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Hip Joint Segmentation from 2D Ultrasound Data Based on Dynamic Shape Priors

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Abstract: In this paper, we present an automatic algorithm for the segmentation of the hip joint from 2D ultrasound data. In a level set framework, the proposed method starts from a segmentation of the nonlinear structure tensor in the tensor domain. This feature includes both gray-level and texture information. Upon this, prior anatomical knowledge is employed for the design of a shape prior. Instead of manually delineating the shape prior or creating it from a training set, which was not available, we propose to dynamically construct the shape prior using the anatomical knowledge as well as the segmentation flow itself. Preliminary results on real images showed promising results.

Key–Words: Developmental Dysplasia of the Hip (DDH), segmentation, shape prior, level set, Geodesic Active Regions, nonlinear structure tensor, Kullback-Leibler distance.

1 Introduction

Developmental Dysplasia of the Hip (DDH) refers to a deformation of the hip joint in newborns, which consists of the partial or complete displacement of the femoral head from the acetabulum, causing an abnormal anatomy of the developing articulation surfaces and a potential dislocation of the hip. If this pathology persists, DDH can develop with growth and alter the development of the hip [1, 2, 3].
In order to achieve early diagnosis and treatment, routine clinical screening was introduced in the 50s, the radiographic screening in the 70s and the US screening in the 80s [3]. Several examination techniques have been formulated for ultrasound [2], with Graf method [4, 5] being the most established in clinical use. This method is based on the quantification of the femoral head coverage by geometric measures from a 2D ultrasound image taken in a defined plane.
The clinical ultrasound screening using Graf's method by experts is a tedious and time consuming task. Therefore, the automation of this procedure is a desirable goal. Furthermore, the automatic analysis of the femoral head coverage can enable the automatic study of the evolution of the pathology in abnormal cases. Some effort has been done in the literature related to the use of 3D ultrasound for the analysis of DDH [6, 7]. However, even though the use of 3D ultrasound might provide certain advantages over 2D screening [8], its use is far from been widespread in clinical practice. Very little work has been done in the literature on the analysis of DDH from 2D ultrasound images.
In this paper, we propose an automatic algorithm for the segmentation of the hip joint from 2D ultrasound data. The segmentation is performed in a level-set framework. Level sets segmentation [9, 10] has gained much relevance recently due to their good properties. Besides, it can easily integrate boundary, region and shape prior information [10, 11, 12, 13, 14]. Based on the Geodesic Active Regions model [13], texture information was incorporated to the segmentation process by means of the nonlinear structure tensor (NLST), and the segmentation was performed in the tensor domain by applying intrinsic tensor dissimilarity measures as the Kullback-Leibler distance [15]. The use of the extended structure tensor and the compact structure tensor allows for the combined use of gray-level and texture information without losing the tensor properties.
The use of the image information alone, however, is not able to successfully drive the segmentation of the structures of interest. It is therefore necessary to use prior knowledge about the problem domain. The incorporation of prior shape knowledge into segmentation in a level set framework has gained a lot of interest recently. Numerous approaches have been proposed based on describing allowable deformations

of a deformable shape. Some of them, for example, employ principal component anaylsis to describe the space of allowable shapes [11, 16]. These methods, however, need a data set of training shapes of appropriate size which is not easy to collect for this kind of medical images. Other approaches introduce the shape prior using parametric curve representations [17, 18]. This parametric representation is a major drawback in order to introduce these priors in a level-set segmentation framework, and an eventual generalization to 3D is not straightforward. Finally, other techniques define a metric on the space of shapes, which is tipically used to compare shapes directly in a level set representation [19, 20, 21, 22]. Invariance with respect to rotation, scale and translation is a major issue in these approaches, algthough it can be achieved by means of minimization of the energy term with respect to the pose parameters.

In order to incorporate prior knowledge into the segmentation process, we propose to dinamically construct a shape prior based on the anatomical knowledge of the problem and the present state of the segmentation process. This way we are able to overcome the limitations of applying a static shape prior and optimizing its pose parameters or using a shape template with a set of statistically derived allowable deformations.

The paper is organized as follows: the different elements on which the proposed segmentation technique is based are explained in the next section. In Section 3, the hip joint segmentation algorithm is introduced with special attention to the shape priors construction. Results are shown and discussed in Section 4 and, finally, a brief summary is presented.

2 Methods

2.1 Nonlinear Structure Tensor

For a scalar image I, the structure tensor is defined as follows [23]:

$$J_\rho = K_\rho * (\nabla I \nabla I^T) = \begin{pmatrix} K_\rho * I_x^2 & K_\rho * I_x I_y \\ K_\rho * I_x I_y & K_\rho * I_y^2 \end{pmatrix} \quad (1)$$

where K_ρ is a Gaussian kernel with standard deviation ρ, and subscripts denote partial derivatives. The smoothing with a Gaussian kernel makes the structure tensor suffer from the dislocation of edges. To solve this problem, Brox and Weickert [24] propose to replace the Gaussian smoothing by nonlinear diffusion. For vector-valued data, the diffusion equation becomes:

$$\partial_t u_i = \text{div}\left(g\left(\sum_{k=1}^{N} |\nabla u_k|^2 \right) \nabla u_i \right) \ \forall i \quad (2)$$

where u_i is an evolving vector channel, and N is the total number of vector channels. The NLST can be obtained, for a scalar image, by applying Eq. 2 with initial conditions $\mathbf{u} = [\, I_x^2 \quad I_y^2 \quad I_x I_y \,]^T$. In practice, however, the original image is added as an extra channel because it can provide valuable information, yielding $\mathbf{u} = [\, I_x^2 \quad I_y^2 \quad I_x I_y \quad I \,]^T$[1].

2.2 Tensor Field Segmentation

Based on the research done in the field of DT-MRI (Diffusion Tensor Magnetic Resonance Imaging) [25, 26], it was proposed in [15] to segment textured images in the tensor domain based on the NLST. Following the Geodesic Active Regions model [13], the image segmentation can be found by maximizing the *a posteriori* partition probability $p(P(\Omega)|I)$ given the observed image I, where $P(\Omega) = \{\Omega_1, \Omega_2\}$ is the partition of the image domain Ω in two regions. If all partitions are equally probable, and the pixels within each region are independent, this is equivalent to the minimization of the energy term obtained after applying the negative logarithm:

$$\begin{aligned} E(\Omega_1, \Omega_2) = & - \int_{\Omega_1} \log p(I(x)|\Omega_1) dx \\ & - \int_{\Omega_2} \log p(I(x)|\Omega_2) dx \end{aligned} \quad (3)$$

Now, let us consider the tensor field $\mathbf{T}(\mathbf{x})$ containing at each pixel the NLST described in Section 2.1. As done in [25, 26], a symmetric positive definite (SPD) tensor can be interpreted as a covariance matrix of a Gaussian distribution. Then, the natural distance between two Gaussian pdfs, given by the symmetrized Kullback-Leibler distance, can be a measure of dissimilarity between two Gaussian distributions, represented by SPD tensors. Besides, it is possible to obtain a very simple closed form for the symmetrized Kullback-Leibler distance in terms of the SPD tensors [25].

Now, let us denote by $\mathbf{T_1}$ and $\mathbf{T_2}$ the mean values of the tensor image over the regions Ω_1 and Ω_2. It is possible to model the distribution of the KL distances

[1] As these components have not the same order of magnitude, a normalization step is performed by replacing the NLST by its square root.

to $\mathbf{T_1}$ and $\mathbf{T_2}$ in their respective domains by the densities $p_{d,1}$ and $p_{d,2}$. Making the assumption that $p_{d,1}$ and $p_{d,2}$ are Gaussian of zero mean and variances σ_1^2 and σ_2^2, the energy term from Eq. 3 will become

$$\begin{aligned} E(\Omega_1, \Omega_2) = & -\int_{\Omega_1} \log p_{d,1}(d(\mathbf{T}(\mathbf{x}), \mathbf{T_1}))dx \\ & -\int_{\Omega_2} \log p_{d,2}(d(\mathbf{T}(\mathbf{x}), \mathbf{T_2}))dx \end{aligned} \quad (4)$$

In order to minimize the corresponding energy functional, we use a level set function $\Phi : \Omega \to \Re$, where $\Phi(\mathbf{x}) = \mathcal{D}(\mathbf{x}, \partial\Omega)$. $\mathcal{D}(\mathbf{x}, \partial\Omega)$ stands for the signed Euclidean distance between $\mathbf{x}$ and the boundary between regions Ω_1 and Ω_2, $\partial\Omega$. Then, we obtain the level set evolution equation (see [27, 28] for details)

$$\begin{cases} \sigma_i = \frac{1}{|\Omega_i|} \int_{\Omega_i} d^2(\mathbf{T}(\mathbf{x}), \mathbf{T_i})dx \\ \frac{\partial\phi}{\partial t}(\mathbf{x}) = \delta(\phi)(\nu div(\frac{\nabla\phi}{|\nabla\phi|}) - \frac{d^2(\mathbf{T}(\mathbf{x}),\mathbf{T_1})}{\sigma_1^2} \\ + \frac{d^2(\mathbf{T}(\mathbf{x}),\mathbf{T_2})}{\sigma_2^2} - \log\frac{\sigma_1^2}{\sigma_2^2}) \end{cases} \quad (5)$$

2.3 Advanced Tensor Architectures

The NLST is a very valuable feature for the segmentation of texture images. However, it is clear that it has the disadvantage of not using any gray information at all. Thus, in order to incorporate this valuable information without losing the nice properties of the NLST, the *nonlinear extended structure tensor* was proposed in [15]. For a scalar image, it is defined as follows:

$$\mathbf{T_E} = vv^T = \begin{pmatrix} \hat{I_x^2} & I_x\hat{I}_y & I_x\hat{I} \\ I_x\hat{I}_y & \hat{I_y^2} & I_y\hat{I} \\ I_x\hat{I} & I_y\hat{I} & \hat{I^2} \end{pmatrix} \quad (6)$$

where $v = [\, I_x \quad I_y \quad I \,]^T$. The *nonlinear extended structure tensor* was employed in this paper for segmentation purposes following Eq. 5.

2.4 Incorporation of Shape Prior

Starting from the model described in the preceding section, we wish to include a new energy term which favors a predetermined shape configuration of the segmenting curve. If we represent the template shape by means of a level set function ψ, and the segmenting level set is denoted by ϕ, we adopt the following energy funcional [19, 21]:

$$E_{shape} = \int_{\Omega} H(\phi(\mathbf{x}))\,(\phi(\mathbf{x}) - \psi(\mathbf{x}))^2\, d\mathbf{x} \quad (7)$$

where $H()$ denotes the Heaviside function. The gradient descent minimization of this measure with respect to ϕ yields the equation:

$$\begin{aligned} \frac{\partial\phi}{\partial t}(\mathbf{x}) &= -2H(\phi(\mathbf{x}))\,(\phi(\mathbf{x}) - \psi(\mathbf{x})) \\ &- \delta(\phi(\mathbf{x}))\,(\phi(\mathbf{x}) - \psi(\mathbf{x}))^2 \end{aligned} \quad (8)$$

As the described prior is static, invariance with respect to the pose parameters of scale, rotation and translation can be achieved by minimizing the energy functional with respect to these paramters (see [19, 21] for details). In order to incorporate the shape prior contraint into the segmentation process described in Section 2.2, the evolution term derived in Eq. 8 is added to that of Eq. 5.

3 Algorithm Description

In this section, we will describe the proposed algorithm for the segmentation of the hip joint from 2D ultrasound images. Such an image is shown in Figure 1. As described in the preceeding section, the pro-

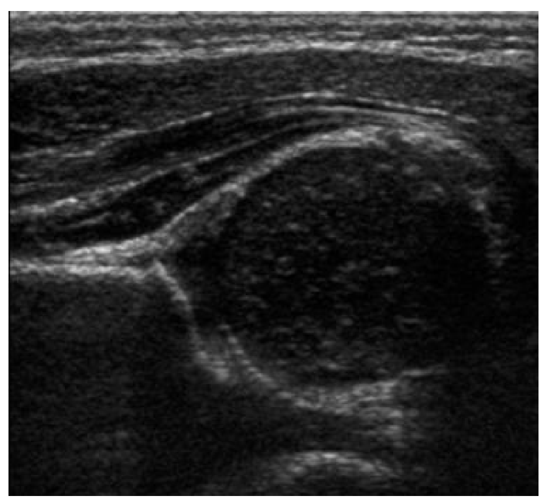

Figure 1: 2D ultrasound image of the hip joint.

posed segmentation algorithm makes use of a shaper prior in order to guide the segmentation process. Usually, shape priors are deliniated or created using manually segmented images from a training set. Then, the optimization of the pose parameters ensures the flexibility for the shape priors to adapt themselves to the particular image to be segmented. The segmentation of the hip joint, however, cannot be achieved using this approach because of two reasons. First, the simultaneous optimization of all the pose parameters is a very difficult problem, and the minimiza-

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tion will very likely get stuck in local minima. Second, even if the pose parameters optimization were successfully achieved, a single shape prior is not suitable for different images, as non-rigid deformations would be needed to adapt the shape prior to different cases. Therefore, and as a large training set of sample images was not available so as to create a statistical modelling of the deformations allowed, a totally different approach was employed. It consists of constructing a shape prior dinamically for each image, exploiting the anatomical knowledge about the problem domain and the present state of the segmentation process. Specifically, the segmentation problem is divided in two stages (segmentation of the femoral head and segmentation of the iliac bone and acetabulum), and the proposed algorithm works as follows:

1. First, an initial shape prior is constructed for the segmentation of the femoral head, $\psi_{1,0}$ (see Figure 2 (a)). This shape prior will be a circle with an empirically found diameter. In order to find the optimal position of the circle, an iterative process is employed starting from the center of the image and succesivelly applying a small displacement of the circle center in order to minimize the standard deviation of the pixel values inside the circle.

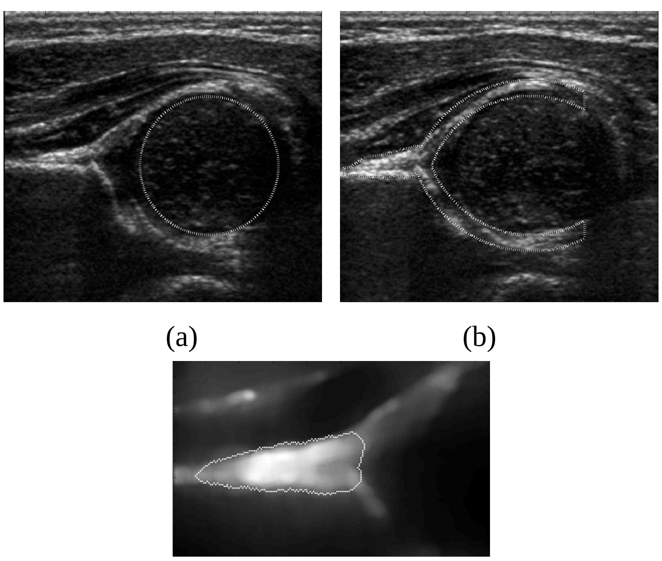


Figure 2: (a) Initial shape prior for the femora head, $\psi_{1,0}$; (b) Initial shape prior for the iliac bone and acetabulum, $\psi_{2,0}$; (c) Segmentation result for the edge of iliac bone, employed to construct $\psi_{2,0}$.

2. Second, the level set ϕ_1 is employed for the segmentation of the femoral head using the evolution terms described in Eqs. 5 and 8. At each iteration step i a shape prior $psi_{1,i}$ is employed. Starting from $\psi_{1,0}$, this shape prior is updated by aproximating the segmenting curve ϕ_1 with a circle, and estimating an horizontal and vertical translation in order to minimize the shape prior energy term defined in Eq. 7.

3. Once the femoral head has been segmented, the initial shape prior for the iliac bone and acetabulum, $\psi_{2,0}$, is constructed based on the femoral head segmentation result, the anatomical knowledge and the image data. Firstly, a ROI is delimited around the iliac bone and it is segmented by means of a level set driven by Eq. 5, i.e. with no shape prior (see Figure 2 (c)). Next, a longitudinal axes is traced for the iliac bone, and point P is found as shown in Figure 3. Using this point and the femoral head final shape prior, $\psi_{1,N}$, two circular arcs are traced which aproximate the acetabulum (see Figure 3). As can be seen in Figure 2 (b) $\psi_{2,0}$ is composed of these structures, and

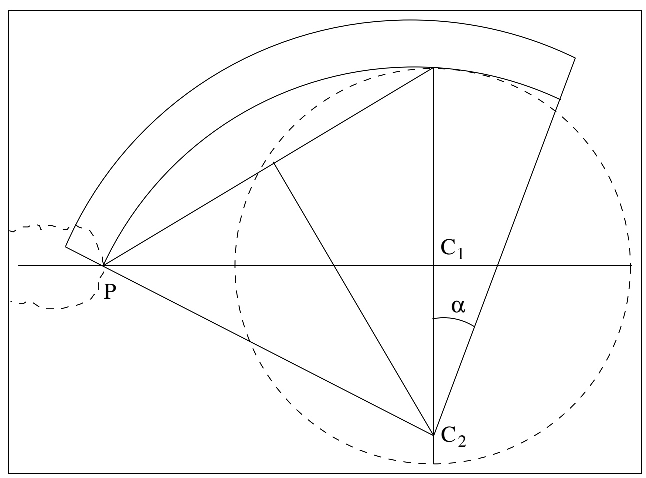
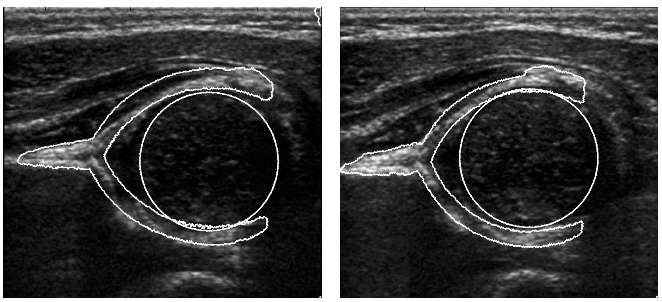


Figure 3: Schematic detail of the procedure followed to construct $\psi_{2,0}$.

4. Finally, and using $\psi_{2,0}$ as initial shape prior, a segmenting curve ϕ_2 is evolved to segment the acetabulum and iliac bone. At each iteration, $\psi_{2,i}$ is also updated by estimating the optimal translation parameters. Besides, a coupling term is added to the evolution equation that aims at preventing the overlapping of ϕ_2 over the femoral head segmentation result ϕ_1 or its circular aproximation, $\psi_{1,N}$ (see [13] for details).

4 Results and Discussion

In order to perform a preliminary test of the prosposed algorithm for the segmentation of the hip joint, six different ultrasound images were used. Although further experimentation will be necessary to carefully validate the segmentation method, results are promising so far. In Figure 4, the segmentation results for the femoral head and the acetabulum and iliac bone are shown. As can be seen, the anatomical structures



(a) (b)

Figure 4: Segmented images of the hip joint. The segmented contours represent the femoral head and the iliac bone and acetabulum.

are very well approximated by the chosen geometrical shapes. The segmented contours, however, do not always accurately fit the bone contours. Results could be improved by reducing the weight of the shape prior term in the segmentation process so that region information is more important, specially in the last stages of the segmentation process. However, this is not really useful from a diagnostic point of view because, as the final goal of the hip joint segmentation is the study and diagnosis of DDH, obtaining a segmentation which is approximated by the described geometrical features will easily allow for an objective measurement of the femoral head coverage in order to perform the diagnosis.

5 Summary

In this paper, a new method for the segmentation of the hip joint from 2D ultrasound images has been proposed. In a level set framework, we start from a model based on the Geodesic Active Regions which performs the segmentation directly in the tensor domain where the gray level and texture features are encoded. Then, the key issue of introducing prior knowledge is addressed by dynamically constructing a shape prior based on the anatomical knowledge and the present state of the segmentation. Preliminary results are promising and show the potential of the proposed approach.

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