Pattern Recognition of inflammatory sacroiliitis in magnetic resonance imaging

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Abstract The standard reference to evaluate active inflammation of sacroiliac joints in spondyloarthritis is magnetic resonance imaging (MRI). However, visual evaluation may be challenging to specialists due to clinical variability. In order to improve the diagnosis of inflammatory sacroiliitis we have used image processing and machine learning technics to recognize inflammatory patterns in sacroiliac joints in MRI spectral attenuated inversion recovery (SPAIR) T2 weighted using gray-level, texture and spectral features. Pattern recognition was performed with the ReliefF method for attribute selection and the classifiers K nearest neighbors (with 5 values for K), Multilayer Perceptron artificial neural network, Naive Bayes, Random Forest, and Decision Tree J48. Classification was assessed by the area under the ROC (receiver operating characteristic) curve (AUC), Sensitivity and Specificity, with a 10-fold cross validation. The K nearest neighbors with K = 5 obtained the best performance with AUC up to 0.96.

Key words: spondyloarthritis, inflammatory sacroiliitis, sacroiliac joints, magnetic resonance imaging, pattern recognition

1 Introduction

Spondyloarthritis(SpA) is a group of chronic inflammatory disease affecting primarily the spine and sacroiliac joints, with high prevalence in some population [13] and with common clinical and radiologic characteristics. SpA affects mainly young adults with start age of 31 years [11] with highly potential of morbidity and socioeconomic impact.

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The main technique to achieve early diagnosis in SpA is magnetic resonance imaging (MRI). MRI may show subchondral bone edema in sacroiliac joints, which is currently the main criteria for active inflammation [10].However, the inflammation patter recognition of sacroiliac joints in MRI is still challenging due to image interpretation inherent difficulties such as high complexity on semiquantitative evaluation standards [9].

In order to improve the diagnosis of inflammatory sacroiliitis we have used image processing and machine learning technics to recognize inflammatory patterns in sacroiliac joints in MRI exams.

2 Material and Methods

Our image database is composed by 51 MRI spectral attenuated inversion recovery (SPAIR) T2 weighted exams, with 6 images (coronal slices) per exam with dimension of 512x512 pixels, of which 22 are positive to the inflammation and 29 are negative. Exams were obtained retrospectively from the hospital PACS (Picture Archiving and Communication Systems) after institutional research board approval. Images were evaluated using the Spondyloarthrites Research Consortium of Canada (SPARCC) score [8] [1].

Regions of interest (ROIs) containing the sacroiliac joints were manually segmented for each image (slice) by a musculoskeletal radiologist. ROIs were then inserted in a square black background and an image processing method called warp was applied to expand the ROIs (Fig. 1).

Gray-level, texture and spectral features were extracted from each warped image. Gray-level features were Mean, Variance, Standard Deviation, Asymmetry, Kurtosis, Deviation Coefficient and Max Pixel Value. [2].

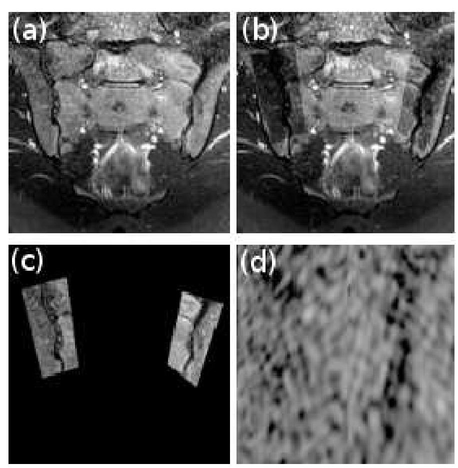


Fig. 1 Segmentation and warping processes. (a) Original MRI; (b) Sacroiliac joints marked by a radiologist; (c) Segmented sacroiliac joints with black background; (d) Segmented sacroiliac joints after the warp processing.

Texture features were those proposed by Haralick et. al. [5],based on the co occurrence matrix, and those proposed by Tamura et. al. [14], based on the image histogram..

The Haralick et al. [5] features used in this work were Second Angular Momentum, Contrast, Correlation, Variance, Moment of Inverse Difference, Mean Sum, Sum Entropy, Sum of Variance, Difference of Variance, Difference of Entropy, two Measures of Information Correlation, and Maximum Correlation Coefficient.

Tamura et al. [14] features were Contrast, Granularity, and Directionality, which is divided in 16 features or directions. All these features have been implemented using the open-source Java library JFeatureLib [6].

Fast Fourier transform (FFT) was applied over the warped images to obtain images frequency spectrum. FFT was implemented using the open-source library ImageJ [12], Features extracted from image frequency spectrum were called Fourier Features and are based on polar coordinates of each pixel of the transformed images.

Some parameters have been defined to implement the Fourier Features, such as 18 angles (from 10 to 180) and 10 radius measured by pixels (from 4 to 40 pixels) close to the center of the image to get only low frequencies (high frequencies correspond to shape and only texture is important to our problem).

Fourier Features used in this work are Max Pixel Value for each radius, Cumulative Energy for each radius, Max Pixel Value for each angle on each radius and Integral of half image, because FFT is a symmetric image, totalizing 39 Fourier Features [4].

The final attribute vector for each patient was constructed using the mean and the standard deviation of each attribute extracted from the 6 images (slices), resulting in a final vector with 154 attributes for each patient.

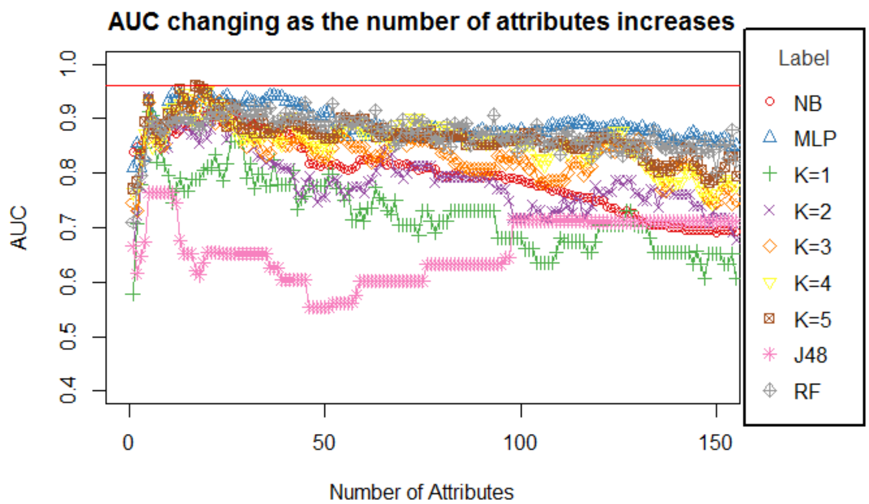
The attribute selection was performed using ReliefF algorithm, which estimates attributes according to their potential to distinguish nearest instances to each other in multi class problems [7]. The algorithm used in this work has been implemented on the open-source software Weka [3], using nearest neighbors equals to ten and a search method based on Ranker algorithm. This method lists the attributes in a decreasing order based on the relevance obtained by the ReliefF.

For the classification we used K nearest neighbors (KNN) (with K from 1 to 5), Multilayer Perceptron artificial neural network, Naive Bayes, Random Forest, and Decision Tree J48. The classifiers have been implemented on the open-source software Weka. The combination method between number of attributes and classifiers was exhaustive, which means that N first attributes given by the Ranker method were used by all the classifiers, where: $155 > N > 0$.

3 Results and Discussion

The Area Under receiver operating characteristic (ROC) Curve (AUC), the true positive rate (Sensitivity) and the true negative rate (Specificity) were used to evaluate the efficiency of each combination of attribute and classifier. Figs. 2, 3 and 4 illustrate respectively the AUC, Sensitivity and Specificity for each combination of attributes and classifiers.

Fig. 2 AUC values for each classifier changing as the number of attributes increases. The red line indicates highest value.



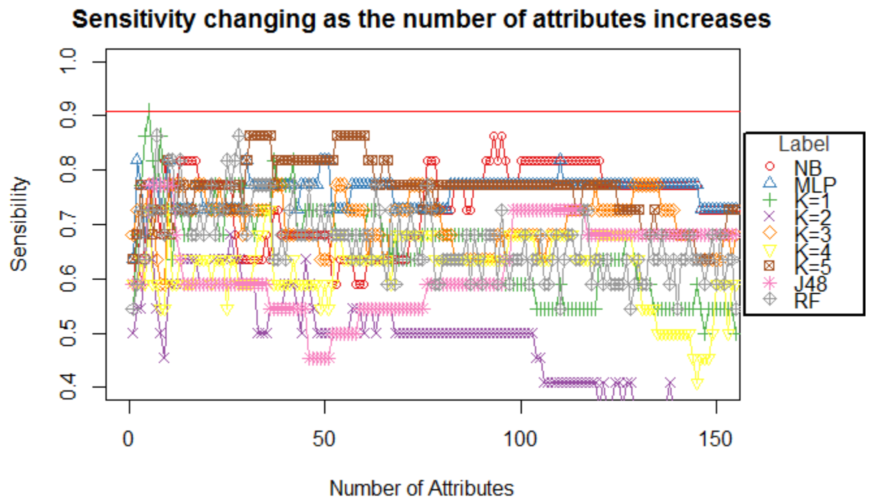
As present in Fig. 2, AUC value decreases as the number of attributes increases, with the highest value of 0.96 obtained for KNN classifier with K equals to 5 using 17 attributes. However, this classifier obtained only 0.77 for sensitivity. Highest sensitivity was obtained for KNN classifier, but using K = 1 and only 5 attributes, with value up to 0.91.

On the other hand, as we can see in Fig. 3, several combinations of attributes and classifiers reached the highest value for specificity, up to 1. KNN with K = 4 is the classifier that reached it with the biggest attribute vector (41 attributes).

KNN classifier with K = 1 and 5 attributes obtained only 0.89 for Specificity, but together with values of 0.91 for AUC and 0.91 for Sensitivity.

In a previous work [2], using the same dataset but different sets of attributes, the classifier that reached the highest value of AUC was Multilayer Perceptron, which reached the value of 0.93. In the present work, Multilayer Perceptron showed an increase of 0.02 in AUC, with value of 0.95 when using 13 attributes, but did not present any increase in sensitivity, which still in 0.73.

Fig. 3 Sensitivity values for each classifier changing as the number of attributes increases. The red line indicates highest value.



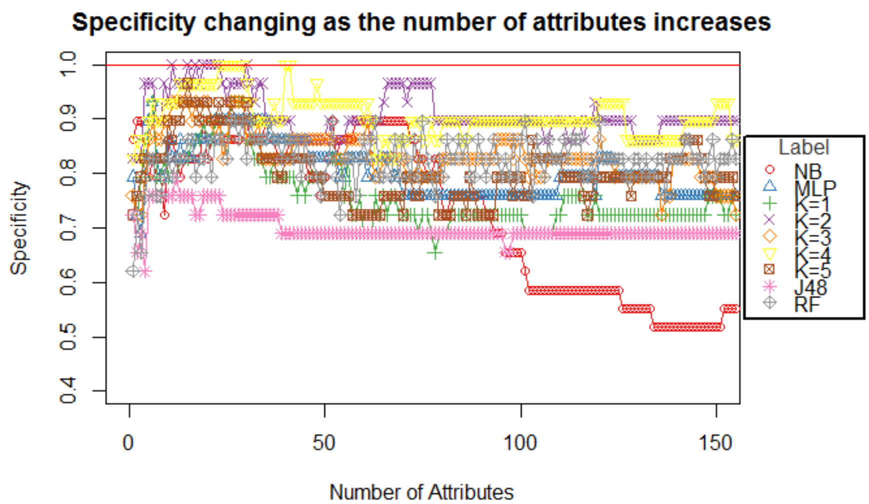
4 Conclusion

Mean and Standard Deviation of the attributes of each image (slice) apparently is a good approach to characterize the exam of a patient with inflammatory sacroiliitis. The mean was chosen because if the patient has more images positive to sacroiliitis, the mean would have a value closer to the value that describes the inflammation. The standard deviation can be useful in the cases that the patient is positive to sacroiliitis, but the number of images with the inflammation is low.

In addition, using the mean and standard deviation promotes a natural reduction over the feature vector dimension. Feature selection using ReliefF and Ranker had also an important role over the reduction of the feature vector associated with classifiers performance improvement.

We consider that the KNN with K = 1 and 5 attributes have the best performance scenario (AUC of 0.91, Sensitivity of 0.91, and Specificity of 0.89), because in our context, sensitivity, that is, the correct classification of patients that really have inflammatory sacroiliitis, is more important than the specificity. But if we only consider AUC, KNN with K = 5 and 17 attributes will be more recommendable than others to inflammatory pattern recognition.

Fig. 4 Specificity values for each classifier changing as the number of attributes increases. The red line indicates highest value.



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