A Novel Machine Learning Algorithm for Computer Aided Diagnosis to Identify Rheumatoid Arthritis

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Abstract:

There are 700,000 Rheumatoid Arthritis (RA) patients in Japan, and the number of patients is increased by 30,000 annually. The early detection and appropriate treatment according to the progression of RA are effective to improve the patient's prognosis. The modified Total Sharp (mTS) score is widely used for the progression evaluation of Rheumatoid Arthritis. The mTS score assessments on hand or foot X-ray image is required several times a year, and it takes very long time. The automatic mTS score calculation system is required. This paper proposes the finger joint detection method and the mTS score estimation method using support vector machine. Experimental results on 45 RA patient's X-ray images showed that the proposed method detects finger joints with accuracy of 81.4 %, and estimated the erosion and JSN score with accuracy of 50.9, 64.3 %, respectively.

Keywords:

Rheumatoid arthritis; X-ray image; modified Total Sharp Score; Machine learning; Computer-aided diagnosis

1. Introduction

There are 700,000 Rheumatoid Arthritis (RA) patients in Japan, and the number of patients is increased by 30,000 annually. Early treatment improves patient's prognosis and Quality of Life (QoL). The appropriate treatment in accordance with RA progression is required for the better prognosis.

The hand or foot X-ray images are used for the RA diagnosis. The modified Total Sharp (mTS) score evaluates the erosion and joint space narrowing (JSN) on 32 hand joints and 12 foot joints [1]. The 5 grades of erosion score and 4 grades of JSN score is manually given for each joint. The sum of calculated score corresponds to the RA progression. The medical doctor calculates the mTS score several times a year for the appropriate treatment, and it requires enormous amount of time for assessments. The X-ray image analysis based automatic mTS score calculation system is needed.

The fully automated mTS score calculation system requires the automatic finger joint detection method. Ref. [2] proposes the deep learning based finger joint detection method. Their focus is not on the RA patients but on the children whose finger joint is growing. Another finger joint detection method detects the finger joints using the X-ray image intensity difference in the joint space [3]. The joint space based method does not provide the good detection result because severe RA patient's collapsed finger joint has no joint space.

The mTS score evaluates the erosion score and JSN score for each finger joints. Ref. [3] automatically estimates the JSN score of the mild RA patient. The method can not evaluate the JSN score of severe RA patient whose joint does not have enough joint space.

This paper introduces the fully automated finger joint detection method and mTS score estimation method for the mild-to-severe Rheumatoid Arthritis patients using hand X-ray image.

2. Subjects and materials

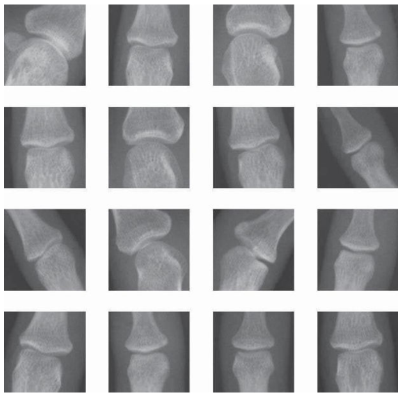
This study uses hand X-ray image of 45 mild-to-severe RA patients. We had obtained informed consent from all subjects. Figure 1 shows the hand X-ray image which have 2010×1572 pixels. There are 14 finger joints in one hand, and the center points of finger joints are manually extracted. The erosion and JSN score is manually determined.

The X-ray image is divided to left and right side, and the right side is inverted horizontally in order to increase the number of subjects.

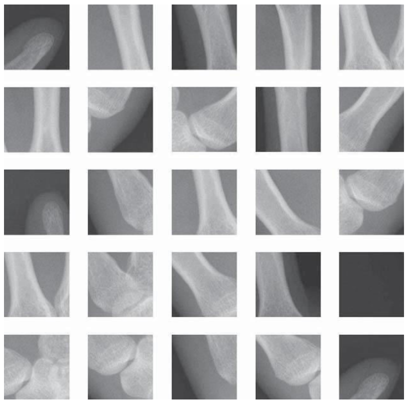
(a) Mild RA patient

(b) Severe RA patient

FIGURE 1. X-ray images of RA patients. The finger joints have been damaged in severe RA patient.



(a) Positive class



(b) Negative class

FIGURE 2. Image patches for the training of the finger joint detector.

3. Proposed methods

RA patients have risk of osteoporosis for many reason. The one reason is the localized and the systemic bone metabolism by the RA itself. Therefore, the X-ray signal intensity difference of bone region and the other body parts is reduced according to the RA progression. The bone contour or the joint space distance based method can not detect with enough accuracy because the finger joints are collapsed in severe cases.

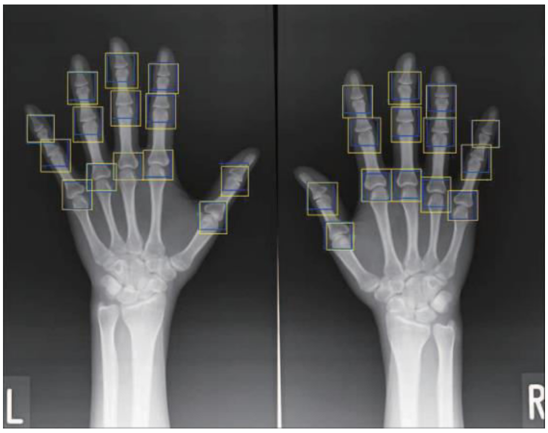
This study expresses the rough shape of finger joint using histogram of oriented gradients (HOG). The support vector machine (SVM) using HOG detects finger joints on the X-ray image, and the modified Total Sharp (mTS) score is estimated by the support vector regression (SVR). The details of the proposed method are described in the following.

3.1. Training of the finger joint detector

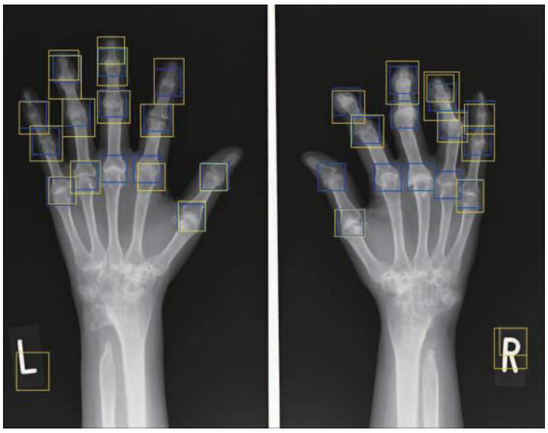
The proposed method detects finger joints from hand X-ray image using two-class SVM. The SVM is trained using 100 × 100 pixels of image patches segmented from hand X-ray image.

The positive class has 28 image patches for each subject, and their center point is manually extracted center points of finger joints. In order to increase the robustness against the finger inclination, the positive class image patch is rotated from -30 to 30 degree at and interval of 15 degree. The proposed method segments 140 image patches from X-ray images for the negative class. The center point of the negative class image patche is randomly determined in the human body region extracted using adaptive thresholding.

The proposed method calculates the HOG of 140 and 140 image patches in the positive and negative class. The two-class SVM is trained using HOG of positive and negative classes.



(a) Mild RA patient



(b) Severe RA patient

FIGURE 3. Detected finger joints. The blue rectangles show the ground truth, and the yellow rectangles show the result of the proposed method.

3.2. Finger joint detection

The proposed method evaluates 100 × 100 pixels of image patches at all points in the subject's hand X-ray image. SVM outputs the value from -1 to 1, and 1 corresponds to the finger joint. Finger joints are detected by clustering the evaluated patches. The patches are sorted in descending order by the SVM output, and 28 patch clusters are extracted in descending order. Note that a patch is merged to the patch cluster when 25 % of the patch region is overlapped to a patch in the patch cluster.

3.3. mTS score estimation

RA reduces the joint space width and deforms bone contour. The proposed method expects the intensity gradients of the RA patient's finger joint is changed according to the RA progression. The proposed method estimates the mTS score by the SVR using HOG feature. The positive class image patches used in the finger joint detection are used for the training data. We manually determined the erosion and JSN score of each finger joint for the teacher data.

4. Experimental results

The proposed method was applied to 45 RA patients' hand X-ray images. Each positive and negative dataset have 6300 image patches. The parameters used in SVC and SVR for the joint detection and mTS score estimation is shown in Table. 1, 2, respectively. The proposed method was implemented using scikit-learn [4].

TABLE 1. Training parameters for the finger joint detection.

parameter	*value*
kernel	linear
C	0.5

TABLE 2. Training parameters for the mTS score estimation.

parameter	*value*
kernel	rbf
gamma	0.1
C	0.5

TABLE 3. mTS score estimation result (erosion).

success rate	50.9 (%)
absolute error	0.59 ± 0.24

4.1. Finger joint detection

Figure 2(a) and 2(b) show the positive and negative class image patches, respectively. We performed the leave-one-subject-out cross validation test in the following experiments. The evaluating subject's image patches were excluded from the training dataset.

Figure 3 shows the finger joint detection results. The blue 100 × 100 rectangle show the ground truth whose center is manually extracted joint. The yellow rectangle show the detected finger joint, and it covers all image patches in the cluster.

TABLE 4. mTS score estimation result (JSN).

success rate	64.3 (%)
absolute error	0.43 ± 0.12

These results showed that the proposed method detects finger joints with high accuracy on the mild RA patient. The proposed method failed to detect 6 finger joints on severe RA patient.

We calculated the success rate of the finger joint detection for the numerical evaluation. We defined the successfully detected finger joints as its yellow rectangle region covers 75 % of the blue rectangle region. The average of success rates was 81.4 %, and 22 finger joints over 28 finger joints were successfully detected by the proposed method.

4.2. mTS score estimation

The leave-one-subject-out cross validation test evaluated the proposed method in which the manually measured erosion and JSN scores were used as the ground truth value. Table 3 and 4 showed the mTS score estimation results. We defined the success as the rounded SVR output has the same value with the manually measured ground truth value. The absolute error showed the average and variance of the difference of SVR output and ground truth value. These results showed that the estimation accuracy was insufficient but the average of the estimation error of both features were not high. These results suggested that the high variance of the absolute error harms the estimation accuracy.

5. Conclusions

This paper introduced the finger joint detection method and mTS score estimation method for mild-to-severe RA patients. The experimental results on 45 RA patients showed that the proposed method detects finger joints with accuracy of 81.4 %. The erosion and JSN score were estimated with accuracy of 50.9 % and 64.3 %, respectively. The estimation error of erosion and JSN score were 0.59 ± 0.24 and 0.43 ± 0.12, respectively. We consider the high estimation error variance harms the estimation accuracy. These results suggested that the image patch based proposed method improves the estimation accuracy by increasing the number of subjects.

References

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