Novel Automatic Tool for Magnetic Resonance Imaging Quantification of Bone Erosion Scoring in Rheumatoid Arthritis

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Abstract. Rheumatoid arthritis (RA) is a systemic disease that affects the synovial joints. Currently, the gold standard measurement for tracking the progression of the disease involves a semi-quantitative assessment of bone erosion, bone marrow edema and synovitis, as seen in magnetic resonance images (MRI). The work presented in this paper identifies how computer automation can be used to quantify bone erosion volumes in MRI without expert and time consuming interventions. This tool is fully integrated in a computer aided diagnosis (CAD) system named RheumaSCORE (Softeco Sismat Srl). Preliminary results of qualitative and quantitative validation are presented and discussed at the end of the paper.

Keywords: Computer aided diagnosis (CAD) · Erosion scoring · Image processing · Principal component analysis (PCA) · Shape reconstruction · Rheumascore · Rheumatoid arthritis

1 Introduction

Rheumatoid arthritis (RA) is a chronic inflammatory autoimmune disease that affects synovial joints and leads to the destruction of periarticular bone. Bone erosions are localized lesions with a break in the cortical shell. Since bone erosions are closely related to disease activity, they are an early prognostic indicator and an important clinical parameter for monitoring treatment efficacy [1,2,3]. It is therefore desirable to detect them as early as possible with high precision in order to quantify small changes. Currently, the gold-standard measurement for tracking the progression of the disease involves a semi-quantitative assessment of bone erosion, bone marrow edema and synovitis, as seen in magnetic resonance images (MRI), by a musculoskeletal radiologist.

The work presented in this paper shows how computer automation can be used to quantify bone erosion volumes in MRI without a radiologists' expert and time

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consuming intervention. A new automatic 3D tool for quantification of bone erosion scoring is described and evaluated for use in a clinical setting. The effectiveness of this approach is demonstrated by presenting both qualitative and quantitative results of wrist bones considering both normal and pathological RA cases. For this purpose, the tool is fully integrated in a CAD system named RheumaSCORE [19,20,21,22].

The paper is organized as follows. Section 2 gives an overview of the existing techniques and tools for RA scoring on MRI. Section 3 provides the description of the diagnostic tool implemented. Section 4 describes the integration of the tool in the RheumaSCORE software and provides an evaluation of the performance of the approach. Qualitative results on various datasets and preliminary quantitative analysis of the performance of the method for wrist bone scoring are presented.

2 Background and Previous Work

Historically, conventional radiographs (CRs) are used to semi-quantitatively assess bone erosions in patients with RA. However, due to their projectional character, the use of CRs results in an underestimation of the number and size of erosions and therefore, probably, disease activity [4].

Other imaging modalities have emerged as methods for more sensitive detection of early bone erosions. MRI has been demonstrated to be more sensitive than radiography in detecting erosive bone changes in RA, especially the subtle changes that occur in early disease [5,6,7]. The Outcome Measures in Rheumatology (OMERACT) Rheumatoid Arthritis MRI Scoring System (RAMRIS) has been developed [10,11] with data from iterative multicenter studies [10,12,13].

Some methods for the semi-automated quantification of erosions have also been developed on MRI datasets. The studies performed by Crowley et al. [8], using MRI data, relied on manual outlining of the erosions slice by slice. While a trained operator may produce reliable results, manual outlining can be very time consuming. Moreover, a slice-wise approach does not take the true 3D erosion structure into account. In contrast, Emond et al. [9] employed a true three-dimensional (3D) segmentation of erosions in MRI data. Only the placement of a seed point and the selection of five parameter were required. Moreover, this approach has the complexity related to the choice of the parameter to segment the erosion.

In addition, to the best of our knowledge, there is no commercial framework for wrist/hand erosion scoring designed for MR images. In that sense, a first result is the tool described in this paper and fully integrated in RheumaSCORE software [19,20], a specific CAD for RA. This tool identifies and measures bone erosions, not segmenting directly the erosion, i.e. the missing part of the bone, but through the segmentation of the bone of interest and then the reconstruction of its original shape. It uses a statistical shape model extracted from a collection of training samples of healthy bone. The resulting model consists of the mean shape and a number of modes of variation obtained with a Principal Component Analysis (PCA). Every healthy bone can be obtained as a linear combination of the mean shape with these modes. The reconstruction of the original shape of the bone of interest is performed finding the best coefficients of this linear combination. The difference between the segmented bone

and the reconstructed bone is the erosion of which it is possible to calculate the volume and then the scoring. Processing takes a few minutes for all wrist bones (or hand bones), which leads to a substantial reduction of diagnosis time and costs.

3 Automatic Bone Erosion Scoring

3.1 Construction of the Statistical Shape Model

Constructing a statistical shape model (SSM) basically consists of extracting the mean shape and a number of modes of variation from a collection of training samples.

Shape is defined as a property which does not change under similarity transformations, i.e. it is invariant to translation, rotation and scaling. In general, shape changes induced by these global transformations should not be modeled by an SSM in order to keep the model as specific as possible. Thus, the first step is to align all training samples in a common coordinate frame. For our application, we are interested in aligning binary images since that is how we encode the training shapes. We use a rigid-based image registration algorithm to align our training set.

The original images for the training set consists of 40 MRI volumes acquired using an Esaote C-Scan, a scanner dedicated for imaging of extremities. The sequence was a sagittal Turbo 3D T1 and the resolution was 0.55 mm x 0.55 mm in each slice with a slice thickenss between 0.60 mm and 0.80 mm (with no gap slices). Each slice is 256x256 pixels and a scan has around 105 slices. All the images are manually segmented by an expert. We choose an Euclidean signed distance function as our representation for shape. So, each registered data set $\tilde{I}$ is transferred into structure specific signed distance maps $D_a^{(i)}$, where a represents the structure of interest, and i the *i-th* registered image sample of the training set (Fig. 1). In these distance maps negative values are assigned to voxels within the boundary of the object, while positive values indicate voxels outside the object.

By taking the average over all these distance maps $D_a^{(i)}$ we define the mean distance map

$$\overline{D_a} = \frac{1}{n}\sum_i^n D_a^i \tag{1}$$

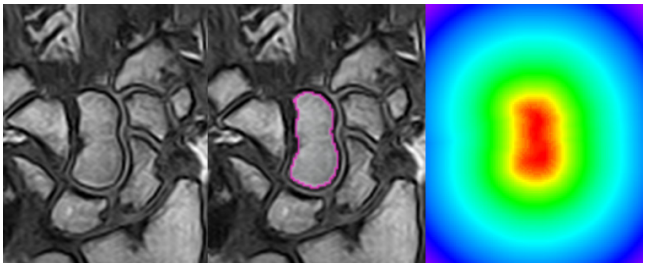
where n is the size of the training set, and the mean corrected signed distance maps

$$\widetilde{D}_a^i = D_a^{(i)} - \overline{D_a} \tag{2}$$

These mean-offset functions are then used to capture the variabilities of the training shapes through the Principle Component Analysis (PCA) [15]. The PCA allows to reduce the dimensionality of the training set, i.e. to find a small set of modes that best describes the observed variation. Then, it is possible to approximate every valid shape by a linear combination of the first c modes

$$D = \overline{D} + \sum_{m=1}^{c} b_m \, \phi_{\mathrm{m}} \tag{3}$$

where $\mathrm{b_m}$ are the weights associated with the eigenvectors ϕ_{m}.



(a) (b) (c)

Fig. 1. Distance map of the registered capitate. In (a) the coronal slice of the original MRI volume, in (b) the segmentation of the capitate overlaid on the grayscale image and in (c) the registered distance map.

3.2 Bone Reconstruction

The reconstruction of the healthy bone of interest starting from its eroded shape and from the PCA describing the variability within the training set of corresponding healthy shapes of the bone is done in two steps as follows:

1. *First adjustment of the real bone and the model*. In this step the registration between the coordinates system of the mean binary shape of the PCA and the eroded bone is performed using a rigid transformation (rotation + translation). The resulting parameters of the transform are used during the next step.
2. *Reconstruction by successive optimizations*. An evaluation function which represents the error between the transformed model by the parameters computed in the previous step and the real bone is calculated. By repeating the optimization process, this evaluation function is minimized by changing the initial model (Fig. 2). Modifying the initial model consists in changing the c shape parameters defined by the PCA (i.e. changing the vector of parameters' weights b defined in formula (3)). The evaluation function chosen for this optimization process is the Dice's Coefficient [18] that is a statistic used for comparing the similarity of two samples. In the bone reconstruction algorithm the similarity is between the binary image of the eroded bone and the binary image made by the modified initial healthy model.

3.3 Volume Evaluation

Volumetric measurements are essential to evaluate the success of a therapy. As an example, the reduction of bone erosion's volume determines the success of the treatment. Once we have selected all voxels of a target structure, the volume represented by these voxels can be approximated for volumetry. In this work we follow the Voxel Counting with Edge Resampling method (VCER) [16].

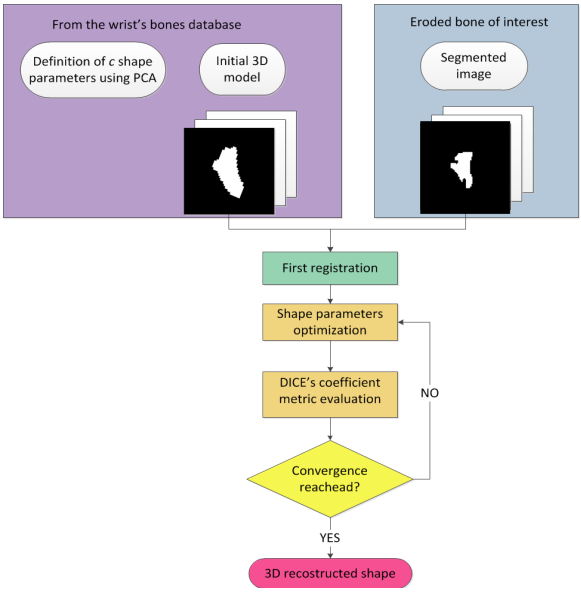
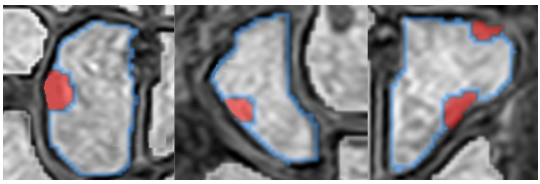


Fig. 2. Overall method for the 3D reconstruction.

After reconstructing the shape of the healthy bone, we make the difference between the original eroded segmented bone and the reconstructed bone. The resulting volume is the erosion. Then, using the voxel counting with edge resampling algorithm, we evaluate the volume and the OMERACT RAMRIS score.

Some preliminary tests have been carried on using real wrist MRI. In order to evaluate both the qualitative performance of the bone reconstruction algorithm and the quantitative reliability of the volume evaluation algorithm, described in the previous section, we simulated some erosions on healthy bones, previously segmented. In this way, it has been possible to make a visual inspection and to understand if the algorithm could fill those missing part manually deleted and reconstruct them taking the bone to its original shape. Fig. 3 shows the erosion identification *via* bone reconstruction on healthy bones segmented in order to simulate some erosions.



(a) (b) (c)

Fig. 3. Bone reconstruction of simulated eroded bones. Some erosions have been simulated on the capitate bone (a), the scaphoid bone (b) and the hamate bone (c). In all the figures the blue area overlaid the MRI corresponds to the segmentation having holes inserted manually. The red part is the reconstructed part of the bone, i.e. the erosion, obtained using our algorithm

4 Automatic Bone Erosion Scoring and Clinical Applications

As the test results of our scoring procedure are very encouraging, this pipeline has been fully integrated in the RheumaSCORE application, a CAD (Computer-Aided Diagnosis) system developed by Softeco Sismat to address the RA disease [19,20,21,22]. Processing takes a few minutes for all wrist bones (or hand bones), which leads to a remarkable reduction of diagnosis time and costs.

Fig. 4 shows the Diagnostic environment of RheumaSCORE after the bones erosions measurement.

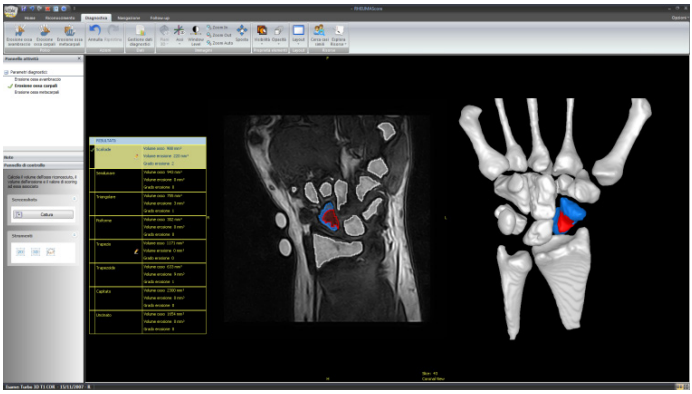


Fig. 4. RheumaSCORE: Diagnostic environment. The selected bone is the scaphoid. This bone is eroded and the missing part is shown in red.

A study comparing traditional RAMRIS score and semi-automated score by RheumaSCORE was performed. 57 patients affected by RA (42 women, median age 52 years, range 20-73 years, median disease duration 22 months, range 1-420 months) diagnosed according to the 1987 revised ACR criteria were studied. Wrist and metacarpophalangeal (MCP) joints were imaged with a dedicated-extremity, 0.2 T MRI (Artoscan, Esaote, Genova, Italy) at baseline and after a median of 15 months (range 6-121 months). Erosions were scored according to the RAMRIS.

The study was concerned on changes in RAMRIS score (single bone and total score). We found that, comparing traditional and semi-automated RAMRIS' erosions score, perfect concordance was 45.2% at baseline and 92.9% at follow up. Further detailed information about traditional and semi-automated score's comparison can be found on the paper "An MRI study of bone erosions healing in the wrist and metacarpophalangeal joints of patients with Rheumatoid Arthritis".

Studies for intra and inter-reader operators evaluation and for comparing the standard RAMRIS and the RheumaSCORE methods were performed: seven patients affected by RA according to the 1987 ACR criteria were studied with two MRIs with a 0.2 T dedicated machine (Artoscan, ESAOTE, Genova, Italy) using a turbo T1-weighted three dimensional sequence (T3-D T1) in the coronal plane, with subsequent multiplanar reconstructions on other planes, of the hand and wrist (baseline and follow-up 17 months apart, range 8-36 months).

The RAMRIS for erosions was calculated in agreement by two experienced readers (FB, MAC). An experienced reader (FB) and 6 inexperienced readers evaluated the 3D reconstructions of MRIs using RheumaSCORE software.

In the evaluation of bones' volumes, the intraclass correlation ICC for FB in 8 consecutive readings, 2 weeks apart, was 0.99. The ICC for the inexperienced readers was also 0.99, independently from the RAMRIS for erosions. The inter-rater agreement (k) between FB and the inexperienced readers varied between 0.77 and 0.86 (mean 0.81) for patients with a low RAMRIS for erosions of 3, and between 0.49 and 0.77 (mean 0.65) for patients with higher RAMRIS of 9. During follow up, the median RAMRIS score for erosions remained unchanged (p=0.12); accordingly, also bone and erosion volume measured by RheumaSCORE did not change (p=0.19).

The semi-automated calculation of bone and erosion volumes in MRI images of the hand and wrist of RA patients is feasible and has a good reliability. Concordance between traditional and automated RAMRIS was modest at baseline but became almost complete in the second examination (follow-up). This finding may be ascribed to a decrease of the possible interference exerted by bone marrow edema on automatic readings.

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