LOCAL TERNARY PATTERN APPROACH FOR CLASSIFICATION OF ARTHRITIS FROM DIGITAL KNEE X-RAY IMAGES

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Abstract

Arthritis is a type of disorder that occurs in bone joints. A number of diagnostic approaches are widely available for the diagnosis of the disease. There are a number of types of arthritis and most of them fall into the category of either inflammatory type or non inflammatory type of disease. Imaging of the joint under study is the followed for analyzing the erosions in bone joints and radiography is the conventional method followed for such analysis. The X-ray image is analyzed manually by the radiographer. So the knowledge of the radiographer plays a vital role in the diagnosis. A computer aided tool can provide an alternate approach for diagnosis and such tool can aid the radiographer for better diagnosis. One such computer aided analysis has been discussed in this paper. The algorithm was developed using Local Ternary Pattern (LTP) and K-NN Classifier. The developed algorithm was evaluated using 50 Knee X-ray samples. The specificity and the sensitivity produced by the algorithm are satisfactory.

Key words: Arthritis, K-NN classifier, Local ternary pattern, Specificity, Sensitivity.

I. INTRODUCTION

The protein substance that is in between the bone joints is called as cartilage. This cartilage is covered by the synovial lining in which synovial fluid is placed in between the synovial lining. Arthritis starts with the erosion of synovial lining which results in the reduction of joint spacing in bone joints. An infra red imaging camera is used to obtain accurate measurements of the erosions in bone joints affected by Rheumatoid arthritis in (1). Temperature measurements of hands are analyzed with first order statistics and significant temperature differences between control subjects and patients for every joint and hand portion measured. Novel patient specific gait modifications that achieve knee arthritis rehabilitation without changing the foot path is proposed in (2). The modified gait motion is designed for a single patient with knee Osteoarthritis using dynamic optimization of a patient specific full-body gait model. The algorithm developed using 3-D ground reaction force (GRF) provided an automatic computer method to distinguish between asymptomatic and Osteoarthritis knee gait patterns in (3). The coefficients of a polynomial expansion and the coefficients of wavelet decomposition are the two different features are investigated. A systematic computer aided image analysis method is used to analyze pairs of weight bearing knee x-rays in (4). The feature extracted from the edges of bones when trained with neural network provided better results. The method provides an automated method for the analysis of cartilage volumes based on the KL grades (5)..Machine vision systems for osteoarthritis assessment in is designed to help doctors to determine the region of interest of visual characteristics found in knee Osteoarthritis, and to provide accurate measurement of joint space width(6). Edge detection operator and its enhanced algorithm are used to detect edges for human knee 4osteoarthritis images in different critical situations in (7). It is shown that the algorithm is very effective in case of noisy and blurs images. An image computing based method for quantitative analysis of continuous physiological processes that can be sensed by medical imaging and demonstrate its application to the analysis of morphological alterations of the bone structure which correlate with the progression of osteoarthritis is proposed in (8). A fully automatic segmentation method of bone compartments in a knee joint on MR images from the osteoarthritis initiative a huge database for research on knee Osteoarthritis is proposed in (9).An automated technique for the visualization and mapping of articular cartilage in magnetic resonance images (MRI) is described in (10). The analysis done on the optical contrast and the intra and extra articular tissue with photo acoustic tomography (PAT) showed a significant difference in the soft tissue changes in bone joints. This imaging technique can be used for used for early diagnosis of arthritis(11).The classification done with K-NN Classifier on the feature extracted higher order statistics on Electromyogram signals on the elbow joints has produced satisfactory results(12) .The similar type of classification done with Electrocardiogram signals to classify sleep apnea has also produced satisfactory classification rate(13). KNN classifier has also produced good classification on images done with computer tomography in the classification of cancer (14). This paper is organized as follows. The proposed system was discussed in section (II).The obtained results were discussed in section (III).

II. PROPOSED SYSTEM

The proposed algorithm was developed by extracting the features from digital X-ray images using Local Ternary Pattern and classifying them using K-NN classifier. The block diagram of the proposed system is shown in figure (1).The brief description of each block is described in the subsequent sections.

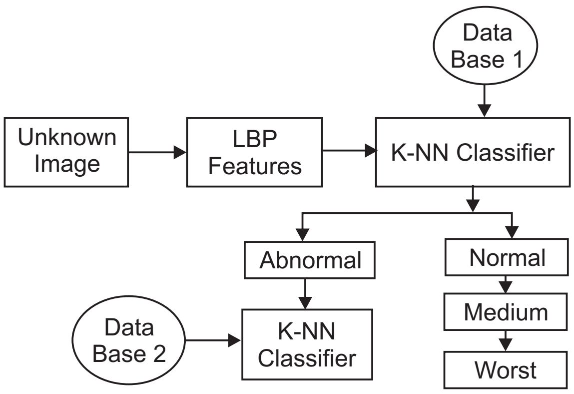

Fig. 1. Block Diagram of the proposed system

A. Data

The Knee X-ray images used in this algorithm are moified as follows. The actual images are in Digital Imaging and Communications in Medicine (DICOM) fromat and they are converted into Joint Pictures Experts Group(JPEG) format. The actual size of the image shown in Figure (2.a) is of 1000×1000 and the region of interest which is the joint space is cropped manually to a size of 200×200 from the actual image is hown in figure (2.b). The joint spacing in knee joints which fall under grade –I and grade-II of Kell –gren Lawrence grading are considered as normal cases,grade-III is considered as medium and grade IV is considered as worst case for the algorithm.The Kellgren Lawrence grading is given in Table.1.The medium and the worst cases are considered as the abnormal cases for the final stage of classification.All those images were maually analysed and reported by a radiographer for the development of training set. These images were used to construct the training set for the classification stage.The algorithm compares the features of the unknown input image with the features of the trained pre-stored data.

Fig. 2(a). Actual Image Fig. 2(b). ROI Image

Table.1. Kellgren Lawrence Grading for Arthritis

Grade I	Unlikely narrowing of the joint space, possible Osteophytes
Grade II	Small Osteophytess
Grade III	Multiple, moderately sized Osteophytes, definite joint space narrowing, some sclerotic areas, possible deformation of bone ends
Grade IV:	Multiple large Osteophytes, severe joint space narrowing, marked sclerosis and definite bony end deformity

B. Feature Extraction.

The feature from the region of interest shown in figure (2.b) is extracted using Local ternary pattern. The extracted feature are stored in data base-I and in Data base –II. Data base –I is comprised of the features of the normal and abnormal joint space width. Data base –II comprise the medium and worst joint space features. The block diagram of the feature extraction stage is shown in fig(3)

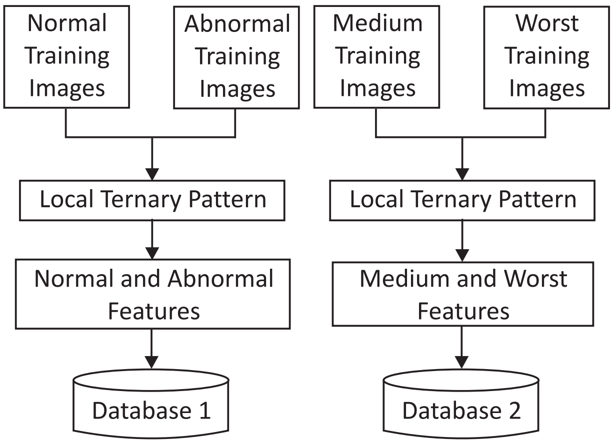

Fig. 3 Block Diagram of Feature Extraction Stage

C. Local ternary pattern

Local ternary operator works over a 3×3 window over the selected region of interest. Local ternary pattern uses a threshold constant to threshold pixels into three values whereas Local Binary Pattern uses only two values to threshold the pixels (either 0 or 1). The LTP operator can be expressed as

$$5x = \begin{cases} 1 & \text{if } p > c + k \\ 0 & ; \text{if } p > c + k \\ & \text{and} \\ & p < c - k \\ -1 & \text{if } p < c - k \end{cases} \quad ...(1)$$

Where

k-Threshold value of the pixel

c-Center pixel value

P-Neighboring pixel value

From the expression (1), its clear that for each of the selected pixel value, any one of the value is obtained according to the deviation of the selected value from the threshold value. The neighboring pixels are combined after thersholding into ternary pattern. The histogram is computed for these ternary patterns. Each ternary pattern selected will comprise

Two binary patterns. The operation of LTP is illustrated in figure (4).

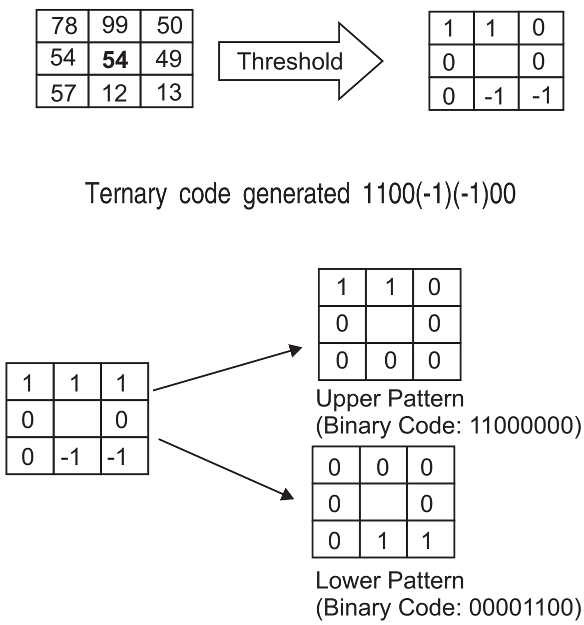

Fig. 4. Illustration of LTP operator

D. K-NN classifier

K-NN Classifier is an instance based classifier. The learning with this classifier is called as lazy learning. ie. The learning is done on the closeness of the features in stored in the memory. The K-NN classification algorithm is explained below.

Let $D^n = \{X_1, X_2 \ldots\ldots X_n\}$ denote a set of n labelled prototypes with $X' \varepsilon D^n$ be the prototype nearest to the test point X. The nearest neighbour rule for classifying X is to assign it to the label associated with X'. Let È' be a label associated with the nearest neighbour which is a random variable. Then

$$P\ (È_i = W_i) = P(W_i / X') \quad ...(2)$$

Where W_i is the width of feature space. When the number of samples is very large then X' can be assumed to be very large to X ,ie.

$$P(W_i/X') \approx P(W_i/X) \quad ...(3)$$

Let $W_m(x)$ be defined as

$$P(W_m/X) = \max P(W_i/X) \quad ...(4)$$

The nearest neighbour rule partition the future space into cells consisting of all points closer to a given training point X' than to any other training point. Thus all the points in such a cell are thus labelled by the category of the training point resulting in a Voronai translation of the space. The classification depends on the closeness of the vectors stored in feature space. To measure the closeness of the vectors in feature space four different distance measures were used (15).

E. Euclidean Distance

The Euclidean distance is the direct measure between two points in the feature space. This distance measure can be done from one dimension to n-dimension. If $u=(x_1, y_1)$ and $v=(x_2, y_2)$, the Euclidean distance between these two points is given by

$$ED\,(u, v) = \sqrt{(x_1 - x_2)^2 + (y_2 - y_2)^2} \qquad ...(4)$$

F. Manhattan Distance

Manhattan distance is defined as the sum of the absolute difference between the vectors in feature space. If $u=(x_1, y_{1)}$ and $v=(x_2, y_2)$ are the two vectors in feature space, then the Manhattan distance between these two points is given by

$$MH\,(u, v) = \left| x_1 - x_2 \right| + \left| y_1 - y_2 \right| \qquad ...(5)$$

G. Cosine angle distance

Let us consider X and Y where

$X = \left(x_1, x_2, x_3, \ldots x_n \right)$ and

$Y = \left(y_1, y_2, y_3 \ldots y_n \right)$ then $\cos\theta$ may be consider as the cosine of the vector angle between X and Y in n dimension. The cosine of the vector angle between and is given by

$$\text{cosine}\,(X, Y) = \frac{\sum_i x_i y_i}{\sqrt{\sum_i x_i^2}\sqrt{\sum_i y_i^2}} \qquad ...(6)$$

H. Correlation distance measure

Correlation defines the similarity between two features in vector space. If $X = \left(x_1, x_2, x_3, \ldots x_n \right)$ and $Y = \left(y_1, y_2, y_3, \ldots y_n \right)$ are the two vectors in feature space then the correlation between these two vectors id given by

$$r = \frac{N \Sigma\, xy\ (\Sigma\, x)\,(\Sigma\, y)}{\sqrt{\left[N \Sigma\, x^2 - (\Sigma\, x)^2 \right]\left[N \Sigma\, y^2 - (\Sigma\, y)^2 \right]}} \qquad ...(7)$$

I. Classification stage

The classification in this algorithm has two stages. They are initial classification stage and final classification stage. The features of images with both normal and abnormal joint space width are used to develop the initial stage classifier. The features of abnormal joint space images with medium joint spacing and worst joint spacing are used to develop the final stage classifier. Table (1.) gives the number of images used to develop the initial stage classifier and table (2.) gives the number of images used to develop the final stage classifier.

Table.1. Number of images used for initial stage classifier

Type of image	No of Images Used as training set	No of Images used as Testing set
Normal	9	15
Abnormal	21	35

Table. 2. Number of images used for final stage classifier

Type of image	No of Images Used as training set	No of Images used as Testing set
Medium	11	16
Worst	13	19

IV. RESULTS AND DISCUSSION

The developed algorithm was evaluated using 50 images. The results obtained are given below. The classification rate of initial stage classifier is given in table (3) and for the final stage classifier is given in table (4). The specificity and the sensitivity of the developed algorithm is given in table (5).

Table 3. Classification rate of Initial stage classifier

Distance Measure	Normal	Abnormal
Euclidean	86.67	91.43
Manhattan	93.33	91.43
Cosine	73.33	82.86
Correlation	73.33	82.86

Table. 4. Classification rate of Final stage classifier

Distance Measure	Medium	Worst
Euclidean	87.50	78.95
Manhattan	81.25	89.47
Cosine	87.50	78.95
Correlation	87.50	78.95

Table. 5. Specificity and Sensitivity

Distance Measure	Specificity	Sensitivity
Euclidean	81.25	91.42
Manhattan	82.35	96.96
Cosine	62.65	85.29
Correlation	62.65	85.29

From the Table 3, 4 and 5 it is observed that the K-NN classifier has produced better classification rate, Specificity and sensitivity with Manhattan distance measure with the LTP features. So this algorithm works well with Manhattan distance measure with the LTP features. On the other hand it has produced poor classification rate with cosine and correlation distance measures. So these distance measures are not suitable for the classification of arthritis with LTP features.

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