ABSTRACT
Pelvic floor disorders cover pathologies of which physiopathology is not well understood. However cases get prevalent with an ageing population. Within the context of a project aiming at modelization of the dynamics of pelvic organs, we have developed an efficient segmentation process. It aims at alleviating the radiologist with a tedious one by one image analysis. From a first contour delineating the uterus-vagina set, the organ border is tracked along a dynamic MRI sequence. The process combines movement prediction, local intensity and texture analysis and active contour geometry control. Movement prediction allows a contour intialization for next image in the sequence. Intensity analysis provides image-based local contour detection enhanced by local binary pattern (LBP) texture descriptors. Geometry control prohibits self intersections and smoothes the contour. Results show the efficiency of the method with images produced in clinical routine.

Keywords: Dynamic MRI, MRI segmentation, pelvis imaging.

Introduction
Pelvic diseases are more and more prevalent within a growing population of older women. While most of the cases are treated with rehabilitation or medication, the most disabling cases require surgery. Urology, gynecology and digestive surgeries are concerned. In addition to the inherent patient variability it seems that patient care differs depending of the surgeon speciality. We advocate that a quantitative analysis of the dynamics of the main pelvis organs involved would help for a better understanding of the pelvic organ mechanics leading to a better understanding of pathology. Nowadays dynamic MRI tends to become the gold standard for pelvic floor disease examination. With a typical rate of one image (256x256 pixels) per second, the radiologist can follow the organ movements and deformations. The typically performed analysis is a qualitative one even though some anatomical anchors are used to build a diagnosis. In the realm of our MoDyPe project which aims at the modelization of pelvic organs dynamics, we have shown that quantitative results can be produced from sequences of organ contours. Displacements and deformation are measured thanks to adequate representations and descriptors leading to automatic and reproducible classification of MRI sequences. The contours used were provided by clinical experts who usually segment the organs on each image. Even if that was a straight mean to get a ground truth in order to validate our processes, this is a kind of tedious task that we cannot afford in clinical routine. Taking into account the segmentation result disparities, we have shown the process robustness in Rahim et al.\(^4\) which opens the door to the use of automatic segmentation. This paper focuses on the method we have developed to perform uterus and vagina segmentations in MR images. These two organ contours are particularly difficult to extract as the uterus is very close to the bowels and the vagina is attached to the perinea in its down part with, in both cases, some very close pixel values. None among existing methods has produced good segmentation results so we present a satisfactory process that we have integrated in the whole MoDyPe project. From the initialization by an expert on the first image, the contour of the uterus-vagina set is tracked along the sequence images. First section of this paper presents the clinical context of the study, then the method is presented in the second section. Some results are shown in the third section and a discussion highlights some details in the fourth.a

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1. PELVIC ZONE MRI ANATOMY

**Uterus and Vagina**

The uterus is an inverted pear-shaped muscular organ of the female reproductive system, located between the bladder and rectum. The uterine body or corpus consists of 3 layers: endometrium, junctional zone, and myometrium. The endometrium is the most central area of the uterus, with a varying thickness that changes during the menstrual cycle. The endometrium is typically high signal area on T2-weighted images (see Fig. 1(a)) although not showing as high signal as simple fluid area in the adjacent urinary bladder. The junctional zone represents the innermost layer of the myometrium with characteristic low signal intensity relative to myometrium. The outer myometrium is structurally different than the junctional zone, with increased cellular free water and decreased cell packing/density. This results in intermediate increased signal intensity on T2-weighted images, substantially higher than the junctional zone but generally lower than the hyperintense endometrium.

The vagina extends from the vulva at the bottom to the cervix at the top and lies between bladder and rectum. For descriptive purposes we divided the Uterus Vagina Set (uv-s) into thirds: the lower third defined as an area below the level of the bladder base with the urethra seen immediately anterior to it; the middle third corresponds to the level of the bladder base; whereas the upper third corresponds to the lateral vaginal fornices.

![Classic anatomical image](image1.png)  ![Contour division](image2.png)

Figure 1: Sagittal T2-weighted images of the female pelvis in midline. The zonal anatomy of the uterus is well demonstrated on T2-weighted images, with high signal intensity in the endometrium (point) and characteristic low signal intensity of the junctional zone (double arrowhead). Outer myometrium demonstrates intermediate signal intensity between the two other uterine layers (vertical arrow). B:Bladder, R:Rectum & V:Vagina. Contour division according to general common patterns. The heterogeneous part demarcates the border between the uterus and de upper organs. The two slopes portion represents the limit with the high intensity organs. Finally, the homogeneous section comprises the limit between the lower third of the vagina with the urethra (on the left) and the anus canal (on the right).

**Uterus Vagina Set Boundaries**

Bladder and rectum present the same high signal intensity therefore, contrast between these two organs and uv-s is extremely high and consequently its border is easy to distinguish. In T2-weighted images the bowel mean intensity is almost similar to the uterus intensity. For this reason, even for a specialist it is quite difficult to delineate the border of the uterus upper part which is next to the bowel. On top of that, the lower third of the vagina is placed between the urethra and the anal canal. None of which can be precisely appreciated in these low contrast dynamic acquisitions. Figure 1(b) shows an example of these boundaries.
Summarizing, for MRI dynamic T2-weighted images acquisitions we find out that we not only have non-homogeneous signal intensities inside the UV-S, but also poor contrast between its limits and many of the surrounding organs.

2. METHOD

We present a segmentation method based on active contour models (AC) to track the contour of the UV-S across the image sequences. The complete segmentation algorithm is depicted in Figure 2. The first contour given by the specialist is provided as an input. Afterwards, the next frame contour is predicted by the motion model and corrected by the observation model. The evolved points usually do not result in a smooth contour, hence a smoothing and a collision steps are used to boost final contour quality.

First Slide Contour \hspace{1cm} Initial Contour \hspace{1cm} Sequence Segmentation

Sequence Segmentation

State Motion Model \hspace{1cm} Observation Model \hspace{1cm} Smooth Contour

$t = 1$ \hspace{1cm} \hspace{1cm} \hspace{1cm} \hspace{1cm} $ut < N$

$ut = N$

Figure 2: Segmentation process. The light gray colored blocks represent the information models while the dark gray blocks are quality enhancing steps.

Contour Topology

A set of $N$ ordered points $\{v_i\}$, $i=1..N$ models a closed polygon which represents the contour of the uterus-vagina region (u-vR). In addition, as we work with a sequence of slices, we denote $v_i^t$, $t=0..S-1$ to the state of point $v_i$ in the slice $t$.

The initial polygonal $\{v_0^t\}$ is generated from a manual segmentation of the u-vR given by a specialist.

LBP Descriptors

Previous works have used LBP descriptors for medical imaging analysis. Based on Nanni, L. et al\textsuperscript{3} we explored different LBP neighborhood topology descriptors including circular, ellipsoidal, parabolical and hyperbolic with a binary encoding with the goal of retrieving critical texture information to accurately and robustly find the UV-S borders. For this purpose, the best results arose from the 8-bit circular neighborhood topology descriptor (CLBP) with bitwise shifting minimization. Each slice image is processed with the CLBP retrieving an useful texture information image lately used to detect UV-S borders (an example is shown in Figure 3).

State Motion Model

Commonly the abdominal effort makes the pelvic organs move down and back towards the sacred vertebrae. Therefore, in order to predict the next frame contour state we use a common rototraslation motion model based on the organ centroid ($c_t$) translation and the mean average rotation angle $\phi_t$ to “estimate” the position of the organ in the next frame taking into consideration the characteristic trajectory of the organ during the sequence previously studied in Rahim, M. et al\textsuperscript{5}.

Transformation Matrix

$$T_t = \begin{bmatrix}
\cos(\phi_t) & \sin(\phi_t) & \Delta c_{x,t} \\
-\sin(\phi_t) & \cos(\phi_t) & \Delta c_{y,t} \\
0 & 0 & 1
\end{bmatrix} \cdot \gamma_t(C)$$

We perceived that the magnitude of the translation of the organ centroid became smaller as the evolution comes to an end. Nevertheless, we discovered that a simple linear estimation does not performs well enough to achive
this goal. For this reason, we added a sigmoid-shaped magnitude parameter function $\gamma_t(C) = \frac{t}{(1 + e^{t \cdot C})}$ to control this phenomenon. Where $C$ is the an input coefficient that changes the function weights across the $t$ frames. As $C$ tends to zero there will be no reduction of the translation vector magnitude.

**Observation Model**

The observation model uses a set of $j$ candidates points ($\{n_{t,j}\}$) placed in both senses of normal direction of the predicted state $\hat{v}_t$. We explore $j/2$ points at each side as well as the predicted state $\hat{v}_t$. Then the best candidate is chosen as the most probable point within $\{n_{t,j}\}$ according to the three following strategies which are related to the different bounding regions shown in Figure 4.

Figure 4: Grey Level Profiles: From left to right: Two Slopes, Homogeneous and Heterogeneous region examples.
Two Slopes Profile These zones are characterized by a grey level profile with two clearly defined slopes as shows Figure 4(a). If we move inwards through the exploration line we find that the grey levels highly decrease until we arrive to the second slope. At this point is where the border should be placed. To detect that the point is in a two slope profile, the outer most exploring point over the normal line must be as twice as bright as the average uterus intensity threshold ($\mu_{uT}$) which is an input parameter. This intensity threshold is placed just above the outer myometrium mean intensity level. The border is placed in the first point under the $\mu_{uT}$. The remaining inner values must also be all under this threshold.

Homogeneous Profile This profile comprehends the part of lower third of the vagina. This region is characterized by the lack of critical information to describe the difference between the urethra, vagina and anal canal layers. For this reason two sources of information are used to decide where to place the point in each slice. To detect whether or not the point is in the homogeneous profile, we measure two different magnitudes over a linear regression of the grey level values over the entire normal line sampled data (see Figure 4(b)). If the slope value of the fitted line is under the slope threshold ($m_{th}$) and the maximum residual value (maximal distance between any point and the fitted line) is under the residual threshold ($r_{th}$), we consider the point in an homogeneous profile. Both ($r_{th}$) and ($m_{th}$) are input parameters.

Under the homogeneous profile we use two pieces of information as probabilities to decide which is the best candidate. The first is a conservative gaussian weighting function:

$$w(n_{i,j}) = e^{-\frac{d(j)^2}{2\sigma^2}}$$  \hspace{1cm} (2)

where $d(j)$ represents the distance of the particle $n_{i,j}$ to the original point $\tilde{v}_i$. The $\sigma$ value is a constant (input parameter) that defines the range distance in pixels over the normal line in both senses. Hence, the total search width is $2 \cdot \sigma$. This weighting function gives more importance to closest solutions. It penalizes moving the point towards distant solutions.

The second characteristic of the observation model under this strategy comes from the CLBP descriptor. We measure the CLBP value in every particle $n_{i,j}$. We normalize this quantity defining an other observation probability named $l(n_{i,j})$. Finally the complete observation model probability for this strategy is defined as:

$$p(y_i|n_{i,j}) = l(n_{i,j}) \cdot w(n_{i,j})$$  \hspace{1cm} (3)

Heterogeneous Profile Finally, the last part contains, in general, the limit between the uterus body and different tissues such as ligaments, muscles, fat, the bowel, etc. All of which have a signal intensity that varies subtly in T2-weighted images. In these regions, although extremely diverse profiles arise, we can still recognize a common pattern. Figure 4(c) shows that borders regularly appear in the exploring points that are below and more distant to the linear regression fitted within themselves. Nevertheless, even if this is a good starting strategy, it is not robust at all. The heterogeneous strategy applies when neither of the two previous strategies constraints are met.

As a result, we pose a more robust approach which considers, in stead of using each exploring point grey level, using the mean intensity value within a sliding window. The sliding window size ($W_s$) is an input parameter. This approach eliminates noisy profiles. We measure the mean gray level value in a window centered in each $n_{i,j}$ point and then fit a line withing these values. Afterwards, each point over this fitted line is treathed as 0 and the ones below the line are weighted with the euclidean distance to the line. We normalize the non zero values to obtain a probability distribution $r(n_{i,j})$ named after the residual distance. Under this strategy we also use the $l(n_{i,j})$ probability distribution. The complete observation model under this strategy comprises the residual distance and the CLBP descriptor as follows:

$$p(y_i|n_{i,j}) = l(n_{i,j}) \cdot r(n_{i,j})$$  \hspace{1cm} (4)

Geometry Control

The resulting contour after the correction step is quite rough and can present outliers. Due to these drawbacks, we use two simple filtering steps: smoothing and collisions treatment to improve the segmentation quality. Figure 5 shows the benefits of these filtering steps.
Smoothing

We use a Taubin filter to smooth the polygonal quality which is based on the laplacian operator as follows:

$$\alpha_i^t = \frac{1}{2} \sum_{j \in N(i)} (v_j^t - v_i^t)$$  \hspace{1em} (5)

where $v_j$ represents the two neighbors of $v_i$. This filter iteratively smoothes the polygonal without shrinking or expanding its area as follows:

$$\tilde{v}_i = \tilde{v}_i + \{\mu, \delta\} \alpha_i^t$$  \hspace{1em} (6)

where $\mu = -0.65$ and $\delta = 0.6307$ are filters constants used in even and odd iterations respectively and the $\alpha_i$ are recalculated in each iteration. The only input parameter is the amount of smoothing iterations $S_{it}$.

Collisions

Collisions sometimes occur when the vagina narrows too much in the homogeneous and “two slopes” regions. After a collision is detected we propose to distinguish these between middle vagina area collisions (two slopes) and general collisions. In the “two slopes” regions, because of a local maximal one of the two sides moves towards wrong direction. The real position is searched across the normal direction until an opposite intensity ramp is found. Collisions generally occur in the lowest third of the vagina. In these cases we apply a repulsive solution. We move towards their normal external direction both of the collided points with a fixed distance and in both cases we also move their closest neighbors.
3. RESULTS

We present experimental results ran over 9 different patients acquisitions. We briefly describe the parameters proprieties, their utilities and used values. Finally, we describe a segmentation quality evaluation and its results obtained in the experiments.

Parameters

The method uses several parameters, nevertheless several were set automatically. We experimentally found the remaining parameters, some of these stood fixed and the rest have to be set by the user in every case.

Automatic parameters setting:

using the specialist first contour segmentation we can gather information to automatically set several of the method parameters. First of all, the uterus greylevel threshold $\mu_T$ is obtained by measuring the average greylevel from the initial contour. Having set this parameter we are able to determine the two slope profile zone. Therefore, using anatomic knowledge we can find the contour points placed in the vagina region where we find the homogeneous profile. Analyzing the given points of the first frame we search for the points of the contour placed between the two slopes zones comprnended between the end of the rectum and the beginning of the bladder as in the green part of Figure 1(b). Having located these points we can measure the slope threshold $m_{th}$ and the residual threshold $r_{th}$ parameter by means of a statistical analysis of the profiles gathering the mean values of these two values. Finally the last automatic parameter is the sliding window size $W_s$. The objective of this parameter is to eliminate noisy profiles. Hence, to achieve this goal, we measure over the heterogeneous profile points the window greylevel deviation over the candidates points. As we have just described, we have already discriminated the two slopes and the heterogeneous points from the original profile, so the remaining points belong to the heterogeneous one. Over these points we measure the greylevel standard deviation over a sliding window varying from 3 by 3 pixels up to 9 by 9 pixels. We choose as $W_s$ the size that minimizes the mean standard deviation over the sampled points.

Experimental parameters setting:

Fixed parameters: Two parameters remained fixed. The LBP descriptor uses a fixed radius of 3.5px and the collision distance parameter was fixed to 3px in every experiment.

Varying parameters: The number of candidates points $j$ varies from 17 to 23. The distance resolution is half a pixel, hence the searching range is between 4 and 6 pixels in both directions.

In the state motion model, the $C$ parameter of the magnitude attenuation varies from 0.18 up to 0.75 depending on the global organ displacement. The larger the parameter, the less the $uv-s$ rotates and moves.

The deviation parameter $\sigma$ for the gaussian weighting function is in the range 0.01 up to 0.2, set experimentally for each case. These last user provided parameters give the fine detail setting to the method.

Segmentation Quality Evaluation

We evaluate the proposed technique results with the ground truth, given by the manual segmentations done by a specialist. We estimate the segmentation quality using two different indicators over the complete sequence but the first frame:

First, the Dice Similarity Coefficient (DSC)\(^1\) which measures the spatial overlap accuracy between the ground truth and the results regions. Second, as to evaluate the shape similcarity of the results, we used a similarity measure based on the Zernike Moments (ZM) shape descriptor. The ZM have crucial properties such as rotation, translation and scale invariance.\(^2\) Therefore, we considered the Zernike Moments Correlation(ZMC) as a robust indicator of shape similarity.

Dice Similarity Coefficient

The DSC basically measures the region correlation or intersection as follows:

$$D = \frac{2|R_1 \cap R_2|}{|R_1| + |R_2|} \quad (7)$$

where $R_1$ and $R_2$ represent the ground truth and the technique segmentation results region respectively.
Zernike Moments

We calculated Zernike polynomials of degree 10, each one having 36 different coefficients. Over this set of coefficients we computed the next magnitudes:

Zernike Moments Correlation:

\[
corr(zm_{R_1}, zm_{R_2}) = \frac{\sigma(zm_{R_1}zm_{R_2})}{\sigma zm_{R_1} \sigma zm_{R_2}}
\]  

(8)

The correlation between the Zernike Moments depicts the overall shape similarity regardless the border orientations, scale and translation. This measure is widely used in image retrieving.

The DSC results in Figure 6 show an overall mean median of 81% presenting a relatively small variance but also some outliers in both directions. The low quality outliers take place in frames with sharp deformations and the high ones on those with almost null movement. The greatest differences appeared in the vagina region where the actual limits are hard to distinguish.

Figure 7 presents promising results, indicating that the overall shape similarity between the gold standard and the technique results are high. The ensemble analysis of the two metrics shows that the technique maintains the UV-s shape but fails to position it correctly, having faults during the tracking process. Nevertheless, it conquers to complete the challenging segmentation task.

4. CONCLUSION AND DISCUSSION

In this paper, we presented a segmentation method that can face the hard goal of segmenting the uterus-vagina set in dynamic T2-weighted MRI acquisitions. We obtained promising results which have already been
integrated in the MoDyPe project. The method gives reproducible segmentation results whereas even radiologist segmentations usually lead to large variability in particular in the lower part of vagina. The segmentation evaluation showed a high shape similarity between the results but not an outstanding overlap accuracy.

REFERENCES


