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A computer-based image analysis method for assessing the severity of hip joint osteoarthritis

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Abstract

A computer-based image analysis method was developed for assessing the severity of hip osteoarthritis (OA). Eighteen pelvic radiographs of patients with verified unilateral hip OA, were digitized and enhanced employing custom developed software. Two ROIs corresponding to osteoarthritic and contralateral-physiological radiographic Hip Joint Spaces (HJSs) were determined on each radiograph. Textural features were extracted from the HJS-ROIs utilizing the run-length matrices and Laws textural measures. A k-Nearest Neighbour based hierarchical tree structure was designed for classifying hips into three OA severity categories labeled as "Normal", "Mild/Moderate", and "Severe". Employing the run-length features, the overall classification accuracy of the hierarchical tree structure was 86.1%. The utilization of Laws' textural measures improved the system classification performance, providing an overall classification accuracy of 94.4%. The proposed method maybe of value to physicians in assessing the severity of hip OA.

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Keywords: Hip; Osteoarthritis; Radiograph; Texture analysis; Pattern recognition

1. Introduction

Osteoarthritis (OA) is a chronic joint disorder characterized by biochemical and morphological alterations concerning both the articular cartilage and periarticular bone [1]. MRI is the most promising tool in the investigation of the disease [2]. However, plain film radiography is considered as the reference technique for assessing the existence of OA, as well as the severity of joint destruction. The characteristic radiographic findings of hip OA comprise Hip Joint Space narrowing (HJS-narrowing), formation of osteophytes, subchondral bone sclerosis, and development of subchondral cysts [3].

Regarding the assessment of the severity of the disease, several scoring systems have been proposed. These scoring systems are mainly based on the subjective grading of radiographic features reflecting various aspects of cartilage loss and subchondral bone reaction in OA [4–6]. The Kellgren and Lawrence (KL) scale [4] is considered the "golden standard" for both cross-sectional and longitudinal studies [7]. KL scale defines five categories of OA-severity, ranging between 0 and 4. Hips with $KL = 0$, 1, are characterized as normal or doubtful for OA, respectively, while the grades 2, 3, and 4 are assigned to hips of mild, moderate, and severe OA, respectively [4].

Texture, as a regional descriptor of a digital image, is related to the distribution and spatial interrelationships of pixel intensities corresponding to the region [8,9]. Texture analysis has been employed in the quantitative assessment of hip OA severity, as well as in monitoring of the progression of the disease [10]. Texture-based classification schemes have been previously implemented in medical imaging [11]. However, to the best of our knowledge, a texture-based pattern recognition approach has not been used in the literature for the assessment of hip OA severity.

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In this study, a computer-based image analysis method was developed for characterizing hips either as normal or as of Mild/Moderate or Severe OA, by employing texture analysis methods on digitized pelvic radiographs.

2. Materials and methods

2.1. Patients and radiographs

The sample consisted of 18 patients with verified, according to the American College of Rheumatology criteria [12], unilateral hip-OA. A standing anteroposterior weight-bearing pelvic radiograph was obtained for each patient. 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 30 cm × 40 cm. Digitization of radiographs was performed at 12 bits (4096 grey levels) and 146 ppi (0.17 mm pixel size), using a laser digitizer for medical applications (Lumiscan 75, Lumisys, Sunnyvale, CA, USA). Radiographic assessment of OA severity was based on the KL grading scale criteria [4] and was performed by an experienced orthopaedist. Accordingly, data were grouped into the following OA severity categories, labeled as Normal/Doubtful (KL = 0, 1), Mild/Moderate (KL = 2, 3), and Severe (KL = 4), comprising 18, 9 and 9 hips, respectively.

On each pelvic radiograph, two HJS Regions Of Interest (ROIs), corresponding to osteoarthritic and contralateral-normal hips, were determined employing custom developed software. Specifically, an algorithm realizing the Contrast-Limited Adaptive Histogram Equalization (CLAHE) method [13] was implemented in Matlab (The MathWorks Inc., Natick, USA) to enhance the digitized radiographs and, thus, to emphasize the articular margins of the hip joint. An acute angle of 45°, encompassing the weight-bearing portion of the hip joint, provided the medial and lateral limits of the HJS-ROI (see Fig. 1) [14].

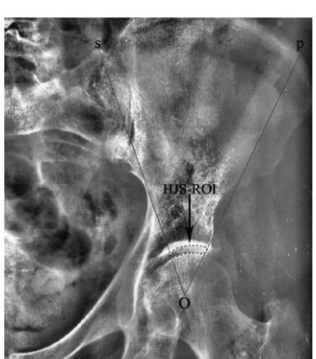

Fig. 1. Determination of the hip joint space ROI. sOp: acute angle defined by patient's standard anatomical landmarks encompassing the examined HJS-ROI. Dotted lines represent the delineated articular margins.

The medial limit was defined by the line joining the centre of femoral head (summit of the angle) and the highest point of the homolateral sacral wing and the lateral limit drawn at 45° to the medial limit. Within this angle, the operator delineated manually the articular margins of the joint (edge of the femoral head, inferior margin of the acetabulum) using a graphics cursor. This ROI was further analyzed for the extraction of textural features.

2.2. Textural features generation

Textural features were extracted employing: (i) the Grey Level Run Length Matrix (GLRLM) method [15] and (ii) the Laws' texture analysis approach [16].

The GLRLM provides information related to the spatial distribution of grey level runs (i.e. pixel-structures of same pixel value) within the image. Textural features extracted from GLRLM evaluate the distribution of small (short runs) or large (long runs) organized structures within the HJS-ROI [15]. From each HJS-ROI, 5 run-length features were extracted. For each one of these features four values were computed for angles $\theta = 0°, 45°, 90°, 135°$ [15]. The mean and the range of these four values were computed for each feature, and they were used as two different feature sets.

According to the method proposed by Laws', textural features were extracted from images that had been previously filtered by Laws' masks or kernels [16]. These filtered images were characterized as Texture Energy (TE) images. Fifteen TE images were thus produced and from each TE image first-order statistics (mean, standard deviation, range, skewness and kurtosis) were computed, giving in total 75 Laws' textural features.

All textural features employed in the present study were normalized to zero mean and unit standard deviation [9], according to the relation

$$x_i' = (x_i - \mu)/\sigma \qquad (1)$$

where x_i' is the normalized value of the x_i textural feature, while μ and σ are the mean value and standard deviation, respectively, of feature x_i over all HJS-ROIs.

2.3. Classification

A k-Nearest Neighbour (k-NN) based hierarchical tree structure was developed for the classification of hips into three OA severity categories labeled as Normal, Mild/Moderate, and Severe. The k-NN classification approach is a more general version of the Nearest Neighbour (NN) classifier. While according to the NN classification approach an unknown pattern is classified as belonging to the same class as that of the most similar (or "nearest") neighbour training pattern [17], the k-NN classifier assigns an unknown pattern to the class with the most numerous nearest neighbours, employing a majority vote rule [18]. In both classification approaches, the term "nearest" is related to the lowest value of a predefined

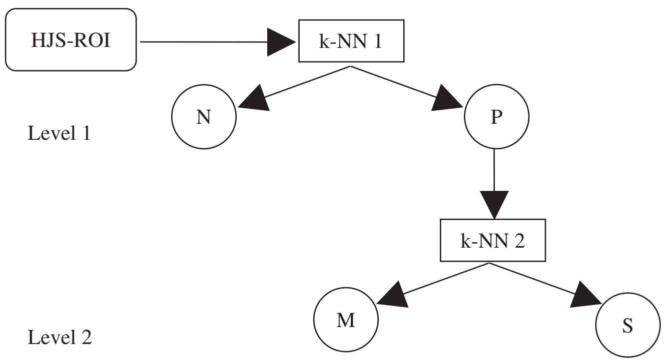

Fig. 2. The k-Nearest Neighbour (k-NN) based hierarchical tree structure for the discrimination between normal (N) and osteoarthritic (P) hips at Level 1, and between hips of Mild/Moderate (M) and Severe (S) osteoarthritis at Level 2.

distance function. For the needs of this study, the Euclidean distance function was utilized. Referring to the n-dimensional feature space, the Euclidean distance between training and the unknown pattern was defined according to the relation

$$D(\boldsymbol{x},\boldsymbol{y}) = [(x_1 - y_1)^2 + (x_2 - y_2)^2 + \cdots + (x_n - y_n)^2]^{1/2} \quad (2)$$

where $D(\boldsymbol{x},\boldsymbol{y})$ denotes the Euclidian distance, $\boldsymbol{x} = [x_1\ x_2\ \ldots\ x_n]$ is the pattern vector to be classified, while $\boldsymbol{y} = [y_1\ y_2\ \ldots\ y_n]$ represents the training pattern [8].

Fig. 2 shows the k-NN based hierarchical tree structure employed in the present study. As it may be observed, the classification scheme comprised two levels. In the first level, the discrimination between normal and osteoarthritic hips was performed. In the second level, the hips that had been characterized by the system as osteoarthritic were further classified as of Mild/Moderate or Severe OA. The performance of the proposed classification scheme was evaluated in terms of sensitivity, specificity and overall accuracy. The classifier was validated employing the Leave-One-Out (LOO) method, i.e. the classifier was designed by all but one sample of the data set, which was then classified to one of two classes [9].

3. Results

Table 1 provides the highest classification accuracies between physiological and osteoarthritic hips achieved by the k-NN classifier at the first level of the hierarchical tree. In the last column of Table 1 best feature combinations for achieving highest classification accuracies per feature sets are provided.

Table 2 gives the discrimination precisions of the k-NN classifier between Mild/Moderate and Severe osteoarthritic hips at the second level of the hierarchical tree. In the last column of Table 2 best feature combinations for achieving highest classification accuracies per feature sets are provided.

Table 1
Classification performance for the various sets of textural features concerning discrimination between normal and osteoarthritic hips

Textural feature	Sensitivity (%)	Specificity (%)	Accuracy (%)	Feature vector
Run length[a]	88.9	100	94.4	LRE[b] GLNU[c] RPERC[d]
Laws' Features[e]	94.4	100	97.2	E5L5 R5W5

[a]Using range values.
[b]Long Runs Emphasis.
[c]GLNU: Grey Level Non-Uniformity.
[d]RPERC: Run Percentage.
[e]Using skewness statistic.

Table 2
Classification performance for the various sets of textural features concerning discrimination between osteoarthritic hips of Mild/Moderate and Severe osteoarthritis

Textural feature	Sensitivity (%)	Specificity (%)	Accuracy (%)	Feature vector
Run length[a]	66.7	100	83.3	SRE[b] RPERC[c]
Laws' features[d]	100	88.9	94.4	S5L5 W5S5

[a]Using range values.
[b]Sort Runs Emphasis.
[c]RPERC: Run Percentage.
[d]Using skewness statistic.

The number of neighbours of the k-NN classifier was determined after multiple trials to be equal to 3 ($k = 3$) for both levels of the hierarchical tree structure.

4. Discussion and conclusion

A computer-based image analysis method is proposed for the automatic assessment of the severity of hip OA. The suggested approach concerns the utilization of a texture-based pattern recognition algorithm for the automatic classification of radiographic images of the hip joint into OA severity categories.

Computer-based texture analysis of digital images provides quantitative information about the spatial distribution of tonal variations in an image [19,20]. In addition, the extracted information can be utilized for distinguishing between tissue structures represented by textures in medical images [21]. The texture of radiographic HJS corresponds to the tissue structures of the superimposed 3-dimensional anatomical structures of articular cartilage, posterior acetabular wall and iliac bone. In hip OA, the degenerative process of the disease causes cartilage and subchondral bone tissues alterations [1]. These joint tissues alterations are expected to affect the radiographic texture of the HJS region. Thus, the textural properties of the radiographic HJS may be valuable in discriminating normal from osteoarthritic hips, even though HJS radiographic texture, to our knowledge, is not used by physicians in the assessment of hip OA severity.

At the first level of the hierarchical tree structure, highest discrimination accuracy between physiological and osteoarthritic hips was 94.4% (see Table 1), employing the run-length textural features (range values). All normal hips were classified correctly (100% specificity) by the k-NN classifier, while two osteoarthritic hips were misclassified, giving a sensitivity accuracy of 88.9%. As presented in Table 1, the utilization of Laws' skewness textural features improved the classification performance of the system. All normal hips were classified properly (100% specificity), while only one osteoarthritic hip was misclassified (94.4% sensitivity) resulting in an overall accuracy of 97.2%.

In previous studies [22,23] threshold values for minimum joint space width have been introduced in order to classify a hip as normal or osteoarthritic. In contrast, the present study introduces a more sophisticated classification scheme, employing the k-NN classifier and textural features extracted from the region of the radiographic HJS. Such a pattern recognition approach for the characterization of a hip as physiological or osteoarthritic has not been previously proposed.

At the second level of the hierarchical tree structure, a classification accuracy of 83.3% was achieved by the k-NN classifier, employing the run-length features. All the hips of Mild/Moderate OA were classified properly, resulting in a specificity accuracy of 100%, while three hips of Severe OA were misclassified, providing a sensitivity accuracy of 66.7%. As presented in Table 2, the Laws' features improved the overall classification accuracy (94.4%), since only one hip of Mild/Moderate OA was misclassified (88.9% specificity), while all the hips of Severe OA were classified properly (100% sensitivity).

Summarizing, regarding the evaluation of the performance of the hierarchical tree structure, the use of the run-length features resulted in an overall accuracy of 86.1%, classifying properly 31 out of 36 hips into the three OA severity categories. The utilization of Laws' features improved the classification performance of the hierarchical tree structure, assigning correctly 34 out of 36 hips, providing a classification accuracy of 94.4%.

Considering the relatively high classification scores achieved for the discrimination: (i) between physiological and osteoarthritic hips, and (ii) among various grades of joint tissues degradation of osteoarthritic hips, the proposed method can be of value to inexperienced physicians and/or as a second diagnosis opinion tool to experienced ones.

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