Automated Estimation of mTS Score in Hand Joint X-Ray Image Using Machine Learning

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ABSTRACT

Rheumatoid arthritis (RA) damages joints, and the destructed and/or deformed joint causes the pain and reduces the joint function. The prognosis can be improved by early treatment, but it requires accurate evaluation of the degree of RA progression to apply appropriate treatment. The modified total sharp (mTS) score in hand or foot X-ray image has been used to quantitatively evaluate the RA progression evaluation. However, the mTS score measurement takes huge labor and it is very time consuming method because a physician should evaluate progression grade for all hand joints, and the evaluation is subjective. This paper proposes an automated finger joint detection and mTS score estimation method using support vector machine. The experiment in 45 RA patients shows that the proposed method succeeded in detecting the finger joint and estimating the mTS score. As the number of learning data increases, the proposed method can estimate the mTS score with higher accuracy.

Keyword :- *Rheumatoid arthritis;, X-ray image ; modified total sharp score*; *Machine learning; Computer-aided diagnosis*

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1. INTRODUCTION

There are 700,000 of rheumatoid arthritis (RA) patients in Japan, and the number of patients is increased by 30,000 annually. The RA damages joints, the joint destruction and joint deformity causes the pain, and reduces the joint function. The prognosis is improved by early treatment, but it is necessary to accurately evaluate the degree of RA progression and to take appropriate treatment. 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 are manually given for each joint by orthopaedicians. The RA progression is calculated by the sum of the calculated scores. However, X-ray images should be taken several times a year for proper assessment, and the mTS score measurement takes huge labor and is time-consuming method because there are many evaluation points and it is difficult to give the score. Also, the mTS score is subjective as it is scored manually by orthopaedicians. Thus, it requires an automated mTS score calculation system based on X-ray image analysis. The fully automated mTS score calculation system requires an automated finger joint detection method. Ref. [2] proposes a deep learning based finger joint detection method. It is applied to children whose finger joint is growing, and cannot be applied RA patients directly. Other method is based on X-ray image intensity difference in the joint space [3]. It cannot analyze severe RA patients because their 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 cannot evaluate the JSN score of severe RA patient whose joint does not have enough joint space. Previously, we proposed a fully automated finger joint detection method and mTS score estimation method for the mild-to-severe RA patients using hand X-ray image [4]. However, the performance of the method has not been evaluated sufficiently. This paper aims to evaluate the performance of a fully automated finger joint detection and mTS score estimation method. In addition, we investigate a possibility of improving the performance by artificially rotating and gamma correction of the training image. We also evaluate details of estimated scores, and total mTS in the sake of clinical application.

1.1 SUBJECTS AND MATERIALS

This study used 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 R.A Patient (b) Severe R.A Patient

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

2.PROPOSED METHOD

A part of the proposed method is introduced in Ref. [4]. This study represents 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.

2.1 Finger joint detection

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 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 patch is randomly determined in the human body region extracted using adaptive thresholding.

For an evaluating subject, it 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 as below. The patches are sorted in descending order of 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

2.1 mTS score estimation

The proposed method expects the intensity gradients of the RA patient's finger joint is changed according to the RA progression. It estimates the mTS score by the SVR using HOG feature. The finger joint image patch is used for training data. These image patches are the same as the positive class data used for finger joint detection. In order to increase the learning data and to compare the estimation results based on the difference in the number of learning data, the image patch is rotated from -30 to 30 degree at interval of 15 degree. Also, brightness conversion of the image patch is performed by gamma correction. The gamma value is three patterns of 0.8, 1.0, and 1.2. We manually determined the erosion and JSN score of each finger joint for the teacher data.

In order to evaluate the proposed method, we compare the estimated mTS score with the true value in all joints, and compare the total of estimated mTS score with the true value in both hands. Also, in order to investigate whether the estimation result is related to each finger, we compare the estimated mTS score with the true value in each finger.

3. EXPERIMENTAL RESULTS

The proposed method was applied to 45 RA patients' hand X-ray images. Each positive and negative dataset have 6,300 image patches. In the mTS score estimation experiment, the number of finger joint image patches was 18,900 after image rotation and gamma correction. The parameters used in SVC and SVR for the joint detection and mTS score estimation is shown in Table 1 and Table 2, respectively. The proposed method was implemented using scikit-learn [5].

TABLE I. TRAINING PARAMETERS FOR THE FINGER JOINT DETECTION.

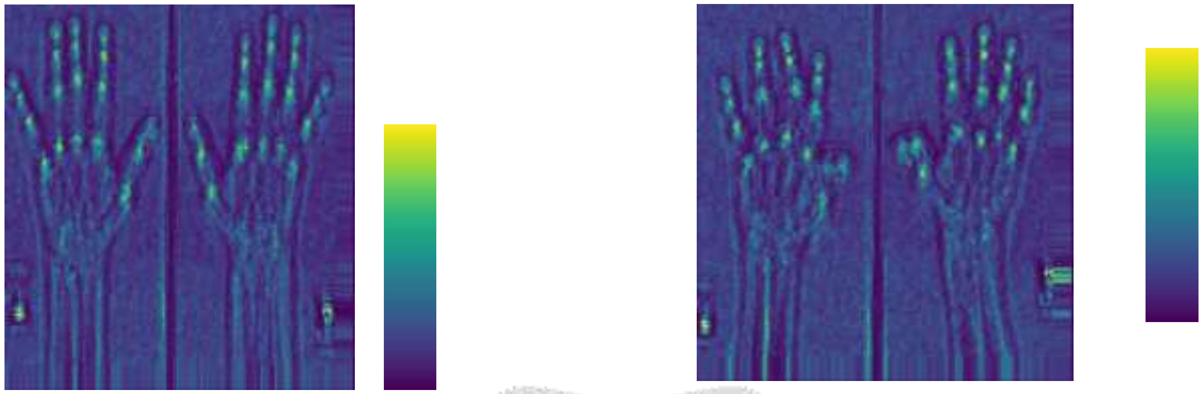
Parameter	***Value***
kernel	linear
C	0.5

TABLE II. TRAINING PARAMETERS FOR THE mTS SCORE ESTIMATION.

Parameter	***Value***
kernel	rbf
gamma	0.1
C	0.5

(a) Positive class (b) Negative class

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



(a) Mild R.A Patient -1.0 (b) Severe R.A Patient

FIGURE 3. Heat map of the detected finger joints

3.1 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 heat map of the finger joint detection results. The heat map shows the SVM output value. The larger the SVM output value, the higher the likelihood of being a finger joint. These figures show that the SVM outputs higher value to the position of the finger joint. These results showed that the proposed method is effective for finger joint detection of RA patients.

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.

3.2 mTS score estimation

The 5-fold cross validation test evaluated the proposed method in which the manually measured erosion and JSN scores were used as the ground truth value. In order to compare the results using the different set of learning data, the mTS score estimation was performed for the following three cases.

Table 3 and 4 show the mTS score estimation results for the three cases. The absolute error (AE) shows the average and standard deviation of the absolute difference of SVR output and ground truth value. The mean squared error (MSE) is calculated by the squired difference of SVR output and ground truth value. The correlation coefficients are calculated using the SVR output real values and ground truth values. We defined the success as the rounded SVR output has the same value with the manually measured ground truth value. These tables show that as the number of learning data increases, the estimation performance improves. High correlation coefficient shows that the proposed method can estimate the mTS score.

Table 5 shows the total estimated mTS score of both hands using learning dataset of (case 3) where the estimation result of the mTS score was the best. The AE shows the average and standard deviation of the absolute difference of the SVR output total value and ground truth value. The mean squareed error (MSE) is calculated from the difference of SVR output. total value and ground truth value. The correlation coefficients are calculated from the SVR output real values and ground truth values. This result shows that the proposed method can estimate the total mTS score of both hands.

Table 6 and 7 shows the mTS score estimation results of each finger on the case of (3) where the estimation result ofthe mTS score was the best. Each element of these tables is the same as Table 3 and 4. From these tables, it is shown that the estimation of the mTS score is almost same among fingers.

TABLE III. mTS SCORE ESTIMATION RESULT (EROSION)

learning datasets	*absolute error*	*error of mean square*	*correlation coefficients*	*success rate (%)*
(case 1) Only the original image	0.669 ± 0.556	0.870	0.394	45.2
(case 2) Original image and rotated image data	0.643 ± 0.530	0.833	0.463	47.1
(case 3) Original image, rotated image and gamma-corrected image	0.635 ± 0.524	0.824	0.475	47.5

TABLE IV. mTS SCORE ESTIMATION RESULT (JSN)

learning datasets	*absolute error*	*error of mean square*	*correlation coefficients*	*success rate (%)*
(case 1) Only the original image	0.461 ± 0.370	0.591	0.567	61.0
(case 2) Original image and rotated image data	0.457 ± 0.370	0.588	0.582	62.0
(case 3) Original image, rotated image and gamma-corrected image	0.448 ± 0.362	0.576	0.599	64.0

TABLE V. TOTAL ESTIMATED mTS SCORE OF BOTH HANDS

mTS score	*absolute error*	*error of mean square*	*correlation coefficients*
Erosion	9.805 ± 7.263	12.201	0.475
JSN	5.285 ± 4.360	6.851	0.724

TABLE VI. mTS SCORE ESTIMATION RESULT OF EACH FINGER (EROSION)

finger		*absolute error*	*error of mean square*	*correlation coefficients*
Left hand	*Thumb*	0.677 ± 0.616	0.915	0.255
	First finger	0.657 ± 0.475	0.811	0.447
	Second finger	0.560 ± 0.482	0.739	0.5417
	Third finger	0.542 ± 0.403	0.675	0.526
	Fourth finger	0.644 ± 0.476	0.801	0.390
Right hand	*Thumb*	0.784 ± 0.716	1.062	0.515
	First finger	0.655 ± 0.496	0.821	0.517
	Second finger	0.591 ± 0.564	0.817	0.492
	Third finger	0.601 ± 0.507	0.786	0.501
	Fourth finger	0.704 ± 0.513	0.871	0.423

TABLE VII. mTS SCORE ESTIMATION RESULT OF EACH FINGER (JSN)

finger		absolute error	error of mean square	correlation coefficients
Left hand	***Thumb***	0.439 ± 0.414	0.604	0.239
	First finger	0.440 ± 0.366	0.572	0.557
	Second finger	0.433 ± 0.320	0.538	0.663
	Third finger	0.415 ± 0.280	0.501	0.699
	Fourth finger	0.478 ± 0.325	0.578	0.625
Right hand	***Thumb***	0.433 ± 0.431	0.611	0.405
	First finger	0.464 ± 0.369	0.593	0.593
	Second finger	0.477 ± 0.398	0.621	0.495
	Third finger	0.478 ± 0.396	0.621	0.609
	Fourth finger	0.414 ± 0.328	0.528	0.691

4.CONCLUSIONS

This paper has introduced a finger joint detection method and mTS score estimation method for mild-to-severe RA patients and evaluated the performance. Especially, it has investigated a possibility of improvements with increasing the number of training dataset by artificial rotation and gamma correction. The finger joint detection experimental results on 45 RA patients shows that the proposed method detects finger joints with accuracy of 81.4 %. And, the proposed method is effective for finger joint detection of RA patients. The mTS score estimation experimental results on 45 RA patients shows that artificial generation of training dataset was effective to increase the performance. The future work is to increase the number of subjects and to examine new features for machine learning.

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