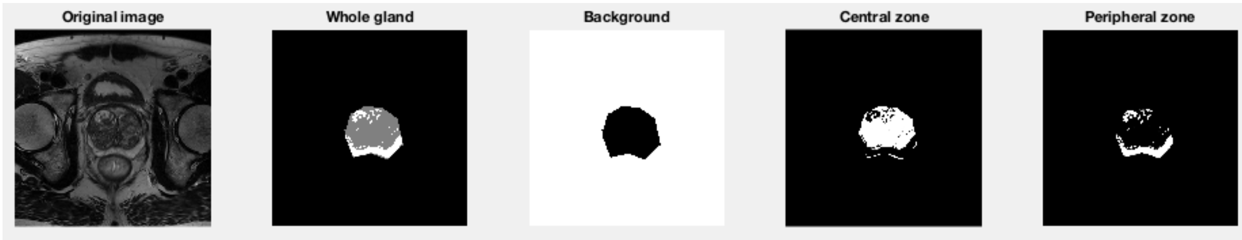


Figure 9: Result 3, Data taken from random patient.

These images were taken from 3 different patients and the initialization of points was performed by 3 different users. The segmented region is highlighted in white and the original image is presented at the beginning as reference.

The results obtained for the background and the whole gland are accurate and correspond to the original image. This demonstrates that the proposed implementation is working accordingly to the methodology stated in the original article. However, the segmentation of the central and the peripheral zones were not perfect.

5 Conclusion

In conclusion the *convex relaxed optimization problem* (8) can be solved equally by computing the continuous max-flow formulation(9). In practice, the proposed duality-based optimization algorithm enjoys a great numerical advantages and high computational efficiency.

The Continuous Max Flow Method was successfully implemented in Matlab for segmenting a 2D MR image of the prostate.The segmentation method extracts the background, the whole gland and its two main regions: the central and the peripheral zone.

The results obtained for the background and the whole gland are accurate and correspond to the original image. This demonstrates that the proposed method is correct and fulfills its objectives.However, the segmentation of the central and the peripheral zones were not perfect. It is necessary to perform more tests to adjust our code so we can obtain accurate results for the central and peripheral zones.

The similarity in the results, when performed by different users and using different patient's data, shows the reproducibility of the method.

The code requires detailed instructions for the user to understand it. One room for improvement is to make a GUI so the program can be more user friendly.The GUI should allow the user to change the color and size of the segments, so as to give more valuable and understandable information for clinical use.

Another improvement that could be made is to apply the proposed method to obtain segments of 3D images.Additionally, as the Continous Max Flow Method was implemented in a separate function, it should be interesting to run this Matlab function to compute and segment other anatomical regions, like the brain or heart.

6 Annex

The presented implementation can be found in the following GitHub repository:
https://github.com/LalandeCh/MRI-Prostate-Segmentation

References

[1] Wu Qiu et al. "Dual optimization based prostate zonal segmentation in 3D MR images". In: *Medical image analysis* 18.4 (2014), pp. 660–673.

[2] Jing Yuan et al. "A continuous max-flow approach to potts model". In: (2010), pp. 379–392.