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IDENTIFY RHEUMATOID ARTHRITIS AND OSTEOPOROSIS FROM PHALANGE CR IMAGES BASED ON IMAGE REGISTRATION AND ANN

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Abstract. *Rheumatoid arthritis and osteoporosis are two of the major diseases related to the phalanges. Diagnostic imaging is often used to diagnosis them. Especially, observing the temporal changes of the shape or internal structure of the phalanges in phalange CR images is an effective way to detect these diseases. However, there are various problems in image diagnosis, such as the evaluation of diagnosis is generally empiric, and the burden of reading images is heavy. In order to solve these problems, in this paper, we develop a computer aided diagnosis (CAD) system for automatically diagnosing, which includes segmentation of knuckles, registration of temporal images and features analysis of phalange regions. In the segmentation part, we perform the multi scale gradient vector flow (MSGVF) snakes to improve the precision of extracted results. Also we have developed an image registration technique based on salient region features (SRF) method. Two image features are used to train the artificial neural network (ANN) to identify the abnormal knuckle regions.*
Keywords: Rheumatoid arthritis, Osteoporosis, Segmentation, Registration, Computer aided diagnosis system, Multi scale gradient vector flow snakes, Salient region features

1. **Introduction.** Rheumatoid arthritis and osteoporosis are common diseases of the phalanges of the hand. If the elasticity is reduced by the reduction of the moisture, inflammatory reaction occurs in the synovium by the motion of the surface of the articular cartilage. Furthermore, by the action of substances called cytokines, inflammatory substances are produced from the synovium. However, cause of rheumatoid arthritis has not precisely been elucidated. It is expected that abnormal reaction of the immune system such as the inflammatory response of the synovium is the cause. If symptoms proceed, the deformation of the joint by bone destruction occurs [1]. In order to diagnose rheumatoid arthritis, visual screening is performed in medical fields [2-4].

In this paper, to enable quantitative analysis using a computer for diagnosing rheumatoid arthritis and osteoporosis, a CAD system is developed which consists of the automatic segmentation, and automatic registration and feature analysis of phalanges regions is an object. In automatic extraction of the phalange region from CR image, the complexity of the process occurring during image registration is eliminated. In addition, reduction of burden on physicians by automatic setting of the region of interest (ROI) is achieved. Furthermore, by using a differential image obtained from the registration process, the detection of temporal changes in the shape of the bone is expected. In the feature analysis, quantitative assessment of osteoporosis is supported by analyzing the state of the bone trabeculae.

The initial segmentation of phalange regions by the estimation of joint position is carried out firstly on the hands of the CR image. Control points are automatically determined from the results of the initial segmentation. And, detailed phalange regions are extracted by MSGVF (multi scale gradient vector flow) snakes [5]. Thereafter, registration technique is performed between the current images and the previous images of the phalange region image. In the study of R. Fergus et al. [6], modeling of the aggregate of the flexible area is utilized for alignment. E. Grimson et al. [7] proposed an interpretation tree algorithm for searching for corresponding global feature points. However, there are optimization problems of calculation order and cost issues in these methods. To solve these problems, we utilize the SRF (salient region feature) [8] in the registration process. Several SRFs are detected from the phalange region image. Then, SRF pair is determined between time series. Optimal deformation amount is derived using information obtained from the pair. In addition, the ROI is set automatically in the interior of the region. Finally, we classified abnormal knuckle regions based on artificial neural network. Our main contributions in this work are as the following.

(1) Automatic segmentation of phalange regions on CR image which obtained previous and current image based on multiple scale gradient vector flow.

(2) Automatic image registration of different time series images using salient region feature.

(3) Classification of abnormal region from unknown image based on artificial neural network (ANN).

The remainder of this paper is organized as follows. In Section 2, we introduce image processing techniques for segmentation of ROI, registration of phalange region, and classification of abnormal regions respectively. The results of the proposed methods as produced by the CAD system are presented in Section 3. Finally, Section 4 ends this paper with several concluding remarks and future works.

2. **Image Processing Techniques.**

To achieve a quantitative assessment of the disease of the phalanges, we propose a CAD system. It is composed of three element technologies, that are: i) segmentation, ii) registration, and iii) feature analysis for classification. To develop a new CAD scheme, phalange area is extracted to accommodate the complexity of the alignment process as the first step. As the second step, registration process is carried out between the previous and current images of the same subject. By generating a difference image, the detection of the shape change in the phalange region is expected. As the third step, analysis of features inside arranged ROI of phalange region is performed. It is possible to quantitatively evaluate each phalange and subjectivity in diagnosis can be eliminated. Figure 1 illustrated overall scheme for our proposed CAD system.

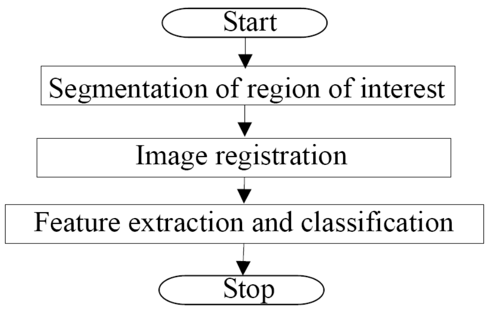


FIGURE 1. Overall scheme for CAD system

2.1. **Segmentation of region of interest.** Firstly, top-hat transformation processing is implemented on the original image in order to remove soft tissue on CR images. Then, the initial segmentation is carried out of the phalange regions by the estimation of the finger and the joint position. The control points are determined automatically from the results of the first segmentation. Finally, phalange regions are extracted by MSGVF snakes algorithm. The MSGVF is a method to represent the vector field using the edge map based on the scale space theory. Since utilizing the smoothed image, we can make a global edge map by this approach. Accordingly, it is possible to suppress the influence of noise. And, energy function is used in the movement of convergence of snakes [9]. It has been widely applied in many image processing applications including tracking, restoration, and segmentation of image.

2.2. **Registration of phalange region.** The purpose of the registration process is detecting the shape or internal structure change between the time series. It is necessary to minimize the computational cost while maintaining highly accurate positioning properties. The entire image is always evaluated in general registration process. This is the cause of increasing the computational cost. In order to solve these problems, we use a salient region on the image. So, we build the image alignment method in order to realize a high-speed method of deriving a highly significant amount of deformation.

In this paper, in order to take advantage of the salient region features, we use a detection method based on entropy. The proposed registration process based on SRF is composed of three steps [8]. In SRFD (SRF detection), SRF composed of a circular area is detected. In RCPM (region component matching), a pair of highly similar SRF is set based on the likelihood between previous images and current one. In RCFM (region configural matching), alignment accuracy of the entire image is improved by binding pair incrementally. Eventually, optimum deformation amount is derived from the unique information of the pair joint. The goal of this approach is to derive the optimum amount of deformation by using only the most salient information.

As the flow of the processing of SRFD step, center coordinates and the radius are set first from the image. And, the entropy of the set circular area is calculated. The entropy function $H(s, X)$ can be represented by the following equation.

$$H(s, X) = -\int_R p_i(s, X) \log_2 p_i(s, X) d_i \tag{1}$$

where i shows intensity. $p_i(s, X)$ is a probability density function (PDF), which is calculated from the radius s and center coordinates X. Then, the saliency value $A(S_x, X)$ is calculated at each center coordinate. Here, S_x is the best scale with a maximum of entropy value. Finally, SRFs with high characteristic value are selected.

As the flow of the processing of RCPM step, first, SRF is selected from the previous image and the current image respectively. Then, the pair is set based on the likelihood. The likelihood is established by entropy correlation coefficient (*ECC*) [10,11].

$$ECC(A, B) = 2 - \frac{2H(A, B)}{H(A) + H(B)} \tag{2}$$

where A, B are SRF, and H indicates the joint or marginal differential entropy of the intensity value random variables of the two regions.

In RCFM step, deformation amount obtained from the specific information of the pair is derived. The entire image is deformed with its deformation amount. Then, the pair joint is updated by adding a pair. Deformation amount T obtained from the pair bond is represented by the following equation.

$$T = \frac{1}{L_{sum}} \sum_{i=1}^{k} L_i T_i \tag{3}$$

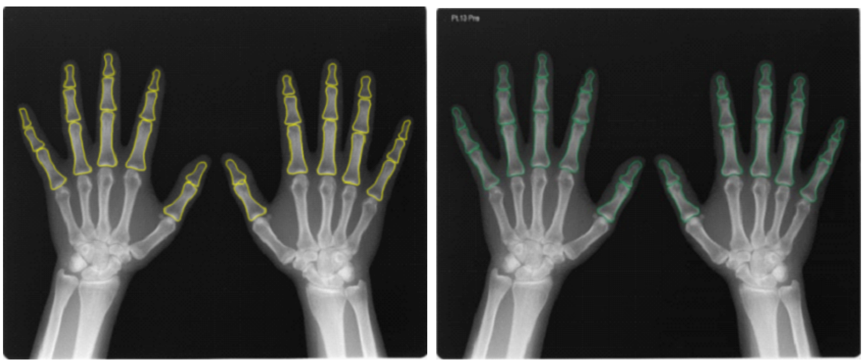
where L_{sum} is the sum of the likelihood. k is the number of pair joint. It should be noted that it is the weighting of the likelihood. By weighting, the amount of deformation of the high likelihood pair is emphasized. This approach is expected to be flexible derivation of the amount of deformation. Eventually, the pair is added until the likelihood is maximized.

2.3. **Classification of abnormal knuckle regions.** In this paper, we identify normal or abnormal region based on artificial neural network. To identify the osteoporosis, we divide the candidate regions of image into two sets, normal samples and abnormal samples. First, ROIs are automatically set inside the phalanges region. Shape feature of the phalanges is used in the determination of the ROI. Leftmost point and rightmost point are searched. And, ROI is placed in the center of the both points. Then, the feature amount with respect to the ROI is computed. The trabecular bone is reduced by progress on the symptom of osteoporosis. Thus, features that the difference is caused by the decrease of trabecular bone are used. In this study we select two statistical features, root mean square and line component to learn in ANN. ANN is intended to reproduce the information processing style in the brain. In this paper, a hierarchical neural network is used. Then, learning is performed based on back propagation.

3. **Experimental Results.** We applied our method on three pairs of CR temporal images of phalanges regions, which consisted of the previous images and the current images from the same subject. A segmentation result is shown in Figure 2. We evaluated the performance using the true-positive and false-positive. The descriptions of these two criteria are as follows.

$$TP = \frac{n(A \cap B)}{n(A)} \times 100, \quad FP = \frac{n(C)}{n(B)} \times 100 \tag{4}$$

Here A, B, C and n represent the correct segmentation region by medical staff, extracted region by our system, over-extraction results, and number of pixels respectively. *TP* represents the degree of overlap of the extraction region for correct answer region. *FP*

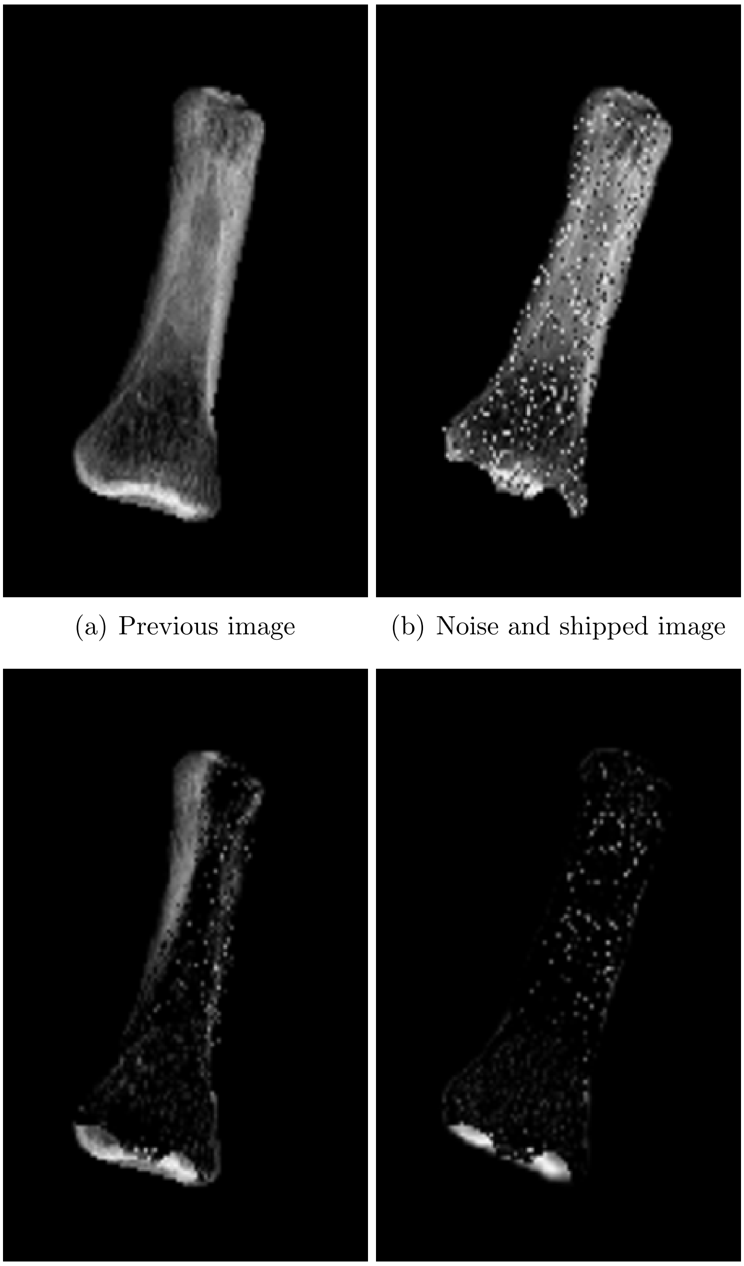


(a) Segmentation result (b) Gold standard

FIGURE 2. Segmentation result

TABLE 1. Results of registration

	GA	Conventional Method [8]	Proposed Method
ECC	0.563	0.597	0.616
Time [s]	59.02	4.102	3.724



(a) Previous image (b) Noise and shipped image

(c) Subtraction image without registration (d) Subtraction image with registration

Figure 3. Registration results

represents the percentage of over-extraction region for the extraction results. In this study, good performance with TP of 92.89[%] was obtained. The results of registration are shown in Table 1. GA in Table 1 is a method of deriving the optimal deformation amount by the genetic algorithm. Computational time for segmentation of each phalange region on CR image requires 107 [sec/image] on Intel core i7-3770 CPU [3.4GHz CPU] with 16 [GB] memory. Also registration time is required 3.7 [sec/phalange] on the same PC specification. Figure 2 illustrates a registration result. In Figure 3, (a) is a phalanges region of the previous image, (b) shows a phalange region with artificial noise having 20% of random noise on previous image. Furthermore, (c) and (d) illustrate a subtraction image without and with registration. The results of classification are 92.89% of true positive rate and 5.96% of false positive.

4. **Conclusion.** In this paper, in order to quantitatively analyze the bone changes caused by disease from the CR image of the hand, we proposed a CAD system and devised a new evaluation method that provides guidance for performing a quantitative evaluation. Especially, to reduce the computational time, automatic image registration of different time series images using salient region feature is proposed. From experimental results, we got a good result. Therefore, the proposed method is effective for segmentation, registration, and classification respectively. In this study, we have achieved the classification rates with 92.89[%] of true positive and 5.96[%] of false positive.

As the future works, improvement of extraction accuracy and the method of determining the control point are required in segmentation process because MSGVF snakes is dependent on the initial control point. Also, accuracy improvement can be expected in registration process by the improvement of the method for calculating the likelihood.

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