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AUTOMATED FINGER JOINT SYNOVITIS LOCALISATION IN ULTRASOUND IMAGES

Summary. Ultrasonography has proved its usefulness in the evaluation of joint inflammations caused by rheumatoid arthritis. The illness severity is scored by human examiners based on their experience, but some discrepancies in the final diagnosis and treatment frequently occur. Therefore, the main aim of this work is the elaboration of an automatic method of the localization of joint inflammation level in ultrasound images. In this work the seeded region growing method is applied for synovitis region segmentation. The region growing method is a technique that extracts a region from the image using some predefined criteria of similarity between initially selected point and the pixels in its neighborhood. The seed points are placed automatically as the darkest patch within a small region between two detected finger bones. The proposed segmentation method requires the manually marked localisation of skin, bones and joint, but there are several works, which allow to detect them in automatic way. The region affected by synovitis is found using the adopted criterion of homogeneity based on patch to patch similarity measure. The obtained results show a high accuracy in comparison with the annotations prepared by the expert.

AUTOMATYCZNA LOKALIZACJA ZAPALENIA STAWU PALCA W OBRAZACH ULTRASONOGRAFICZNYCH

Streszczenie. Ultrasonografia udowodniła swoją przydatność w ocenie stanów zapalnych wywołanych przez reumatoidalne zapalenie stawów. Nasilenie choroby jest oceniane przez ekspertów-lekarzy w oparciu o ich doświadczenie, jednak często występują pewne rozbieżności w procesie diagnozowania i leczenia. Głównym celem niniejszej pracy jest opracowanie automatycznej metody lokalizacji stanów zapalnych na podstawie obrazów USG. Wykorzystano tutaj metodę ziarnistego rozrostu obszaru do segmentacji obszarów zapalenia błony maziowej, która ekstrahuje z obrazu obszar przy użyciu kilku predefiniowanych kryteriów podobieństwa pomiędzy punktem-ziarnem, a pikselami jego sąsiedztwa. Punkty-ziarna są umieszczane automatycznie w najciemniejszym fragmencie małego obszaru pomiędzy dwiema wykrytymi kośćmi palców. Proponowany algorytm wymaga dostarczenia lokalizacji stawu, kości oraz skóry, jednakże w literaturze zaproponowano już metody, które pozwalają wyznaczać je automatycznie. Obszar zapalenia jest znajdowany za pomocą przyjętego kryterium jednorodności opartego na mierze podobieństwa pomiędzy sąsiedztwami. Uzyskane wyniki wykazują wysoką zgodność z opisami przygotowanymi przez ekspertów.

1. Introduction

Ultrasound imaging (US) is an inexpensive and real time method of human body structures visualisation. This technique is also a very sensitive imaging modality that facilitates an accurate diagnosis at the early stages of rheumatoid arthritis (RA) and makes it possible to monitor the responses to the applied therapies [17]. Although its initial use was limited to the inspection of larger joints, the latest improvements in resolution and tissue contrast have enabled the evaluation of smaller joints [21] and the detection of RA induced pathology in the early stages of joint diseases [17, 18].

RA is a chronic inflammatory disease, whose prevalence is estimated as being 1% of the population [6] and its early screening allows for its progression to be prevented. Many researchers have reported a high sensitivity in ultrasonography that is based on the detection of joint effusion, synovitis or bone erosions in joints affected by RA [17, 19, 2].

US can be used in the evaluation of synovitis, which is a sensitive marker of disease activity and severity in RA. However, there are some discrepancies in the final diagnosis and treatment regarding its validity and reproducibility especially between different examiners.

Synovitis is defined as as inflammation of the synovial membrane and is a characteristic symptom for RA [14]. Synovial changes are scored from 0 to 3 by radiologists or trained rheumatologists based on their experience or by using standardised atlases [20, 8]. According to this semiquantitative scoring system, 0 means no synovial thickening and 3 denotes synovial thickening that bulges over the line that links the tops of the periarticular bones with extension to at least one of the bone diaphyses [17]. However, such an evaluation of the disease involves some degree of subjectivity and therefore an automated method for the assessment of joint inflammation level in RA using ultrasound images must be developed. Exemplary ultrasound images with different degrees of synovitis and manually marked ROIs (Regions of Interest) are presented in Fig 1.

The degree of synovitis can be assessed by estimating of the size of the dark gray/black area above the finger bones or the joint using computer software. Consequently, the task of the automated determination of the level of synovitis can be considered to be a problem of segmentation of dark image regions in the vicinity of the bones and the joint. In order to determine the synovitis position on the image domain, it is necessary to detect the bone, skin and joint to limit the region of interest.

In this work, we have applied seeded region growing (SRG) technique introduced in [1] in order to detect the synovitis region in ultrasound images. In this method, an initial pixel known as seed is chosen and then at each step of the algorithm a pixel in small neighborhood for which the difference in intensity level to the initial pixel is smallest than an assumed threshold is added to that region. The initial seed is typically chosen manually, but in our work it is localised automatically as the darkest patch in small neighborhood of the joint limited by the bones curves. At this stage of work, we used manually detected bones and joint to be independent from the accuracy of bone and joint detection algorithms. However, these stages can be changed by the currently proposed automated methods of bones, joint and skin localisation [22, 16, 12].

Our main contribution is extension of basic SRG by applying the patch-based similarity measure instead of basic pixels intensity comparison. It means that a new pixel is added to the region if the patch centered at this pixel is similar to the patch centered at

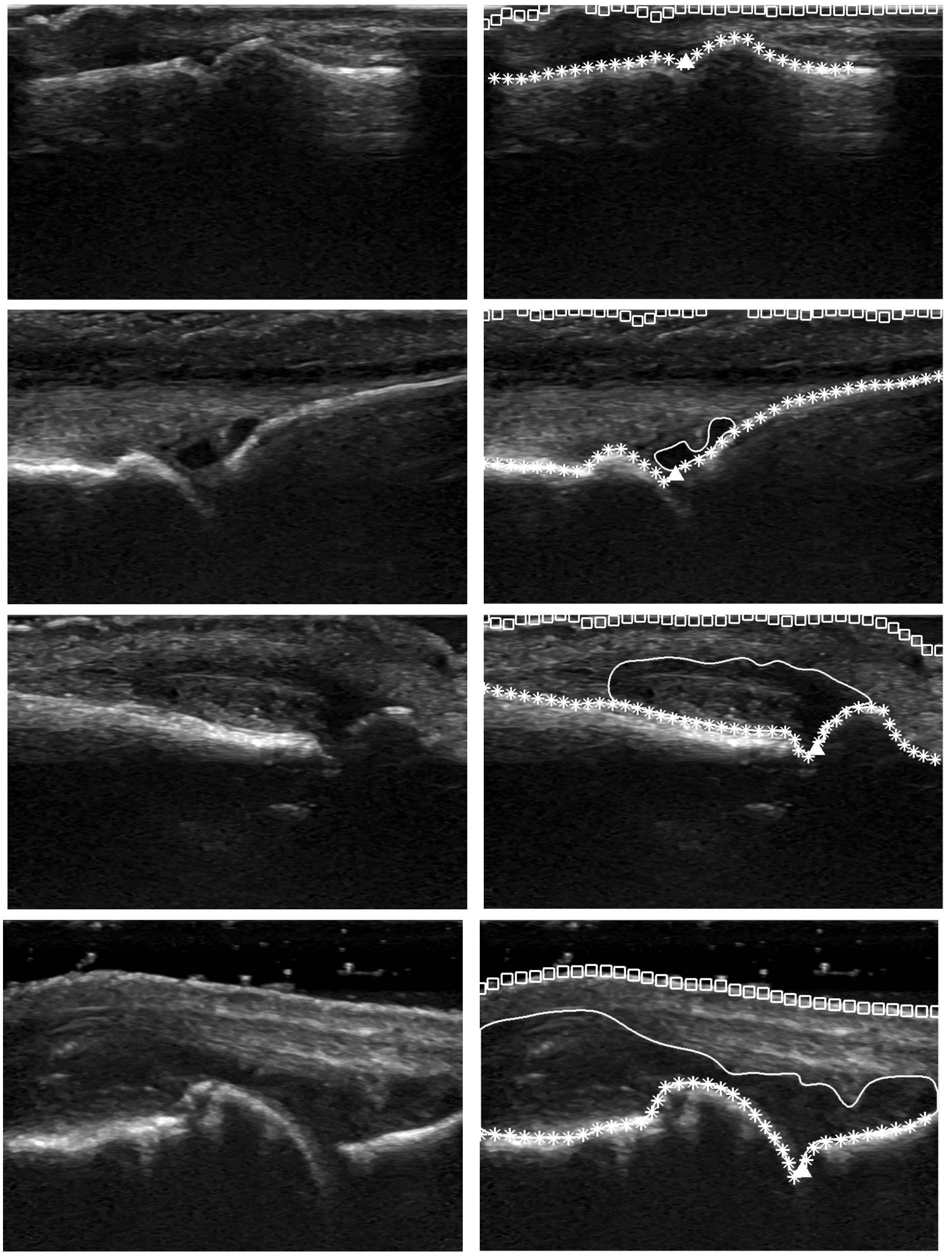

Fig. 1. Ultrasound images on the left and a manually delineated synovial region (solid line), bones (asterisks), skin (squares) and joint (triangle) on the right. The subsequent rows illustrate the level of synovitis in RA from 0 to 3.

initial seed. The patch-based methods are widely studied in many applications such as texture synthesis [5], image denoising [3] and image segmentation [23].

To evaluate the novel methodology of the automated synovitis localisation, a large set of ultrasound images with manually prepared annotations was collected [1] from patients with RA during routine visits at the Rheumatology Department of Helse Førde in Norway within the MEDUSA project. The obtained results were evaluated on the MEDUSA database, which contains manually annotated markers of the bone, skin, joint and synovitis regions. This research is a preliminary step in the development of fully automated system that will support a diagnosis of RA.

[1]MEDUSA project, http://medusa.aei.polsl.pl, Accessed: 2016-05-30

The paper is organised as follows. The next Section provides a brief description of the basic SRG and proposed Patch-Based SRG. Section 3 presents the numerical results of accuracy of synovitis segmentation, which was evaluated on manually marked synovitis regions utilising the MEDUSA database and Section 4 concludes the paper.

2. Proposed methods

Segmentation is the process dividing an image into regions with similar properties such as gray level, color, texture, brightness, and contrast [13]. The role of segmentation is to identify homogeneous regions in image that represent objects or meaningful parts of objects present in a scene. Automatic segmentation of ultrasound images is a difficult task due to the complex in nature of this kind of data, speckle noise and they rarely have any simple linear feature. Further, the output of segmentation algorithm is affected due to: (i) partial volume effect, (ii) intensity inhomogeneity, (iii) presence of artifacts closeness in gray level of different soft tissue [13]. In literature hundreds of methods have been proposed, but any of those techniques can be considered as universal for different type of images and very often a single algorithm does not work well for images for which it was developed. The basic segmentation techniques can be divided into several groups: thresholding, clustering, region growing, edge detection, active contour.

Region growing method is technique that extracts a region from the image using some predefined criteria. The easiest way is to select the seed point manually and attaching to it the next pixel on the basis of the adopted criterion of homogeneity. The choice of homogeneity criterion is therefore crucial to the success of segmentation. These methods can be divided into a methods in which the seed is selected manually or semi-manually (seeded region growing method, eg. [1]) or in an automatic way (unseeded region growing method, e.g. [9]).

Seeded Region Growing method was initially proposed in [1] and its properties as robustness, rapidness, free of tuning parameters makes it suitable for large range of images. In this approach initially the seeds or regions are to be specified by the user. A seed is a pixel or a group of pixels with ideal characteristic that belongs to the region interested in. The choice of seed is very crucial since the overall success of the segmentation is dependent on the seed input. For the given set of seeds, the algorithm adds pixels to one of the seed sets. The input seed point can be determined automatically for example as the centroids of the segmented regions from other type of segmentation. Next the pixels are connected to the seeds using some predefined criteria. The simplest criterion might be to grow the region until the difference in intensity level of the new pixel and the seed is below assumed threshold.

In this work we test simple seeded region growing algorithm adjusted for the finger ultrasound images and we chose only the single seed point within the inflammation area as the pixel for which the patch centered at this pixel has the lowest sum of the intensity levels. This algorithm is defined as:

1. Determine seed points to start the segmentation process.
2. Add the pixel in the neighborhood to the current region if all properties are fullfilled. This properties are:
    a) the pixel intensity is within range of the assumed threshold,

b) the spatial distance between the analyzed pixel and the seed is lower than assumed,

c) the region can grow up only in limited range (this assumption is based on the physical properties of this kind of ultrasound images, because the texture below the bones should be treated as noise.).

3. Finally fill the holes in the produced region.

This algorithm can be extended by introduction a patch comparison instead of simple pixel intensities analysis. In this approach local intensity context around the pixel can be used to produce a robust comparison of samples. Let us consider an ultrasound image I as a set of pixels X_i, where i determines the position of the pixel on the image domain, $i = 1, 2, \ldots, N$, and N denotes the number of image pixels. Let x_s represent the pixel chosen as the seed and R denotes the segmented synovitis region. Let $\mathcal{W}_i = (x_{i,1}, x_{i,2}, \ldots, x_{i,n})$ denote the set of pixels from a small square window centered at pixel x_i with size parameter $n = p \times p$. Let also denote the distance $d(W_i, W_s)$ between patches W_i and W_s that is defined as

$$d(W_i, W_s) = \frac{1}{n}\sum_{j}^{n} |x_{i,j} - x_{s,j}| \tag{1}$$

In the proposed modification a new pixel x_i is added to the region R if $d(W_i, Ws) < t$, where t is some predefined threshold. In novel approach, we consider not only the pixel intensity, but we are able to compare the texture properties around the seed and the currently processed pixel.

To evaluate obtained results of segmentation we used two similarity coefficient indices: Jaccard's similarity coefficient - Jaccard's index [7]:

$$J(I_{seg}, I_{ref}) = \frac{|I_{seg} \cap I_{ref}|}{|I_{seg} \cup I_{ref}|} \tag{2}$$

where: I_{seg} - segmentation result of synovial region, I_{ref} -manually delineated synovial region (ground truth image) and Dice's similarity coefficient (Sørensen index) [4, 15]:

$$D(I_{seg}, I_{ref}) = \frac{2|I_{seg} \cap I_{ref}|}{|I_{seg}| + |I_{ref}|} \tag{3}$$

Both similarity coefficients have a range of 0 to 1 with higher scores indicating better result of segmentation.

3. Results

In this paper, we tested our automated segmentation methods on 100 images from MEDUSA project. The proposed methods was compared with manually delineated synovial regions. For simple SRG method with fixed threshold we obtained best mean Jaccard index equal to 0.66 and mean Dice index equal to 0.78. The influence of tolerance parameters on mean Jaccard and Dice indices are presented in Fig. 2 for both indices.

Applying modification to SRG leads to improve the segmentation results, to increase the mean Jaccard index to 0.69 and mean Dice index to 0.81 and the method is

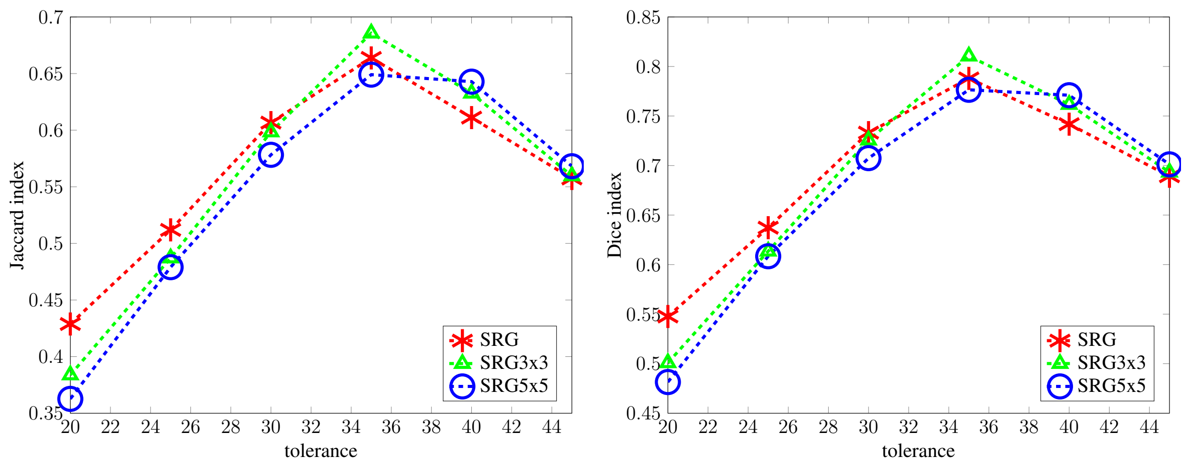

Fig. 2. Influence of tolerance parameter on mean values of Jaccard and Dice indices.

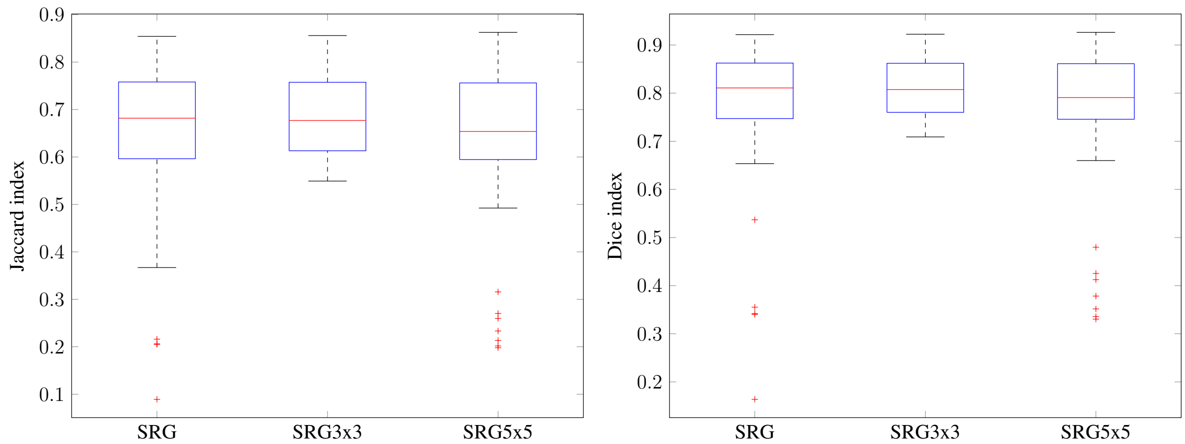

Fig. 3. Boxplots that visualise Jaccard and Dice indices for tolerance equals 35.

more robust as shown in Fig. 3. Some results with the highest Jaccard and Dice indices are shown in Fig. 4 where the obtained regions of RA are very close to manually delineated area. Fig. 5 presents difficult cases of segmentation where we obtained lowest similarity coefficients. To improve readability of Fig. 4 and Fig. 5 the brightness of original images have been increased.

4. Conclusions

Application of simple seeded region growing segmentation method and proposed modification of SRG for automated finger joint synovitis localisation in ultrasound images leads to obtain high-quality segmentation results. For many images obtained synovitis area coincides very well with manually delineated regions which gives the possibility to support diagnosis of RA however there are still cases with significant differences. Proposed segmentation methods are based on manually marked localization of skin, bones and joint, but authors have experience in the detection and localization these type of objects in images which can leads in future to build a fully automatic method.

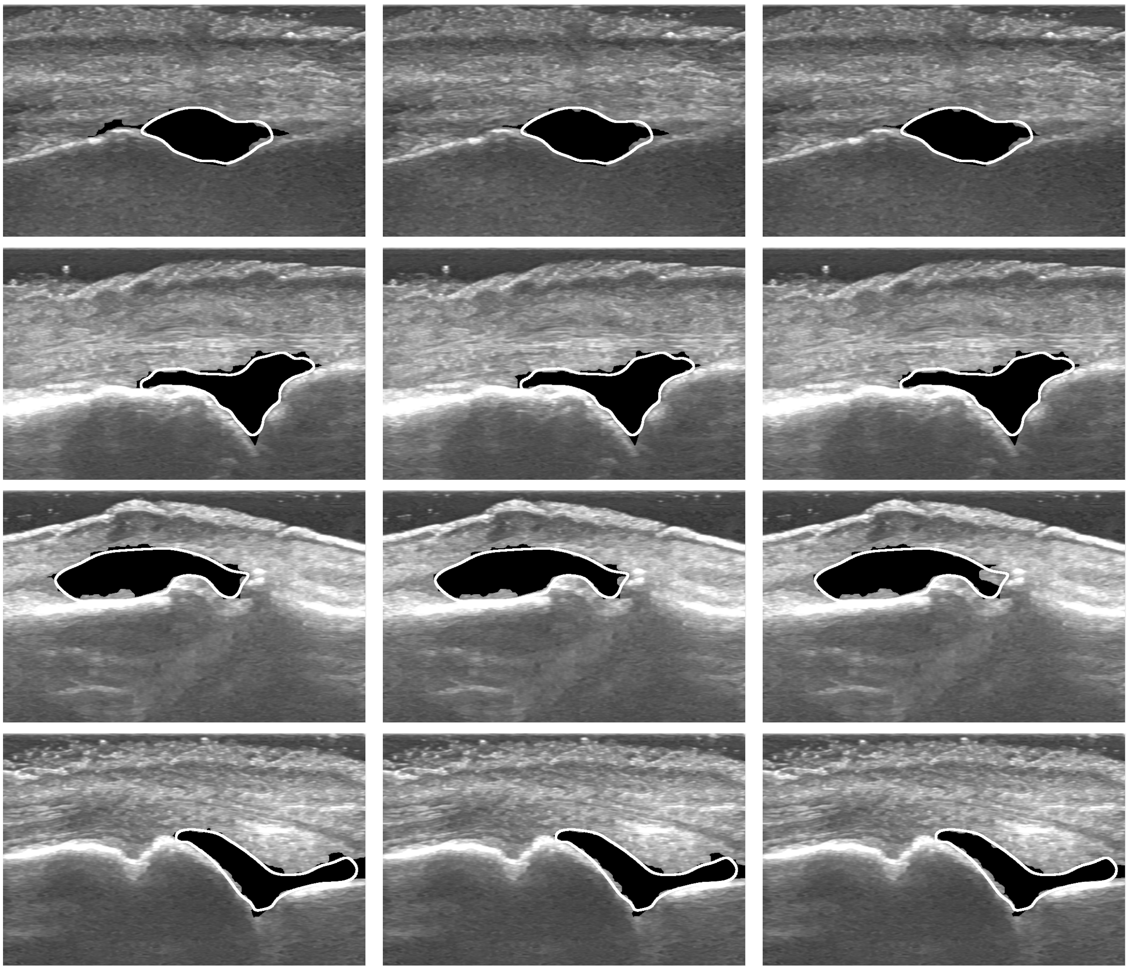

Fig. 4. Comparison of automated segmentation results of RA (black regions) with manually delineated regions (solid white lines). The subsequent rows illustrate different US images and subsequent columns illustrate methods: SRG, SRG3x3, SRG5x5.

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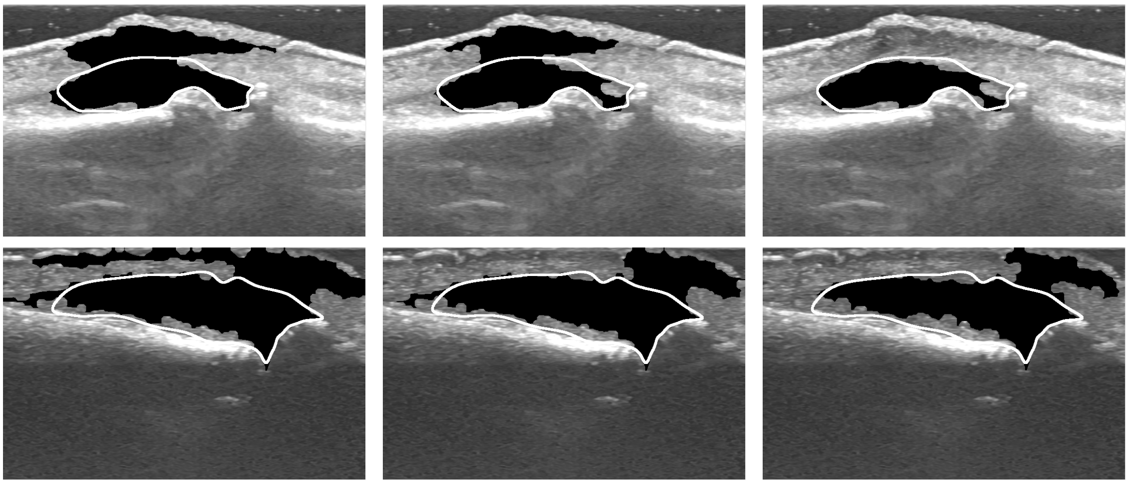

Fig. 5. Examples of difficult cases of segmentation of RA: results of segmentation (black regions) and manually delineated RA (solid white lines). The subsequent rows illustrate different US images and subsequent columns illustrate methods: SRG, SRG3x3, SRG5x5.

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