

A technique for improving 2D X-ray to 3D MRI registration in fluoroscopy-guided orthopedic interventions

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Introduction Orthopedic interventions are often performed using x-ray fluoroscopic guidance. Although bony structures can be seen on fluoroscopic images, soft tissue contrast in such images is poor. In addition, fluoroscopy can only provide 2-dimensional projection images, which has no spatial resolution along the projection axis. For these reasons it would be beneficial to use preoperative 3D data with adequate soft tissue contrast for real-time intra-procedural navigation. Three-dimensional or multi-slice MRI can provide such data. However, using 3D MRI data during the intervention requires registration of the data to intra-operative fluoroscopic images. Registering MRI to x-ray data is technically challenging because fundamental differences in physical imaging principles lead to very different tissue contrasts. For vascular interventions, the enhanced vasculature itself can be used for x-ray angiogram to MRA registration, but in orthopedic interventions there are no obvious landmarks or structures similar in appearance in both techniques that can be used. To circumvent this problem Van de Kraats et. al. [1] have investigated the possibility to define a mapping function from multispectral MRI signal intensity values to computed tomography (CT) Hounsfield units in order to create CT-like data from multiple MRI datasets. Such image data can be used to digitally reconstruct radiographs that would have a similar appearance as fluoroscopic X-ray images of the same object and this method would therefore improve registration. We have elaborated on this idea in order to make it more robust and applicable to scan sequences commonly used in clinical practice. The method we propose now is based upon a voxel classification strategy. Its feasibility is demonstrated in *ex vivo* animal models.

Materials & Methods We have investigated the applicability of a multispectral MRI to CT mapping function based on a k-nearest neighbor (KNN) method. Multispectral MRI and 3D CT-like datasets (XperCT) acquired with a rotational X-ray source (Allura Xper FD20, Philips Healthcare, Best, The Netherlands) were acquired of 2 different porcine hind limbs. For the feasibility test, one dataset was used as a training set and the other as a test set. Multislice coronal MR data of both legs was acquired using a T_1 -weighted Turbo Spin Echo (T_{1w} TSE) sequence [$T_R = 529$ ms, $T_E = 11$ ms, TSE-factor = 4, NSA = 2], a T_2 -weighted Turbo Spin Echo (T_{2w} TSE) sequence [$T_R = 3500$ ms, $T_E = 120$ ms, TSE-factor = 31, NSA = 4], and a T_2 -weighted Short T_1 Inversion Recovery sequence (T_{2w} STIR) [$T_R = 2500$ ms, $T_E = 80$ ms, $T_1 = 170$ ms,

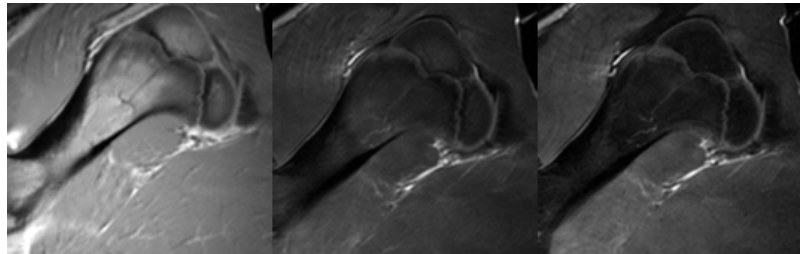


Figure 1 Three coronal slices out of the multispectral MR data of one of the porcine hind limbs: T_{1w} TSE (left), T_{2w} TSE (middle) and T_{2w} STIR (right).

TSE-factor = 13, NSA = 2]. All MR data had an acquired in-plane resolution of 0.94×0.94 mm², a slice thickness of 3 mm and a slice gap of -1 mm (Achieva, Philips Healthcare, Best, The Netherlands). The XperCT data had a voxel size of 1.37 mm in all directions. **Training stage:** In the training stage, registered multispectral MRI and CT data of one object was used to generate a 3-dimensional feature space. For all voxels inside the object a 3-dimensional feature vector was generated which consisted of the modulus signals acquired by the three MR sequences and the vector was assigned the corresponding x-ray attenuation coefficient expressed in Hounsfield units (HU) from the CT data. The intensity values of the MR datasets were rescaled to [0, 10000]. The attenuation coefficients (HU) used for labeling were divided into three categories: soft tissue and fat (-100 HU), spongy bone (200 HU) and compact bone (1000 HU). **Test stage:** A simulated CT data set was created from the test set during the classification phase. For each voxel a feature vector was constructed containing the three corresponding MRI signals. This vector represents a point in the 3-dimensional feature space. The Euclidean distance from this new point to all points of the training data was calculated and the 50 nearest points were selected.

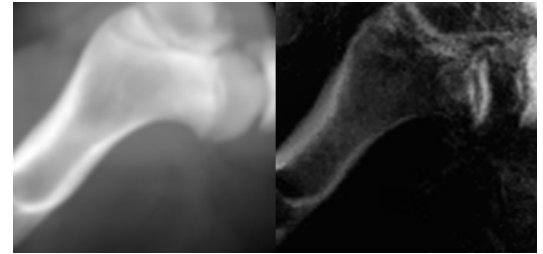


Figure 2 DRRs generated from the XperCT data (left) and the simulated CT data (right).

The Hounsfield unit labels of these 50 nearest neighbors were counted and the label for the new point was determined by a majority vote. The value of the classification method was demonstrated for registration. By registering the simulated CT of the test data to the XperCT data and creating digitally reconstructed radiographs (DRRs) created from the XperCT data, registration experiments of the DRRs and the simulated CT data with known ground truth could be performed. The DRRs were generated with different rotational parameters, keeping all other parameters fixed, using a divergent beam ray-casting algorithm. The angles of projection, θ (along longitudinal axis) and ϕ (along the left-right axis) were varied ± 5 degrees in 1 degree increments. The registrations were performed using a gradient difference method [4]. The ground truth was given by the parameters used for the generation of the corresponding DRR. For each DRR exhaustive search experiments were performed with offsets of 5 and 10 degrees from the ground truth and a step size of 0.1 degrees. The output parameters were the projection angles which showed maximal similarity calculated with the gradient difference measure. The registration errors ϵ_θ and ϵ_ϕ were defined as the absolute difference between each of the projection angles used for the DRR generation and the projection angles found by the exhaustive search experiment.

Results In Figure 1 three coronal slices out of the multispectral MR data of one of the porcine legs is shown. Figure 2 shows DRRs of the XperCT and the simulated CT that was generated from the multispectral MRI data. The average errors of the exhaustive search experiments are given in table 1.

Discussion & Conclusion We have investigated whether it is feasible to create a simulated CT image based on 3 common clinical MRI sequences using a k-nearest neighbor method. The method was tested using *ex vivo* datasets of porcine hind limbs, where one set was used to train the algorithm and the other to test classification. The quality of the simulated CT image was tested by performing gradient difference-based 2D-3D registration experiments. The results show that the average registration error was 0.7 degrees for rotations along the x-axis, 1.8 degrees for rotations along the y-axis and 1.5 and 2.5 degrees for rotations along both axes. It should be noted that the registration errors are also influenced by the success of the registration of the simulated CT to the XperCT, which was necessary for the validation of the experiments. From these preliminary results we can conclude that the creation of a simulated CT from multispectral MR data is a feasible tool to aid the 2D-3D registration of X-ray to MRI data.

Table 1 The average registration errors of the exhaustive search experiments. DRRs were generated by varying one of the angles of projection and keeping the other fixed (column 2 and 3) and varying both angles simultaneously (column 4).

Offset (degrees)	ϵ_θ (degrees)	ϵ_ϕ (degrees)	ϵ_θ & ϵ_ϕ (degrees)
5	0.7 (n = 10)	1.8 (n=10)	1.3 & 2.0 (n = 100)
10	0.7 (n = 10)	1.8 (n=10)	0.4 & 1.4 (n = 6)

References [1] Van de Kraats E. et al. Image Registration III: 911-918, MICCAI '05 [2] Rohlfing T. et al. Lecture Notes in Computer Science: 469-476, MICCAI '02 [3] Tomažević D. et al. Lecture Notes in Computer Science: 461-468, MICCAI '02 [4] Tomažević D. et al. IEEE Trans. on Medical Imaging: 2003 vol. 22(11): 1407-1416