Computer-aided classification of inflammatory sacroiliitis in magnetic resonance imaging

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Propose

The reference standard to evaluate active inflammation of sacroiliac joints (SIJ) in spondyloarthritis (SpA) is magnetic resonance imaging (MRI). However, this evaluation may be challenging to specialists due to clinical variability [1]. In order to aid the diagnosis of inflammatory sacroiliitis, we aim to develop a computerized semiautomatic classification of SIJ using gray-level and texture MRI features. We also aim to assess the performance of the classification with features extracted from manually segmented SIJ images and from images processed by the warp geometric transformation method.

Methods

We retrospectively evaluated the SIJ MRI from 51 patients. Patients had inflammatory low back pain and were investigated for inflammatory sacroiliitis related to SpA. According to ASAS group MRI criteria [2], 22 patients presented active SIJ inflammation, and 29 were negative for SIJ active inflammation. A musculoskeletal radiologist performed manual SIJ segmentation independently and blinded to clinical and MRI diagnosis. Segmentation was performed in 6 consecutive SPAIR T2 coronal plane MRI for each patient. On each image we applied the warp processing method, in order to remove the black background of the segmented regions of interest (Figure 1), which could introduce noise in the feature extraction and classification processes. A total of 39 features were extracted from each image (7 gray-level features, 14 texture features proposed by Haralick and 18 proposed by Tamura [3,4]). Each patient was characterized by four vectors of feature categories: (a) Gray-level (7 features x 6 images = 42 dimensions); (b) Haralick (14 features x 6 images = 84 dimensions); (c) Tamura (18 features x 6 images = 108 dimensions); and (d) All features combined (39 features x 6 images = 234 dimensions). Classification was performed by the multilayer perceptron (MLP) artificial neural network, with a 10-fold cross-validation. The diagnostic performance was assessed by the area under the receiver operating characteristic curve (AUC).

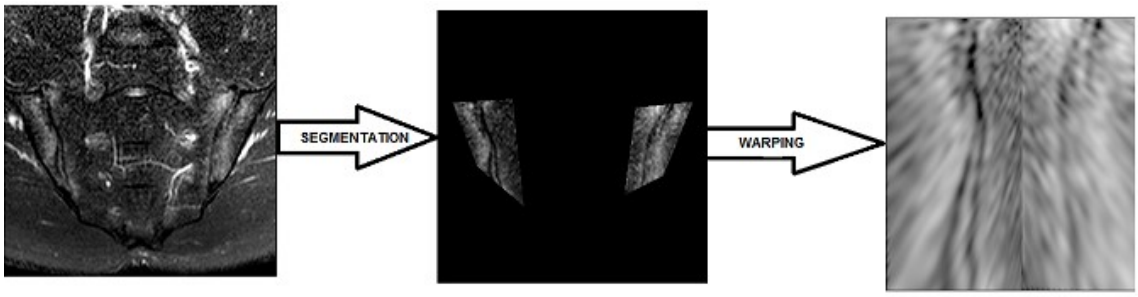

Figure 1 – Sacroiliac joints MRI segmentation and warping processes.

Results

Figure 2 presents the classification results obtained using warped and segmented images with different vectors of feature categories. The warp method improved the classification performance in the majority of scenarios, and the highest difference was obtained by the gray-level feature vector, with an increase of 0.21 in AUC. On the other hand, the segmented images obtained highest performance only with Tamura features, with an increase of 0.30 in AUC. However, the best result with highest AUC (0.93) was obtained using all features extracted from the warped images, with sensibility of 0.73 (95% confidence interval of 0.50 to 0.88) and a specificity of 0.9 (95% confidence interval of 0.72 to 0.97).

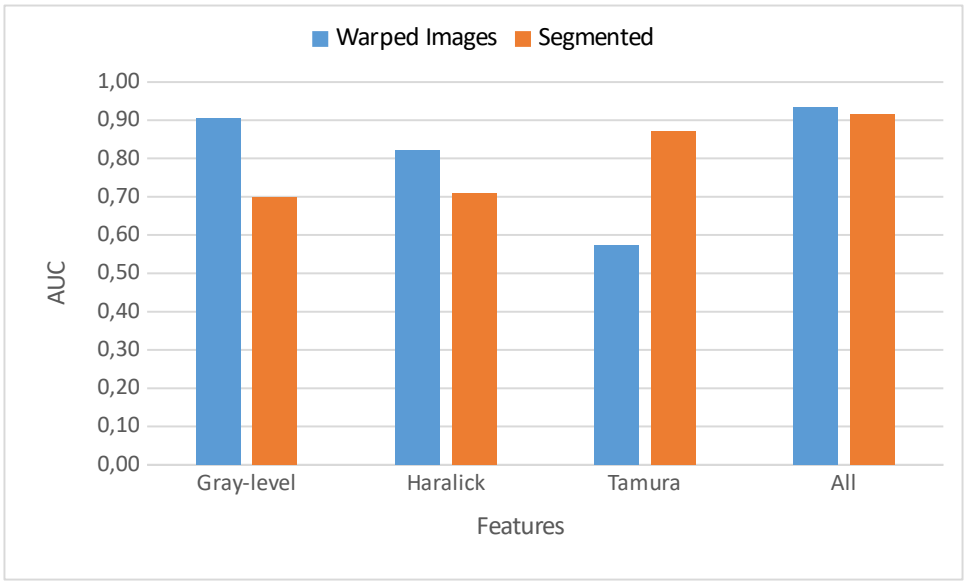

Figure 2 – Classification performance of categories of features extracted from warped and segmented SIJ images.

Conclusion

This study on semi-automatic classification of active sacroiliitis in SpA achieved promising results for a case-based evaluation, with AUC of 0.93 using gray-level and texture MRI features extracted from SIJ images. The warp image processing method increased the overall classification performance compared to segmented images with a black background, except when Tamura features were employed. In future studies, we will extract different features from the warped images, e.g. Fourier and wavelet transformations, and perform an image-based evaluation for each SIJ MRI coronal slice. Further experiments will include an observer test to validate the semi-automatic classification as a computer-aided diagnosis tool.

References

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