

# Radial Measures of Hip Joint Space Outline for Computer-Aided Characterization of Osteoarthritis Severity

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**Abstract**— Hip osteoarthritis (OA) is a major cause of disability worldwide. The radiographic assessment of hip OA-severity is, mostly, based on qualitative grading scales, evaluating various aspects of structural alterations in the joint. In this study, a computerized scheme for the characterization of hip OA-severity from pelvic radiographs is proposed. Sixty four hips (18 normal and 46 osteoarthritic), corresponding to 32 patients with verified unilateral or bilateral-OA were studied. Two experienced orthopaedists assessed OA-severity employing the Kellgren and Lawrence grading scale. Accordingly, hips were grouped into three major OA-severity categories: “Normal-Doubtful”, “Mild-Moderate”, and “Severe”. Patients’ pelvic radiographs were digitized and were processed by applying the adaptive wavelet transform, in order to enhance the articular margins of the hip joint. On each processed radiograph, 2 Regions of Interest (ROIs) corresponding to patient’s both Hip Joint Spaces (HJSs) were determined and 64 HJS-ROIs were obtained. Employing custom developed algorithms, the outline profile of the HJS (HJS-OPR) was generated by calculating the radial distances of the HJS-ROI’s centroid from its outline pixels. Six descriptors, quantifying shape and size aspects of the HJS-ROI, were computed from the HJS-OPR. These descriptors were employed in the design of a Probabilistic Neural Network (PNN) based classifier for the discrimination between: (i) normal and osteoarthritic hips, and (ii) hips of “Mild / Moderate” and of “Severe” OA. The highest accuracy achieved by the PNN classifier in discriminating normal from osteoarthritic hips was 84.4%, since 54 out of 64 hips were assigned to the correct categories. Regarding the characterization of an osteoarthritic hip as of “Mild / Moderate” or of “Severe” OA, the PNN classified correctly 38 out of 46 hips, providing an overall accuracy of 82.6%. The proposed computer-based system could be of value to orthopaedists in grading hip OA-severity.

## I. INTRODUCTION

OSTEOARTHRITIS (OA) is a multi-factorial disease, which causes alterations of the synovial joint tissues. The main characteristic of OA concerns the progressive degeneration and the final loss of the articular cartilage [1],

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[2]. Despite the fact that Magnetic Resonance Imaging (MRI) is the most promising tool for the investigation of OA [3], plain film radiography is considered as the modality of reference for the assessment of the severity of the disease in daily clinical routine [4]. Osteophytes (‘bony growths’), Hip Joint Space (HJS) narrowing, subchondral cysts as well as the sclerosis of the subchondral bone are typical radiographic hallmarks characterizing the disease [5]. So far, the assessment of OA-severity has heavily relied on the use of qualitative grading scales. In this context, a severity grade is assigned to the studied hip joint, while the definitions of severity grades are based on aspects of joint structural alterations visualized on plain radiographs [6]. The Kellgren and Lawrence (KL) grading scale [7] is considered as the gold standard for epidemiological studies of the disease, despite its deficiencies [8].

Shape is a visual feature of cardinal importance regarding the description and the recognition of an object within a digital image, while shape analysis techniques attempt to provide a descriptive quantitative characterization of shape [9]. Several pathological conditions are associated to alterations concerning the morphology of anatomical organs and regions. Thus, the shape and the size of anatomical structures in biomedical images, may provide useful information regarding the physiology or the pathology of the structures [10].

Referring to hip OA, a characteristic shape alteration associated to the disease is the narrowing of HJS, perceived on radiographic images. The particular radiographic finding has been considered as a defining criterion for epidemiologic studies of the disease [11]. In addition, the monitoring of HJS-narrowing has been accepted as the most reliable index for the monitoring of the disease progression [5]. HJS-narrowing reflects, indirectly, the progressive and non-uniform loss of the articular cartilage due to OA, which results in the differentiation of the shape of radiographic HJS in osteoarthritic hips. Thus, the implementation of shape analysis techniques in order to extract quantitative information concerning osteoarthritic alterations could have a positive contribution in the investigation of hip OA.

Previous studies [11], [12] have introduced HJS-width thresholds for characterizing a hip as normal or osteoarthritic. In a previous study performed by our group, hip joint alterations associated to OA were assessed by means of the radiographic texture of HJS [13].

In addition, textural information extracted from the region

of radiographic HJS has been utilized in the design of pattern recognition schemes for the discrimination among OA- severity categories and the quantification of the severity of the disease [14], [15]. However, to the best of our knowledge, a computer-based approach for the assessment of osteoarthritic alterations of the hip joint by means of shape analysis of radiographic HJS has not been referred to the literature.

The objective of the present study was to develop a computerized scheme for the characterization of hip OA-severity from pelvic radiographs. For this, shape and size descriptors of radiographic HJS were calculated from the outline profile of the specific anatomical region, and (ii) these descriptors were employed in the design of a pattern recognition scheme for the discrimination among various grades of hip OA-severity, formed in accordance with the KL grading scale.

## II. MATERIALS AND METHODS

### A. Patients and radiographs

For the needs of the present study, 64 hips corresponding to 32 osteoarthritic patients (mean age: 66.7 years, range: 49 years to 83 years) were studied. OA diagnosis was based on the clinical and radiographic American College of Rheumatology criteria. In particular, a hip was characterized as osteoarthritic if pain (associated to hip joint use) and limited mobility of the joint were reported in combination with the presence of osteophytes (femoral or acetabular) and HJS-narrowing on radiographs [16]. Accordingly, 18 patients were diagnosed as of unilateral OA and 14 as of bilateral OA. For each patient a pelvic radiograph was available. All radiographs were performed following a specific radiographic protocol, which comprised use of the same X-ray unit (Siemens, Polydoros 50, Erlangen, Germany), tube voltage 70-80 kVp, 100 cm focus to film distance, alignment of the X-ray beam 2 cm above the pubic symphysis, use of a fast screen and film cassette (30x40 cm). Digitization of radiographs was performed at 12 bits (4096 gray levels) and 146 ppi (5.75 pixels / mm) spatial resolution, using a laser digitizer for medical applications (Lumiscan 75, Lumisys, Sunnyvale, CA, USA) [17]. Digitizer performance was evaluated employing a quality control protocol [18].

### B. Radiographic assessment of hip osteoarthritis severity

The radiographic severity of OA was assessed by two experienced orthopaedists, who used the KL grading scale. The latter defines five severity categories via an equal number of grades ranging between 0 and 4. Grade 0 is assigned to a normal hip joint, while grade 4 indicates a severe osteoarthritic condition. Intermediate levels of OA-severity, characterized as “Doubtful”, “Mild”, and “Moderate” are described by the grades 1–3, respectively. According to the KL classification of OA, the radiographic features corresponding to each one of the grades of the KL

scale are: grade 0, no features; grade 1, possible narrowing, possible osteophytes; grade 2, definite HJS-narrowing, definite osteophytes and slight sclerosis; grade 3, marked HJS-narrowing, moderate osteophytes, some sclerosis and possible cysts formation, possible deformity of femoral head and acetabulum and grade 4, large osteophytes, gross HJS-narrowing, severe sclerosis, cysts and marked deformity [7]. Each of the orthopaedists examined visually the pelvic radiographs and evaluated OA-severity by assigning a KL grade to the examined hips. In order to establish a golden standard only those exams of common consent were retained and used for further analysis. For the needs of the present study, three major KL-based severity categories were formed: “Normal-Doubtful (KL=0,1)”, “Mild-Moderate (KL=2, 3)”, and “Severe (KL=4)”. In this context, 18 hips were assigned to the “Normal-Doubtful”, 16 to the “Mild / Moderate”, and 30 to the “Severe” category.

### C. Determination of radiographic Hip Joint Space

On each pelvic radiograph two Regions Of Interest (ROIs), corresponding to patient’s both HJSs, were determined. In order to facilitate the determination of HJS-ROIs, the digitized radiographs were processed by custom developed algorithm [19]-[21], implementing the adaptive wavelet transform. This resulted in the contrast enhancement of the radiographic image, while the articular margins of the joint were emphasized. On the processed radiograph, an acute angle providing the medial and lateral limits of the studied HJS portion was formed by utilizing patient’s anatomical landmarks (see Fig. 1) [22].

As presented in Fig. 1, the medial limit was defined by the line joining the centre of the femoral head and the highest point of the homolateral sacral wing, while the lateral limit

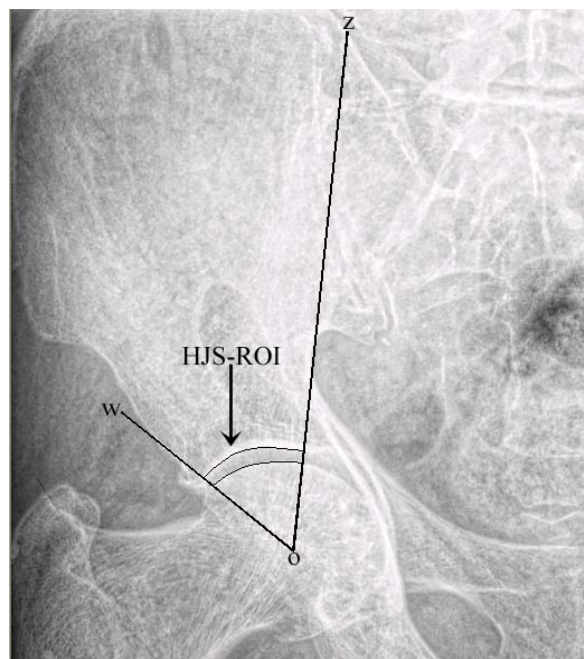


Fig. 1. Determination of the Hip Joint Space (HJS) Region Of Interest (ROI). wOz: acute angle defined by patient’s standard anatomical landmarks, encompassing the examined HJS-ROI.

was determined by the line joining the centre of the femoral head and the lateral rim of the acetabulum.

Within this region, the articular margins of the HJS, (i.e. the upper edge of the femoral head and the inferior margin of the acetabulum) were manually delineated by the orthopaedists.

The segmented HJS-ROI (see Fig. 2) was further subjected to shape analysis.



Fig. 2. Segmented Hip Joint Space Region Of Interest, corresponding to Fig. 1.

#### D. Generation of Hip Joint Space Outline Profile

The outline profile represents the shape of an object by a one dimensional profile derived from shape boundary points [23], [24]. For the needs of the present study, the outline profile of radiographic HJS (HJS-OPR) was generated employing custom developed algorithms in Matlab (The MathWorks Inc., Natick, MA, USA), according to the following steps:

- (i) Determination of the centre of “mass” (“centroid”) of the HJS-ROI.
- (ii) Tracing of the exterior boundary of the HJS-ROI.
- (iii) Calculation of the radial Euclidean distances between the centroid and each point of the exterior boundary of the HJS-ROI.

In particular, assuming that the exterior boundary of the ROI comprises  $N$  pixels, the coordinates of the centroid  $(\bar{x}, \bar{y})$  are given by:

$$\bar{x} = \frac{1}{N} \sum_{n=1}^N x(n), \quad (1)$$

$$\text{and } \bar{y} = \frac{1}{N} \sum_{n=1}^N y(n) \quad (2)$$

where  $x(n)$  and  $y(n)$  are the discrete coordinates of each boundary pixel [24]. The HJS-OPR is then defined as :

$$r(n) = \sqrt{[x(n) - \bar{x}]^2 + [y(n) - \bar{y}]^2} \quad (3)$$

In order to compensate for orientation changes, and thus to render the HJS-OPR invariant to rotation, the same starting point was selected for the computation of the radial distances [23].

After the generation of the HJS-OPR, the following distances (in pixels) were determined:

CA: the minimum distance between the centroid and the upper boundary (roof of the acetabulum) of the HJS-ROI, CH: the minimum distance between the centroid and the lower boundary (upper margin of the femoral head) of the

HJS-ROI,

CM: the maximum distance between the centroid and the medial boundary of the HJS-ROI, and

CL: the maximum distance between the centroid and the lateral boundary of the HJS-ROI.

The position of abovementioned distances in the HJS-OPR generated from the HJS-ROI of Fig. 2 is presented in Fig. 3.

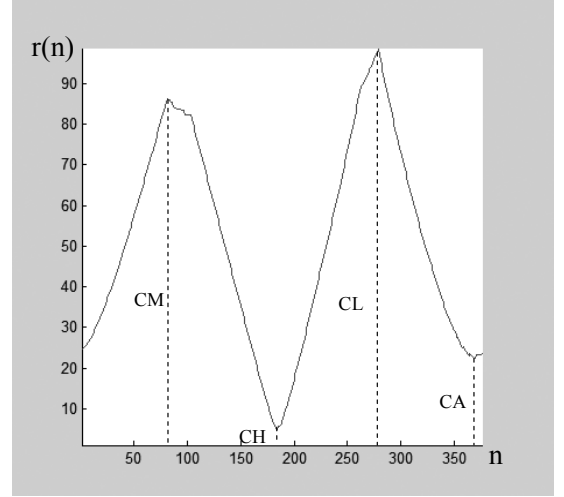


Fig. 3. Outline Profile generated for the Hip Joint Space (HJS) Region Of Interest (ROI) of Fig. 2. The vertical dotted lines indicate the distances CA, CH, CM, CL.

Besides CA, CH, CM, and CL, the following metrics were defined, according to (4) and (5):

$$DCAH = \text{abs}(CA - CH), \quad (4)$$

$$\text{and } DCML = \text{abs}(CM - CL). \quad (5)$$

The distances CA, CH, CM, CL as well as the DCAH and DCML metrics were used as shape and size descriptors of radiographic HJS.

#### E. Design of the classification system

A Probabilistic Neural Network (PNN) [25] based classifier was used for the discrimination between: (i) Normal and osteoarthritic hips, and (ii) hips of “Mild / Moderate” and of “Severe” OA. The PNN classifier is a fast-training non-parametric classification approach, that does not require Gaussian forms for the probability density functions of the pattern vectors forming a class. The specific discrimination algorithm encompasses both the Bayes’ classification approach and the Parzen’s estimators of probability density functions. The decision function of the PNN classifier employed in this study was of the form:

$$d_k(\mathbf{x}) = \frac{1}{(2 \cdot \pi)^{n/2} \cdot \sigma^n \cdot N_k} \sum_{i=1}^{N_k} e^{-\frac{\|\mathbf{x} - \mathbf{x}_i\|^2}{2 \cdot \sigma^2}} \quad (6)$$

where  $\mathbf{x}_i$  is the  $i$ -th training input pattern,  $\mathbf{x}$  is the unknown pattern to be classified,  $N_k$  is the number of patterns forming the class  $\omega_k$ ,  $n$  is the number of features

forming the input pattern whereas sigma ( $\sigma$ ) is an adjusting parameter. The unknown pattern was classified to the class with the highest value of decision function [10], [25].

In order to determine the feature combination providing the highest classification accuracy with the minimum number of features (“optimum” or “best” feature combination) the exhaustive search procedure was followed in conjunction with the Leave One Out (LOO) classification error estimation method. In particular, features were exhaustively combined each other (i.e. combinations of two, three, etc. features) in order to form a pattern vector. For every feature combination, the classifier was designed employing all the patterns of the sample, but one (“Leave One Out”). This pattern was considered as an unknown one and was used in order to determine the committed classification error. The whole procedure was repeated as many times as the number of the patterns of the sample. By this way, the performance of the classifier was evaluated employing patterns that were not used for its design. The classification performance was expressed in terms of overall accuracy, specificity and sensitivity [10].

All the shape / size features employed in the present study were normalized to zero mean and unit standard deviation, according to:

$$sf_{norm} = \frac{sf - \mu}{\sigma} \quad (7)$$

where,  $sf_{norm}$  is the normalized value of the  $sf$  shape / size feature, while  $\mu$  and  $\sigma$  are the mean value and standard deviation, respectively, of feature  $sf$  over all HJS-ROIs [10].

#### F. Statistical analysis

The normality of distributions for the generated features was assessed by means of the Lilliefors test [26]. The student’s t-test was used in order to investigate the existence of statistically significant differences between normal and osteoarthritic hips for shape / size features values following a normal distribution. On the other hand, for non-Gaussian distributions, the existence of significant differences was assessed by means of the Wilcoxon ransksun test [27]. In both cases, the significance level was set at 0.05. Intra-observer and inter-observe reproducibility concerning the determination of HJS-ROIs were evaluated by means of Coefficient of Variation (CV) [27]. Accordingly, each one of the experienced orthopaedists evaluated separately all radiographs twice, with about a month’s interval between evaluations. The obtained scores were utilized for the calculation of the CV. Student’s paired t-test was used in order to investigate whether shape / size features extracted from the two evaluations differed significantly. Matlab Statistics Toolbox was used for the statistical analysis.

### III. RESULTS AND DISCUSSION

The present study proposes a computer-based image analysis method for the characterization of hip OA by means of shape / size descriptors generated from the region of radiographic HJS.

Hip osteoarthritis is characterized by the progressive and non-uniform loss of the articular cartilage. In a radiographic image this loss is indicated by the narrowing of HJS, which induces alterations in the morphology of the specific anatomical region. Thus, the shape and the size of radiographic HJS in osteoarthritic hips is expected to differ in comparison to normal ones. This differentiation was verified by the results of statistical analysis, which revealed the existence of statistically significant differences ( $p < 0.01$ ) between normal and osteoarthritic hips for the generated features. Regarding the latter, all but one (DCML), were found to follow a Gaussian distribution. Mean values ( $\pm$  Standard Deviation) of significantly differing features are presented in Table I.

TABLE I  
MEAN VALUES AND STANDARD DEVIATIONS OF STATISTICALLY SIGNIFICANTLY DIFFERING FEATURES

Feature	Normal hips <sup>a</sup>	Osteoarthritic hips <sup>a</sup>
CA	18.5±4.5	9.1±4.7
CH	9.2±4.4	3.8±2.6
CM	65.5±11.5	53.7±18.5
CL	65.4±12.6	53.8±17.9
DCAH	9.3±5.1	5.5±4.3
DCML	1.3±1.4	3.1±2.6

<sup>a</sup>Values in pixels.

As it can be observed, the osteoarthritic hips of the sample were characterized by significantly lower values for the radial distances CA, CH, CM, and CL, in comparison to the normal ones. This finding can be justified by taking into consideration that in the case of osteoarthritic hips, the abovementioned features were generated from narrower radiographic HJSs. The osteoarthritic hips were also found to have significantly lower values for the feature DCAH, expressing the absolute difference between the CA and CH distances. In contrast to DCAH, the DCML feature, defined on the basis of the absolute difference between CM and CL, was higher for osteoarthritic hips.

All measurements were found to be reproducible. Regarding the intra-observer and the inter-observer reproducibility of HJS determination, the CV was found equal to 3.3% and 4.1%, on average, indicating the reliability of the determination process. In addition, feature values that were generated from the twice-determined HJS-ROIs did not differ significantly ( $p > 0.05$ ).

The utilization of the proposed radial measures for the

assessment of osteoarthritic alterations of the hip joint can be justified according to the following: considering the segmented HJS-ROI as an object within a digital image [23], the shape of the HJS-ROI (object) is expected to determine the position of its centre of “mass” (‘centroid’). In the osteoarthritic condition, the progressive destruction of articular cartilage, perceived as the narrowing of radiographic HJS, is expected to differentiate the shape of the specific anatomical region, and thus, its centroid position. On the other hand, the distances CA, CH, CM, and CL were defined taking as reference point the centroid of the segmented HJS-ROI. Thus, differentiation in the HJS shape is finally expected to influence the lengths of abovementioned distances as well as the values of DCAH and DCML, since the latter are defined on the basis of CA, CH, CM, and CL.

Regarding the discrimination between normal and osteoarthritic hips, the overall classification accuracy achieved was 84.4%. In particular, the classifier characterized correctly 54 out of 64 hips employing the optimum feature combination [CA CH CL]. After multiple trials, the sigma ( $\sigma$ ) parameter was determined to be equal to 0.8.

Table II represents the truth table for the discrimination between normal and osteoarthritic hips. In general terms, the truth table tabulates the correct classification against the predicted classification for each class. The number of correct predictions for each class falls along the diagonal of the matrix, while the off-diagonal elements represent the numbers of misclassified patterns for each class.

TABLE II  
TRUTH TABLE DEMONSTRATING CLASSIFICATION RESULTS FOR THE DISCRIMINATION BETWEEN NORMAL AND OSTEOARTHRITIC HIPs

Hip	Normal	Osteoarthritic	Accuracy (%)
Normal	16	2	88.9
Osteoarthritic	8	38	82.6
Overall Accuracy			84.4

As it can be observed from Table II, the classifier performed better in terms of specificity. In particular, 16 out of 18 normal hips were properly discriminated providing a specificity accuracy of 88.9%. Referring to the osteoarthritic hips of the sample, 38 hips were assigned to the correct category, while 8 hips were misclassified as normal, resulting in a sensitivity accuracy of 82.6%.

The PNN classifier was also employed for the characterization of osteoarthritic hips as of “Mild-Moderate” or of “Severe” OA. The accomplished overall accuracy for the specific classification task was 82.6%, since 38 out of 46 hips were assigned to the correct categories (see Table III). Twelve out of 16 hips of Mild / Moderate OA were correctly

classified, providing a discrimination accuracy of 75.0%. The corresponding score concerning the characterization of hips as of Severe OA was 86.7% since 4 hips were incorrectly characterized as of Mild / Moderate OA.

TABLE III  
TRUTH TABLE DEMONSTRATING CLASSIFICATION RESULTS FOR THE DISCRIMINATION BETWEEN HIPs OF MILD / MODERATE AND OF SEVERE OSTEOARTHRITIS

Hip	Mild / Moderate	Severe	Accuracy (%)
Mild / Moderate	12	4	75.0
Severe	4	26	86.7
Overall Accuracy			82.6

The abovementioned scores were accomplished when the PNN classifier was designed employing the feature DCAH and for sigma ( $\sigma$ ) equal to 0.1. The classification errors associated to the grading of OA-severity must be mostly attributed to the formation of the severity categories in accordance with the KL scale. In particular, the definition of the KL severity grades is heavily relied on the presence of osteophytes [8], while the proposed radial distance measures are entirely associated to the radiographic feature of HJS-narrowing. However, it has to be stressed that the KL grading scale has been adopted by the World Health Organization as the reference standard for epidemiological studies [28], despite its deficiencies [8]. Thus, the utilization of the KL scale for the needs of the present study was considered as a necessity, in order to reinforce the compliance of the proposed system with the established clinical standards.

Taking into consideration the relatively high classification scores accomplished by the system, the latter could be considered as a supportive tool for the grading of hip OA-severity in clinical routine.

#### IV. CONCLUSION

In conclusion, radial measures generated from the outline profile of radiographic HJS can reliably assess osteoarthritic alterations of the hip joint in radiographic images. These features were utilized for the characterization of hip OA severity, according to a computer-based approach. The proposed computerized scheme accomplished high classification scores regarding the discrimination between normal and osteoarthritic hips as well as among various grades of hip OA-severity. In addition, the system was designed so as to be compatible with the KL grading scale, which is considered as the gold standard for epidemiological studies of OA. The proposed system could be used as a diagnosis decision support tool to orthopaedists in clinical environment.

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