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FINGER JOINT DETECTION METHOD FOR THE AUTOMATIC ESTIMATION OF RHEUMATOID ARTHRITIS PROGRESSION USING MACHINE LEARNING

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Abstract—The number of Rheumatoid Arthritis (RA) patients increases recently in Japan. Early treatment improves patient's prognosis and Quality of Life. The appropriate treatment in accordance with RA progression is required for the better prognosis. The hand X-ray image based modified Total Sharp Score (mTSS) is widely used for the diagnosis of RA progression. The mTSS measurement is essential to achieve the appropriate treatment, but its assessment is time consumed. There are some finger joint detection and mTSS estimation methods for the fully automated mTSS measurement, which focus on the mild RA patients. This paper proposes the automatic joint detection method and discusses about the mTSS estimation for the mild-to-severe RA patients. Experimental results on 90 RA patients' hand X-ray images showed that the proposed method detected finger joints with accuracy of 91.8%, and estimated the erosion and JSN score with accuracy of 53.3% and 60.8%, respectively.

INTRODUCTION

There are 700,000 of Rheumatoid Arthritis (RA) patients in Japan, and the number of patients increases by 30,000 annually. Early treatment improves patient's prognosis and Quality of Life. The appropriate treatment in accordance with RA progression is required for the better prognosis. In order to evaluate the progression of RA, modified Total Sharp Score (mTSS) [1] is measured on hand and foot X-ray images. mTSS is composed of 4 grades of erosion and JSN (Joint Space Narrowing) score of some hand or foot joints. The medical doctor should calculate mTSS several times a year for the appropriate treatment, and the assessment requires enormous amount of time. Thus, the X-ray image analysis based automatic mTSS calculation system is required in order to increase the efficiency of assessment.

In conventional methods [2]–[4], JSN score was automatically estimated based on the length of finger joint space. These methods provide good estimation results on mild RA patients whose finger bones are clearly separated in finger joint. Compared to mild RA patients, it is difficult to measure the joint distance of severe RA patients because finger joints are collapsed and deformed. Additionally, due to the joint deformation, all fingers cannot be acquired in appropriate angle (*e.g.* perpendicular to finger joint). Unlike JSN estimation, there are no established methods for erosion estimation. Ref. [4] visualized the progression of erosion and mentioned that the texture information on finger bone contour is useful for the erosion score estimation. However, it does not report results on RA patients and it is difficult to extract finger bone contour from a severe RA patient whose fingers are crossed due to the joint collapse.

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The fully automated mTSS calculation system requires the automatic finger joint detection. Ref. [5] proposes the deep learning based finger joint detection method. The study does not measure RA patients but on the children whose finger joint is growing. There are image intensity analysis based finger joint detection methods for RA patients' hand X-ray images [2], [3]. These methods are not suitable to severe RA patients, because RA is often complicated by osteoporosis which reduces signal intensity of bone in a X-ray image. The finger joint structure model based finger joint detection method [4] can detect finger joints of patients with progressed osteoporosis. As finger joints are deformed and collapsed by RA, it is difficult to detect finger joints of severe RA patients by the model based method.

We have proposed the fully automated finger joint detection method and mTSS estimation method for mild-to-severe RA patients using hand X-ray image [6]. The method was achieved by the patch image analysis using SVM (Support Vector Machine) [7]. The finger joint detection accuracy of 81.4% and the mTSS estimation accuracy of 50.9% and 64.3% [6] were insufficient for clinical use. In order to improve the finger joint detection accuracy, this paper proposes a new patch extraction method because the previous method did not extract enough number of image patches from the hand area. The other problem of the previous method is no distinguished between the right hand and the left hand in the finger joint detection. The left and the right hand have different number of finger joints in the failed results. This paper detects equal number of finger of joints to measure the erosion and JSN score to 16 and 15 hand joints respectively, and Hejide et.al. added foot joints for the measurement [1]. The differences of these definitions are the number of evaluating joints, therefore, this study focuses on 9 finger joints where both of erosion and JSN scores are measured. Erosion and JSN scores at each joint is measured according to the definition shown in Table In short, erosion measures the existing joint width and JSN measures the length between two bones. As shown in Table I, erosion score has four-grade on a scale of 1 to 5. For simplicity, this study treats score 5 of erosion as score 4.

HAND X-RAY IMAGE

This study employs 90 mild-to-severe RA patients' hand X-ray images acquired in Hyogo Prefectural Kakogawa Medical Center, and the joints from× the left and the right hand X-ray images. Informed consent of all subjects were obtained. In addition, the optimal patch size for the joint detection is considered in this study because the patch size was visually determined to include the whole finger joint region in our previous method. We will consider about the machine learning algorithms for the mTSS estimation. This paper is organized as follows: Section II describes mTSS and hand X-ray image used in the proposed method, Section III introduces the proposed methods including the patch extraction, the finger joint detection, and the mTSS estimation, the proposed method is evaluated using 90 subjects' hand X-ray images in Section IV, and finally Section V concludes this paper with future works.

PRELIMINARIES

MODIFIED TOTAL SHARP SCORE

Modified Total Sharp Score (mTSS) [1] is a method to measure the progress of RA in X- ray images, which is calculated as the sum of erosion and JSN (joint space narrowing) scores of some joints in hand and foot X-ray images. There are some definitions of mTSS: Sharp et.al. proposed the original method [8] in which mTSS is measured in 27 hand joints, Ref. [9] reduced the number Figure 1 shows the hand X-ray images which have 2010 1572 pixels. The lower-middle area has relatively higher signal value because these images were acquired using point X-ray source system. As shown in Fig.1(b), the finger tips and lower-middle area have similar signal value, therefore, hand bones cannot be clearly segmented by the simple thresholding.

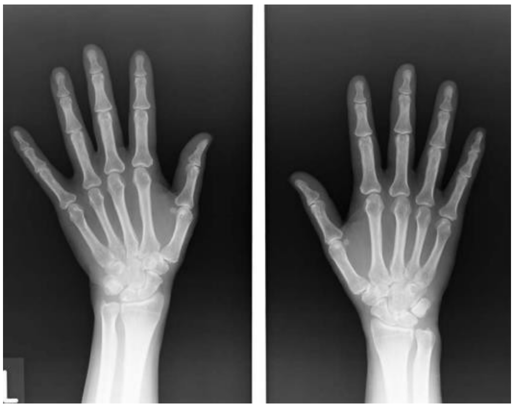


Fig:Mild RA patient

Severe RA patient
Fig. 1: X-ray images of RA patients

TABLE I: Definition of mTSS [1]

Score	description
1	if exist discretely
2	larger
3	extend over the middle of the bone 5 complete collapse
1	focal or doubtful
2	> 50% original joint space
3	< 50% original joint space, subluxation
4	anylosis, complete luxation

PROPOSED METHODS

This paper proposes a method to enhance the finger joint detection and mTSS estimation accuracy which are proposed in our previous method [6]. The proposed method is composed of 3 steps: the first step extracts image patches from raw X-ray images, the second step trains the finger joint detector using extracted image patches and finger joints detected based on the detector output, and the final step estimates the mTSS at all finger joints using a regression algorithm which is trained using finger joint patches and manually determined mTSS. Our previous method [6] can detect 22 finger joints over 28 finger joints, that is, the method failed to detect 6 finger joints in average. In failed cases, some finger tips and hand neck bones were detected as a finger joint. The cause of these failures was that finger tips and hand neck bones were not correctly included in the training dataset. This paper proposes

IMAGE PATCH EXTRACTION

The conventional methods detect finger joints based on finger middle lines which are automatically detected by the image intensity analysis. Those finger middle line detection based methods work well on the mild RA patient. As shown in Fig.1, the finger middle line is expected to be a straight line in the mild RA patient, but it is not shown as the straight line in severe RA patient (*e.g.* The thumb is bent at 90 degrees). To avoid the affection by the joint deformation, the proposed method employs the patch image based machine learning techniques for the finger joint detection. The proposed method utilizes variance filter to calculate the variance image Ij from the raw X-ray image I by following equations.

$$I'_{ij} = \frac{1}{W_x W_y} \sum_{l=j-\frac{W_y}{2}}^{j+\frac{W_y}{2}} \sum_{k=i-\frac{W_x}{2}}^{i+\frac{W_x}{2}} (I_{kl} - \overline{I}_{ij})^2$$

$$\overline{I}_{ij} = \frac{1}{W_x W_y} \sum_{n=j-\frac{W_y}{2}}^{j+\frac{W_y}{2}} \sum_{m=i-\frac{W_x}{2}}^{i+\frac{W_x}{2}} I_{mn}$$

Where *Wx* and *Wy* are the width and height of the image filter, and *i* and *j* are the x and y position in the raw image *I*. The proposed method extracts image patches from the raw X-ray image. The set of center points of positive classimage patches **P**1 = **p**11, **p**21, · ·, **p***n*1 is manually given. The set of negative class patch point candidates are given byevery 10 pixel along x- and y-axes. To avoid negative classpatches overlap the positive image patch, the proposed method eliminates the negative class patch point candidate which satisfy the following condition.

$$\bigwedge_{\mathbf{p}_1 \in \mathbf{P}_1} ||\mathbf{p'}_0 - \mathbf{p}_1|| > \frac{1}{2}\sqrt{W_x^2 + W_y^2}$$

Where pj0 is a negative class patch point candidate, and ||x − y|| is Euclidean distance between two points x and *y*. The area with high variance is expected to have many anatomical features in the hand X-ray image. In order to reduce the number of negative patches by excluding the patch with less feature (e.g. background region), the proposed method calculates the averaged variance Ij from the variance image Ij by the following equation.

$$\overline{I'}_{ij} = \frac{1}{W_x W_y} \sum_{l=j-\frac{W_y}{2}}^{j+\frac{W_y}{2}} \sum_{k=i-\frac{W_x}{2}}^{i+\frac{W_x}{2}} I'_{kl} \qquad (4)$$

According to the calculated averaged variance Ij, top m points with highest averaged variance are extracted from the negative patch candidates. They are used as negative image patch points P0 = p1, p2, ··· , pm

FINGER JOINT DETECTION USING SVM

RA patients have risk of osteoporosis for much 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. This study expresses the rough shape of finger joint using HOG (Histogram of Oriented Gradients) [10] which is robust to the intensity difference. The extracted HOG feature is affected by the difference of the object's rotation angle. The proposed method rotates positive image patches at the angle of 30, 15, 0, 15, 30 degrees. Finally, the two-class SVM is trained using *{− −}* the augmented positive image patches and negative image patches.

Based on the SVM output, the finger joints are detected by the following steps.
[Step 1] The output of the trained SVM is calculated at all points in the raw X-ray image.
[Step 2] The following steps are applied to all points which are sorted in the descending order by the SVM output value. In the initial time, the point with highest SVM output is added to the new patch set **C**0.
[Step 3] The distance d between the evaluating point p and the i-th patch set **C***i* is calculated by;

$$d = ||\mathbf{p} - \overline{\mathbf{C}_i}|| \qquad (5)$$

$$\overline{\mathbf{C}_i} = \frac{1}{card(\mathbf{C}_i)} \sum_{\mathbf{cp} \in \mathbf{C}_i} \mathbf{cp} \qquad (6)$$

Where ||*x*−*y*// is Euclidean distance between point *x* and *y*, and **C***i* is the center point of **C***i* which is calculated by;
Where *card*(**X**) is the number of elements in the set **X**. When the nearest patch set **C***j* satisfies the condition of *d* < *thd* (*thd* = 50 was used in the experiment), the evaluating patch is added to the patch set **C***j* .
Otherwise, the evaluating patch is added to the new patch set. [Step 4] When the number of patch set is 15, center points of first 14 patch sets *{***C**0,**C**1, · · · ,**C**14*}* are determined as the finger joints. Otherwise, it goes back to the 3rd step.

mTSS estimation

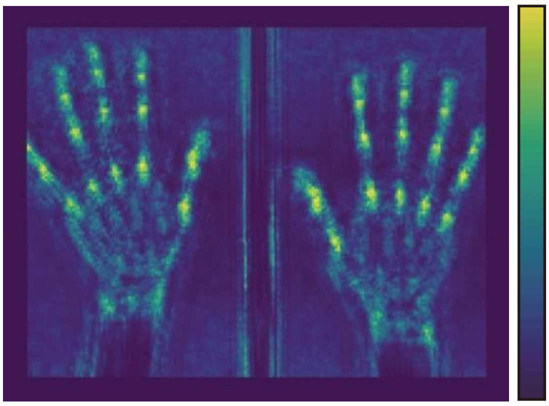
In the original definition of mTSS [1], the erosion and the JSN score is measured as the discrete value based on ambiguous definitions. The progress of the erosion and JSN should be presented as the continuous change of the bone morphology and structure in the X- ray images. Therefore, the proposed method estimates the erosion and JSN score as continuous value by using machine learning based regression algorithm. We used SVR (Support Vector Regression) [11] and RR (Ridge Regression) [12] in the experiment. Since the erosion and JSN change the joint shape, the proposed method employed HOG feature for the mTSS estimation. Finally, the regression model is trained using the HOG feature of augmented finger joint patches and manually measured erosion and JSN scores.

EXPERIMENT

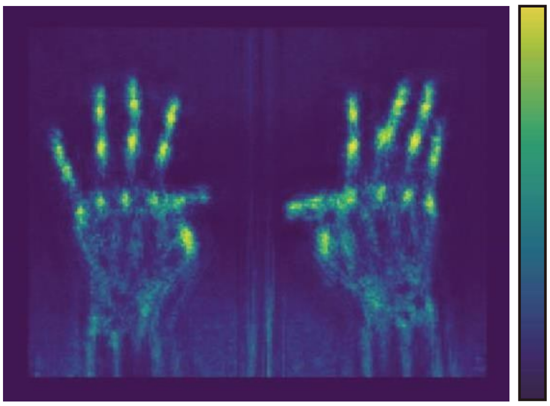
The proposed method detects center points of 28 finger joints, and estimates mTSS at each finger joint. We validated the performance of the proposed method by using manually given 28 finger joints and whose mTSS in 90 subjects' hand X-ray images. This paper employs the leave-one-out cross-validation test in which one subject's joints are handled as one data. The proposed method was implemented using Python and scikit-learn [13]. In following experiments, parameters were optimized using grid search.

Finger joint detection results

The patch size was visually determined to include the whole of the joint region in our previous paper. The optimal patch size ca×n be determined by maximizing the number of successfully detected finger joints. Figure 2 shows thedependence of the number of successfully detected fingerjoints on the patch size. The computational time increases as the patch size is increased, but is sufficiently short. The result showed that the patch size of 190 190 (pixel) achieved the highest detection accuracy. We used patch size of 190 190 (pixel) in the following experiments for the finger joint detection.Figure 3a and 3b show the heat map of the SVM output of mild and severe RA patients shown in Fig.1a and 1b, respectively. These figures showed that the proposed method is valid to detect finger joints because pixels.



Mild RA patient

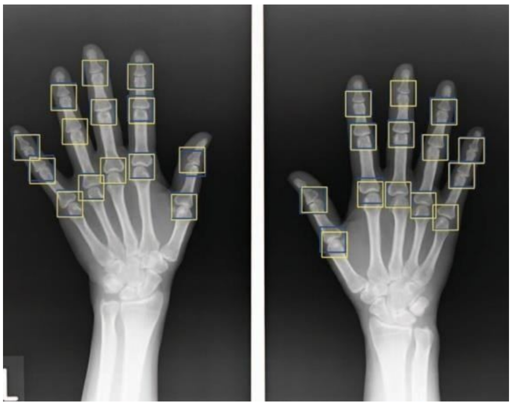


Severe RA patient

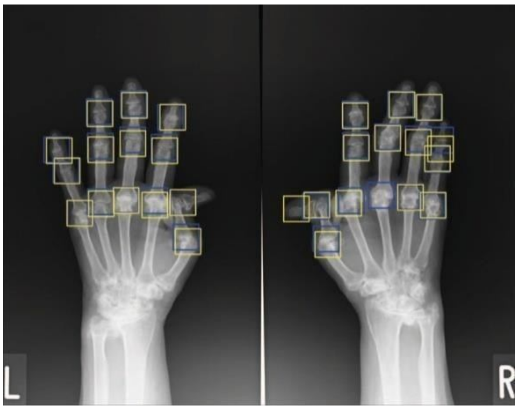
TABLE II: Comparison of finger joint detection accuracy.

# of finger joints	accuracy	(%)
Previous method (100 × 100) [6]	22.8	81.4
Previous method (190 × 190)	22.6	80.9
Proposed method (combined)	25.6	91.3
Proposed method (separated)	25.7	91.8

The result showed that the proposed method successfully detected all of 28 finger joints in the mild RA patient, and 26 finger joints in the severe RA patient around finger joints have higher SVM output even in the severe RA patient's collapsed joint. Figure 4 shows the finger joint detection results by the proposed method. Blue rectangles show the manually determined finger joints, and yellow rectangles show finger joints detected by the proposed method. In order to objectively evaluate the finger joint detection accuracy, we recognized the yellow rectangle which covers 75% of blue rectangle region as the successfully detected finger joint. Table II compares the finger joint detection accuracy of the previous and the proposed method. The previous method [6] employed the patch size of 100 100, and it detects 28×finger joints from a X-ray image including both of right and left hands ("combined" detection). To compare the detection accuracy of the previous and the proposed method in same patch s×ize, the previous method was also performed in the patch size of 190 190 (pixel). These results showed that the proposed method has higher detection accuracy. In the proposed method, we performed the separated detection which detects 14 finger joints from each of left and right hand X-ray images. The accuracy improvement by the separated detection was small (improved from 91.3% to 91.8%), but t- test showed that there was significant difference (p = 0.006). Finally, the detection accuracy was improved from 81.4% to 91.8% by the proposed method.



Mild RA patient



Severe RA patient

Fig. 4: Result of finger joint detection. Blue and yellow rectangles show the manually determined and automatically detected finger joints, respectively.

mTSS estimation results

Table III shows the comparison of mTSS estimation accuracy using ima×ge patch of 100 performance, the proposed method employed SVR (Support Vector Regression) [11] and RR (Ridge Regression) [12]. The proposed method estimates the mTSS in continuous value because it employs machine learning based regression methods. The estimation error was evaluated by using the absolute difference between the estimated mTSS and the manually given ground truth mTSS. For the evaluation of the estimation accuracy, we calculated the concordance rate of the ground truth mTSS and the estimated mTSS value which was rounded after the decimal point.

As the result, RR has small estimation error and better estimation accuracy in both of erosion and JSN. Figure 5 shows the box plot of the mTSS estimation result by RR, in which the horizontal and the vertical axes show the ground truth mTSS and the estimated mTSS, respectively. There was difference between box plots of JSN, in contrast, box plots of erosion (Fig. 5a) have no obvious difference between mTSS of 0 and 1. Figure 6 shows the distribution of the absolute estimation error of one hand (sum of 14 finger joints). The figure describes that the imbalanced training data reduced the estimation accuracy because the estimation error is increased as the number of data decreases.

CONCLUSION

This paper introduced the finger joint detection method and mTSS estimation method for mild-to- severe RA patients. The experimental results on 90 RA patients' hand X-ray images showed that the finger joint detection accuracy increased from 81.4% to 91.8% by the proposed method. We compared the mTSS estimation accuracy of SVR and RR. As a result, RR estimated the erosion and JSN scores with accuracy of 53.3% and 60.8%, respectively. In the future, we will improve the finger joint detection accuracy by evaluating the detected finger joint candidates based on the hand bone structure. The mTSS estimation accuracy was insufficient for the medical diagnosis, therefore, we will consider about the Convolutional Neural Network based feature extraction to improve the mTSS estimation accuracy.

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