POLAR APPEARANCE MODELS: A FULLY AUTOMATIC APPROACH FOR FEMORAL MODEL INITIALIZATION IN MRI

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ABSTRACT

Various segmentation approaches in medical image processing, such as Level Sets, Active Shape Models, and Active Appearance Models require initial localization of the structure of interest (SOI). In this work we present a novel fully automatic model initialization approach in MRI, that is applicable for structures that are mostly convex in the axial plane. We propose a training model, namely the Polar Appearance Model, that encapsulates both the transition from the structure of interest to its vicinity in polar space and the intensity distribution within the structure in euclidean space. We present our approach on the example of femoral model initialization in MRI and compare our results to a standard voxel-based registration approach that allows similarity transformations.

Index Terms—model initialization, hough transform, appearance model, femur segmentation

1. INTRODUCTION

Patient-specific models of anatomical structures allow simulations for various areas of tailored patient treatment. For these kind of patient-specific simulations, first the 3D models need to be generated by segmenting the anatomical structures of interest (SOI). Active Shape Models (ASM) [1], Active Appearance Models (AAM) [2], and Active Contours such as Snakes [3] and Level Set methods [4] are sufficient traditional segmentation approaches to solve this problem. The segmentation quality of these methods, however, heavily depends on their initialization. While these methods have been extended for better segmentation results in several ways ([5], [6], [7], [8], [9]), research regarding model initialization has been receiving reasonably less attention. Li et al. [10] propose a Poisson inverse gradient approach, which is however restricted to the initialization of Active Contours. Chu et al. [11] on the other hand use Random Forest based landmark detection, and Xia et al. [12] use a multi-atlas registration method to fit the model for their fully automated segmentation work flow. While Random Forest based detection requires a large training data set, non-rigid registration methods are computationally expensive, whereas voxel-based similarity registration methods tend to inaccuracy, since the SOIs are surrounded by various anatomical structures that also influence the resulting similarity transform. To this end, we propose a model based initialization approach, applicable for structures that are mostly convex in the axial plane, initializing a shape model in a similarity transformation manner.

2. METHOD

We propose a three stage borderline estimation method to extract the approximate boundary of the SOI, in order to apply an Iterative Closest Point (ICP) approach to fit a SOI shape model into the borderline approximation. The fitted model can then be used as initialization for various subsequent segmentation approaches.

2.1. Polar Appearance Model

Let \( A_1, \ldots, A_N \) denote \( N \) MRI training data sets, where the \( i \)-th data set consists of the MRI volume \( I_i \) and a label volume \( L_i \), i.e. \( A_i := (I_i, L_i) \). A training data set will be synonymously referred to as an atlas. For each axial slice, in which the SOI is present, the normalized intensity distribution within the area of interest is computed with a fixed amount of \( n_{\text{bins}} \) intensities. This distribution can be viewed as a vector of \([0, 1]^{n_{\text{bins}}} \). Given \( N \) atlases, each consisting of \( M_i \) axial slices containing the SOI of the \( i \)-th data set, a first training set \( \mathcal{S} \) can be generated. This training set consists of \( K := \sum_{i=1}^{N} M_i \) training vectors \( w_1, \ldots, w_K \) of dimension \( n_{\text{bins}} \) describing the SOI intensity distribution. Dimensionality reduction by means of Principal Component Analysis (PCA) yields a matrix \( \mathcal{E}_\mathbf{v} := (\tilde{v}_1, \ldots, \tilde{v}_{n_{\text{PCA}}} \) containing \( n_{PCA} < n_{\text{bins}} \) eigenvectors, and a set with the corresponding eigenvalues \( \mathcal{S}_\lambda := \{\lambda_1, \ldots, \lambda_{n_{PCA}}\} \). Given the mean intensity distribution \( \mathbf{w} := \frac{1}{K} \sum_{w \in \mathcal{S}} w \), the first part of the Polar Appearance Model is defined as \( \mathcal{M}^{(1)} := (\mathcal{E}_\mathbf{v}, \mathcal{S}_\lambda, \mathbf{w}) \).

For the second part, the border transition from the SOI to its surrounding is investigated in polar space. For this, each axial slice, in which the SOI is present, is transformed into...
Fig. 1. Hough Transform on axial slices results in a large set of center line point candidates. Some candidates even seem to form a decent path, but are not within the SOI (femur), e.g. the marked candidates on the right.

polar space, where the center of the SOI is used as the origin. In the following the x-axis describes the phase and the y-axis the radius of the polar space. For each phase an intensity profile of length $n_{PC}$ > 1 along the y-axis is acquired at the border between SOI and its surrounding. The use of these profiles in polar space is closely related to the Appearance Model of Active Shape Models [1] in euclidean space. Applying the same notation and steps as for the first part, PCA finally leads to the definition of the second part of the model component $\mathcal{M}^{(2)} := (\mathcal{E}_b, S_{\lambda}, \mathcal{w})$. In order to differentiate these two parts, their components are addressed accordingly, i.e. $\mathcal{M}^{(1)} := (\mathcal{E}_b^{(1)}, S_{\lambda}^{(1)}, \mathcal{w}^{(1)})$ and $\mathcal{M}^{(2)} := (\mathcal{E}_b^{(2)}, S_{\lambda}^{(2)}, \mathcal{w}^{(2)})$. Thus, the final model is defined as $\mathcal{P} := (\mathcal{M}^{(1)}, \mathcal{M}^{(2)})$.

2.2. Center Line Extraction

Having trained the PAM, the next step is to localize the center line of the SOI. Since we assume a convex shape in axial slices, a straightforward approach is the use of the Hough Transform for the detection of circular structures in each slice. The center points of the detected circles can be used as proposals for the center line points. A major challenge, however, is the detection of many different candidates in each axial slice and even more candidates in the whole volume. This renders the localization of a sufficient center line a difficult task (see Fig. 1). We propose modeling this problem as an optimization problem. For each candidate point $p$ we associate a cost $c(p)$ that is defined by means of the trained model component $\mathcal{M}^{(1)}$. Let $w(p)$ denote the intensity distribution vector of length $n_{bins}$, regarding the area encapsulated by the circle candidate with radius $r(p)$. Then the similarity distance $s(p)$ of $w(p)$ to the learnt distributions is defined as the weighted distance of the distribution $w(p)$ to the origin in eigenspace, i.e.

$$s(p) := \frac{n_{bins}}{\lambda_i^{(1)}} \left( \mathbf{v}_i^{(1)} T \cdot (w(p) - \mathbf{w}^{(1)}) \right)^2.$$  \hfill (1)

Dividing by the corresponding eigenvalues results in punishing deviations in major principal directions less than deviations in minor principal directions. Let $p_i$ denote a candidate in slice $i$ and $p_{i-1}$ a candidate in slice $i - 1$. The cost of connecting these candidates is denoted as $c(p_{i-1}, p_i)$ and may comprise the use of mean intensity, intensity variance of the circular area, the radius, and the topographic distance of the points. Connecting candidate points in subsequent slices yields a path through all slices. Thus, detection of the center line is reduced to the solution of the optimization problem

$$\arg\min_{p_1, \ldots, p_M} \sum_{i=1}^{M} c(p_i, p_{i-1}) + s(p_i).$$  \hfill (2)

This can be achieved by means of dynamic programming in defining $F_1(p_1) := 0$ for all candidates $p_1$ in the first slice and recursively defining

$$F_{i+1}(p_{i+1}) := \arg\min_{p_i \in P_i} \{ F_i(p_i) + c(p_{i+1}, p_i) + s(p_{i+1}) \},$$  \hfill (3)

where $P_i$ denotes the set of candidates in slice $i$. Solving the multi-stage optimization problem (3) results in the extraction of a center line within the SOI as can be seen in Fig. 3 (b). Although there are some non-circular sections within the femur, shaft and head slices mostly yield near-circular bone areas, such that the proposed optimization procedure compensates possible erroneous SOI localizations in the corresponding slices e.g. by penalizing large distances between center points. To restrict the length of the center line, specifically for the femoral model initialization we propose cutting off the path at a slice where a rapid change of center line radius occurs. This is, however, task dependent.

2.3. Boundary Detection in Polar Space

Given the center line and the corresponding radii from previous section, it is possible to restrict the search area for the SOI...
in each axial slice to a circular area around the center line with a radius approximately as large as the largest center line radius. Each axial MRI slice can be transformed into a restricted polar space with the corresponding center line point as origin (see Fig. 2 (a)). For each column, i.e. phase, a profile vector of length \( n_{PC} \) is iterated along the y-axis. Again, the similarity of each profile vector is measured in the eigenspace of \( \mathcal{M}^{(2)} \) in the same way as described in Eq. (1). In each column the most likely borderline candidates are distinguished by means of this similarity measure (see Fig. 2 (b)). Fig. 2 (c) shows the probability map of the selected borderline points of (b) according to the similarity measure. The borderline detection problem can be reduced to a sequential multi-stage optimization problem as in the previous section by introducing a pairwise cost function of two subsequent candidate points in columns, e.g. incorporating the topological distance of these two points in polar space. The multi-stage optimization problem is defined similarly to Eq. (2). A major difference is that the similarity distance is additionally weighted with the intensity at each point. This is motivated by the fact, that the borderline is ordinarily located in dark regions of the MRI. Formulating a recursion as in Eq. (3) for dynamic programming leads to an optimal path from the left to the right column, representing the approximated borderline in polar space. Transforming these approximations back to euclidean space yields a coarse estimation of the SOI’s contour (see Fig. 3 (c)). This coarse estimation is finally used to apply an ICP approach to calculate a similarity transformation of some SOI shape model to fit into the point cloud consisting of the border estimates. Fig. 3 (d) shows the initial position of the SOI shape model, that needs to be fitted into the point cloud, whereas Fig. 3 (e) and (f) depict the resulting transformed shape model.

### 3. Results

We applied our proposed PAM method on the example of femoral model initialization and compared our results to the initializations achieved by a voxel-based similarity registration MATLAB implementation. We chose a similarity registration approach as baseline, since our method also results in a similarity transformation of the SOI shape model. We used a data set, approved by our institution’s ethics committee, consisting of eight MRI femur atlases comprising six different patients. For two of these patients MRI scans were obtained before and after a surgical procedure. We denote the data sets as \( P_1, \ldots, P_6 \) and mark the post operative data sets as \( P_1 \) and \( P_2 \). We positioned the label volume of each atlas into every other data set by means of similarity registration and by our proposed PAM approach. For comparability we only used one atlas to train the PAM for each shape model initialization, although our model canonically provides the option to use multiple atlantes to train it. The registration approach achieves a mean Dice Similarity Coefficient (DSC) of 18.3% with a standard deviation of 10.8%, whereas our PAM approach results in a significantly improved average DSC of 72.0% with a standard deviation of 22.5%. Comparing the resulting Dice Similarity Coefficients (DSCs) of each initialization by the registration approach (Table 1), and by the suggested PAM based method (Table 2), it is easy to notice that the PAM approach outperforms the registration method in almost every initialization except for three cases. When investigating these cases, it becomes clear, that the automatic detection of the

![Image](89x614 to 159x720)

Fig. 3. (a) Overlay of label image of model (red) and ground truth (green). (b) Extracted center line from test image. (c) Resulting SOI border. (d) Overlay of label image of model (red) and SOI border. (e) Fitted label image (blue) to SOI border. (f) Overlay of transformed label image (blue) and ground truth (green).

<table>
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<tr>
<th>DSC</th>
<th>P1</th>
<th>P1</th>
<th>P2</th>
<th>P2</th>
<th>P3</th>
<th>P4</th>
<th>P5</th>
<th>P6</th>
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<td>24.7</td>
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<td>-</td>
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<td>5.8</td>
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<td>13.0</td>
<td>-</td>
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<td>-</td>
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<td>26.6</td>
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<td>21.7</td>
<td>-</td>
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Table 1. Resulting DSCs from similarity registration. The first row denotes the atlas data set, the first column depicts the test data set.
Table 2. Resulting DSCs from proposed PAM approach. The first row denotes the training data set, the first column depicts the test data set.

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<th>P1</th>
<th>P2</th>
<th>P2</th>
<th>P3</th>
<th>P4</th>
<th>P5</th>
<th>P6</th>
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<td>30.9</td>
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<td>0</td>
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<tr>
<td>P3</td>
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<td>81.6</td>
<td>85.0</td>
<td>84.1</td>
<td>-</td>
<td>88.8</td>
<td>47.6</td>
<td>83.1</td>
</tr>
<tr>
<td>P4</td>
<td>57.2</td>
<td>78.2</td>
<td>85.4</td>
<td>83.3</td>
<td>88.8</td>
<td>-</td>
<td>0.1</td>
<td>83.9</td>
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<tr>
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<td>76.4</td>
<td>5.8</td>
<td>81.7</td>
<td>73.3</td>
<td>74.7</td>
<td>-</td>
<td>82.2</td>
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<tr>
<td>P6</td>
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<td>86.2</td>
<td>88.0</td>
<td>75.8</td>
<td>78.6</td>
<td>82.1</td>
<td>81.4</td>
<td>-</td>
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The robustness may be further increased by either slicing the femoral shaft or by extracting ellipsoids instead of circles. Additionally, we seek an extension of the PAM to non-convex structures, by developing a replacement for the Hough transform.

4. CONCLUSION

In this paper, we present an appearance model approach, namely the Polar Appearance Model, that incorporates modeling both the normalized intensity distribution within the SOI and the intensity profiles along the SOI boundary in polar space. This model is used in our proposed three stage borderline estimation pipeline to fit a label image into the resulting point cloud via ICP. The fitted label image can then be used for subsequent segmentation techniques such as ASM, AAM and Active Contour approaches. On the example of femoral model initialization, we demonstrated that our proposed approach outperforms similarity registration on whole MRI volumes, and that a single labeled MRI data set already yields reliable initializations in most cases. However, we are aiming to improve the robustness of center line extraction by incorporating more expert knowledge into the candidate selection process and involve a learning based cost function. The robustness may be further increased by either slicing along the femoral shaft or by extracting ellipsoids instead of circles. Additionally, we seek an extension of the PAM to non-convex structures, by developing a replacement for the use of the Hough transform.

5. REFERENCES


