Automated Bone Segmentation and Bone-Cartilage Interface Extraction from MR Images of the Hip

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INTRODUCTION: Osteoarthritis (OA) is a common disease of the hip joint characterized by changes in structure and degeneration of cartilage tissue. Magnetic Resonance (MR) imaging has been shown to be an ideal modality for OA assessment, providing direct and non-invasive visualization of joint structure. Morphological measurements (volume, thickness and surface area) of the cartilage tissue have been shown to be important in characterizing and monitoring OA progression, which allows the prediction of its subsequent changes and in-time therapeutic treatment before permanent damage has been developed. In this paper, we present the validation of our fully automated scheme for the bone segmentation and qualitative bone-cartilage interface (BCI) extraction and initial cartilage segmentation from MR images of the hip joint.

METHOD: An anonymized database of 16 normal subjects with no history hip joint complaints was acquired with a large flex coil on a 3T Siemens Trio MR scanner at University of Queensland. MR images were acquired bilaterally using three different sequences, which included T2w weDESS (water excitation Dual Echo Steady State), T1w weVIBE (water excitation Volumetric Interpolated Breath-hold Examination), and T2w MEDIC (Multi Echo Data Image Combination). In each MR image, four parts of the bones in the hip joint (left femur (LF), right femur (RF), left acetabular bone (LA) and right acetabular bone (RA)) were manually labeled using ITK-SNAP [1] by Y. X with expert guidance from C.E.

The shape model is built using NRR segmentation scheme from a dataset of 28 CT images of the Pelvis from a Prostate Cancer study at Calvary Mater Newcastle Hospital. The automated segmentation of the bone and BCI extraction are based on a 3D active shape model (ASM) segmentation scheme previously used for the knee [2]. From the segmentation scheme shown in Fig. 1, ASM segmentation was initialized by an affine registration [3] from the CT atlas. In each iteration of the ASM, the surface was actively deformed to bone edges using image gradient information. The shape constraint brought the deformed surface back to an anatomical reference. After the combined segmentation, the individual ASM for each of the four bones was computed to reduce global pose constraints in the combined SSM. As the SSM is overconstrained, the bone surfaces were relaxed onto the local boundary using a simple surface regularization constraint.

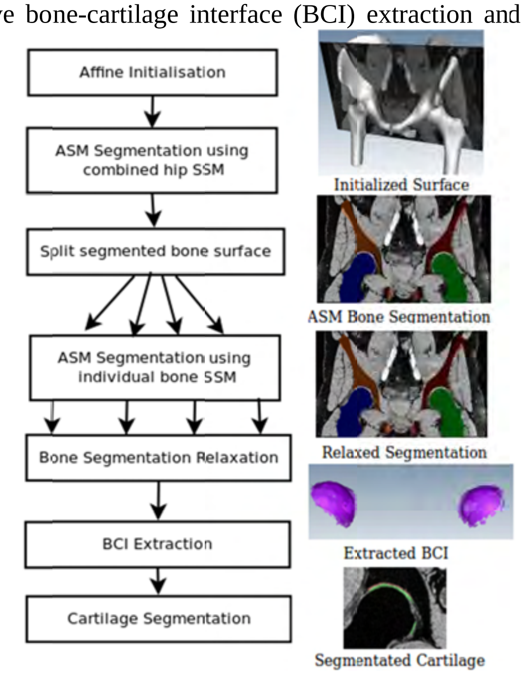

Figure 1. Automated segmentation scheme with example results

After segmenting the bones, the initial BCI was estimated from the cartilage distribution model and evolved iteratively by checking more than two neighbors on the BCI for cartilage tissue along the normal profile. Based on the extracted BCI, simple cartilage segmentation was performed using Otsu [4] threshold at the region of interest in the image (Euclidean distances of femoral and acetabular BCI < 6 mm), and further subdividing the cartilage based on femoral and acetabular distances.

RESULTS: The bone segmentation results were validated against the manually labeled images for all 16 cases (Table 1). The segmentation of four bone parts (LF, RF, LA, RA) reached a median DSC of (0.954, 0.947, 0.850, 0.851). An example of the bone segmentation and extracted BCI is illustrated in Fig. 2. Using the BCI, initial cartilage segmentation is performed (Fig. 3). It shows reasonable BCI was extracted for initial estimation of cartilages, which can be improved using advanced segmentation methods.

Table 1. Average of Volume-based Validation

	DSC		MASD
	Average	Std	
LF	0.952	0.009	0.851
RF	0.947	0.011	0.956
LA	0.818	0.077	2.071
RA	0.843	0.077	1.840

DSC: Dice's Similarity Coefficients
MASD: Mean Absolute Surface Distance

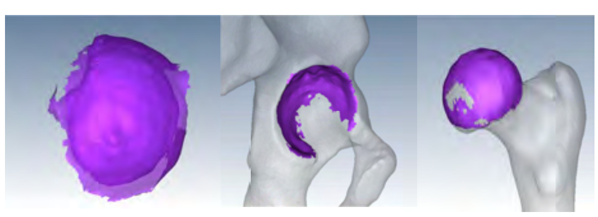

Figure 2. Example of the extracted BCI: (Left) left side joint; (Middle) acetabular BCI; (Right) femoral BCI

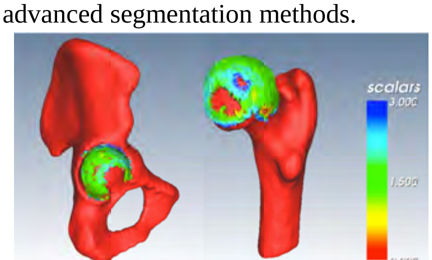

Figure 3. Representative cartilage segmentation results, with colormap reflecting cartilage thickness

CONCLUSION: In this paper, we present the validation of an automated bone segmentation scheme, qualitative results for the BCI extraction and simple cartilage segmentation. The extracted BCI can be used to provide a good initial frame from which advanced cartilage segmentation can be performed [5]. Future work will focus on quantitatively validating the extraction of the BCI and the development of an advanced cartilage segmentation scheme for the hip.

REFERENCES: [1] P. A. Yushkevich et al., *Neuroimage*, 2006. [2] J. Fripp, et al., Physics in Medicine and Biology, 2007. [3] S. Ourselin, et al., Image and vision computing, 2001. [4] Otsu N, *IEEE Trans. Syst. Man Cybern*, 1979 [5] J. Fripp, et al., *IEEE Transactions on Medical Imaging*, 2010