A modified Seeded Region Growing algorithm for vessel segmentation in breast MRI images for investigating the nature of potential lesions

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Abstract. The role of Magnetic Resonance Imaging (MRI) as an alternative protocol for screening of breast cancer has been intensively investigated during the past decade. Preliminary research results have indicated that gadolinium-agent administrative MRI scans may reveal the nature of breast lesions by analyzing the contrast-agent's uptake time. In this study, we attempt to deduce the same conclusion, however, from a different perspective by investigating, using image processing, the vascular network of the breast at two different time intervals following the administration of gadolinium. Twenty cases obtained from a 3.0-T MRI system (SIGNA HDx; GE Healthcare) were included in the study. A new modification of the Seeded Region Growing (SRG) algorithm was used to segment vessels from surrounding background. Delineated vessels were investigated by means of their topology, morphology and texture. Results have shown that it is possible to estimate the nature of the lesions with approximately 94.4% accuracy, thus, it may be claimed that the breast vascular network does encodes useful, patterned, information, which can be used for characterizing breast lesions.

1. Introduction

In the presence of abnormal growth, the need for oxygen and nutrients rapidly increases. Mechanisms for stimulating vascular growth are activated and new vessels are generated to support the increased metabolic demands of the tumour. This effect is captured by proper MRI scan protocols, such as T1-weighted scans, and, thus, diagnostic assessments are feasible [1-4]. These assessments are made on the basis of the so-called Time Intensity Curves (TIC) or Kuhl Curves [5, 6], which are divided into three categories: a/ type I characterized by a continuous increase in the measured signal (contrast-agents uptake) over time; these curves are indicative of benign cases, b/ type II characterized by signal increment upon a plateau value, raising concerns that malignant formations might be present, and c/ type III characterized by a rapid signal increase following by a rapid decrease, which has been shown as typical pattern in the presence of malignancy. Although angiogenesis is an important diagnostic lead strongly correlating with malignancy, it is also appears in non-malignant cases, such as benign lesions, inflammations etc. The latter complicates assessments. Extensive clinical reviews have shown a great sensitivity (around 90%) of the method with controversial specificity (from 37% to 100%) [7] that increases the overall cost of the exam and distress of the patients, since biopsies are obtained

needlessly. The latter has initiated a number of studies aiming in standardizing the procedures and protocols for breast MRI scans assessments. Yabuuchi et al [8] have proposed a method that combines DCE and DWI (Diffusion Weighted Imaging) leading to increased sensitivity, specificity, positive predictive value, negative predictive value, and accuracy. Sivarajan et al [9] have concluded that the introduction of morphologic and perfusion parameters in the interpretation of breast DCE-MRI improves both sensitivity and specificity. Macura et al [10] concluded that intensity enhancement measured in various time intervals after the contrast agent administration (thus, the TICs) is the most crucial. In this study, we attempt to investigate whether the quantification of the vascular network of the breast might lead to the same diagnostic conclusions as the investigation of the TICs. For this reason, a structured sequence of image processing step was developed with basis a modified Seeded Region Growing (SRG) algorithm in order to effectively delineate blood vessels.

2. Material and Methods

2.1. Material

Clinical material comprised 20 breast MRI images from 20 female patients, 18 with confirmed cancer. The MRI examinations were carried out on a 3T system (Signa, GE Healthcare) and the array spatial sensitivity encoding technique (ASSET) or parallel imaging technique was used. Two MIP (maximum intensity projection) images were obtained from each patient, one 1.5 minute after the administration of the contrast agent (pre-contrast) and one after 1.5-3 min (post-contrast). The contrast agent administration consisted of injection of 0.1 mmol/kg of gadopenate dimeglumine (Omniscan, Magnevist, Multihance) followed by a 10-mL saline solution flush, over a period of 5-8 sec. Detailed information regarding the data and protocols used can be found in [11].

2.2. Methods

The methodology consisted of a structured sequence of image processing algorithms:

Step 1: Background removal by subtracting from the original image a morphological opened image using a 7x7 disk component to remove structures that had similar grey level values with vessels (i.e. dense breast regions and masses) [12]. **Step 2:** Median filtering (3x3) to reduce noise [13]. **Step 3:** Otsu's thresholding [14] for an initial estimation of seed points used by subsequent step of the SRG algorithm. **Step 4:** Application of the SRG algorithm, which was constructed using a hysteresis criterion (see section *2.2.1*), for the finalization of the segmentation (white pixels in the binary image represented vessel regions). **Step 5:** Based on the segmented image, **t**he total area of vessels was calculated as the sum of white pixels for both the pre- and post contrast image of each patient. By dividing this area with the total number of pixels of the breast (Whole Breast Area - WBA) the percentage of vessels within the breast (Vascular Coverage - VC) was computed:

$$VC_{pre/post-contrast} = \frac{Segmented\ Vessel\ Area_{pre/post-contrast}}{WBA} \quad (1)$$

WBA was calculated as the sum of all segmented pixels found after applying thresholding to the morphologically processed image (using a 7x7 opening filter). **Step 6:** The ratio of VC of the pre- and the post-contrast image was computed as an index of the Vascular Growth (VG). Values of VG<1 meant that the vascular coverage appeared increased in the post-contrast image.

$$VG = \frac{VC_{pre-contrast}}{VC_{post-contrast}} \quad (2)$$

2.2.1. Seeded Region Growing (SRG)

The SRG algorithm aims in partitioning the image into meaningful regions on the basis of a set of initial predefined points, the so called seeds. The seeds can be manually set or automatically labelled. Given the seeds, the algorithm searches the seeds' immediate (connected) neighbours to find those

sharing some common similarity. The seeds are also referred to as allocated pixels, whereas the rest of the pixels as non-allocated. Considering a set of initial seeds S_1, S_2, S_3, …, S_n, n is the number of total seeds, then non-allocated pixels found in the immediate vicinity of S are [15]:

$$U = \left\{ x \notin \bigcup_{i=1}^{n} S_i \middle| N(x) \mathrm{I} \bigcup_{i=1}^{n} S_i \neq 0 \right\} \tag{3}$$

where $N(x)$ is the set of non-allocated immediate neighbours of pixel x. Usually the immediate neighbourhood is considered rectangular with 8 neighbour-pixels surrounding x, which is found at the center of this region. To estimate whether the neighbours will be allocated to the 'seed-class', a similarity criterion should be defined. The simplest criterion $\delta(x)$ is

$$\delta(x) = \left| g(x) - mean_{y \in S_i(x)} \left[g(y) \right] \right| \tag{4}$$

where $g(x)$ is the grey value of pixel x. When this criterion is minimized then pixel x is classified as a seed-class pixel. In this study a modified version of the SRG algorithm was developed and applied. The modified version uses a different criterion for investigating the immediate neighbourhood of the seed-class pixels. The proposed criterion separates the immediate neighbourhood into strong pixels belonging to the seed region (Region 1), strong pixels belonging to the background region (Region 2) and weak pixels, which are the non-allocated candidate pixels (Region 3), according to:

$$REGION\ 1: \delta(x) = \left| g(x) - mean_{y \in S_i(x)} \left[g(y) \right] \right| < 0.2\left(\max\{S\} - \min\{S\} \right) \tag{5}$$

$$REGION\ 2: \delta(x) = \left| g(x) - mean_{y \in S_i(x)} \left[g(y) \right] \right| > 0.8\left(\max\{S\} - \min\{S\} \right) \tag{6}$$

$$REGION\ 3: \delta(x) = \left| g(x) - mean_{y \in S_i(x)} \left[g(y) \right] \right| \tag{7}$$

3. Results and Discussion

Figure 1 illustrates an example of the application of the proposed structured sequence of image processing steps to a post-contrast image of a female patient with breast cancer at the center of the right breast with type III TIC curve. Figure 1(a) is the original image. Figure 1(b) is the background removed median filtered image, where it is clearly visible that the intensity and grey level distribution of pixels belonging to the mass at the center of the right breast are greatly weakened. In this way, vessel segmentation is facilitated. Non-informative texture other than vessels was smoothed, since this kind of texture did not constitute useful information. Figure 1(c) depicts the result of an Otsu-based thresholding, which was used as a gross estimation of the initial seeds for the subsequent SRG. This segmentation result was incomplete since many vessels were lost. The result was greatly enhanced (Fig 1(d)) following the application of the modified SRG. More vessels were detected as compared with thresholding, and corrupted vessels were completed. However, there were still vessel regions undetected. The latter did not significantly affect the computation of vascularity, since it is a reasonable to assume that the magnitude of under-segmentation was approximately the same in both the pre- and post-contrast images. Thus, the ratio of VC of the pre- and post-contrast images eliminated this under-segmentation error. Figure 1(e) illustrates the superposition of the segmented vessel pixels to the original image (Fig 1(a)), clearly indicating a segmentation underestimation. It is logical to assume that this underestimation in the first and second time interval image is the same, thus, the computation of the VG factor is not biased. Figure 1(f), which is a scatter diagram of the VG factor for each case included in the study, illustrates the Vascular Growth factor for all 18 cancer cases tested. For all cases with breast cancer except one (for the 94.4% of the cases), the vascular network appeared more prominent in the post-contrast image (VG<<1) confirming that abnormal formations do require an increase metabolic, and, thus, blood circulation coverage. Moreover, this increment of

vascularity was found as high as 60% for the more advanced malignancies. Only one case was found as of no change (VG≈1). In the two control images (normal cases), no change of the appearing vascular network was computed (VG≈1) between the pre- and post-contrast images. Thus, results indicate that it is possible to estimate the presence of cancer in breast MRI images by estimating the extent and the area of the vascular network.

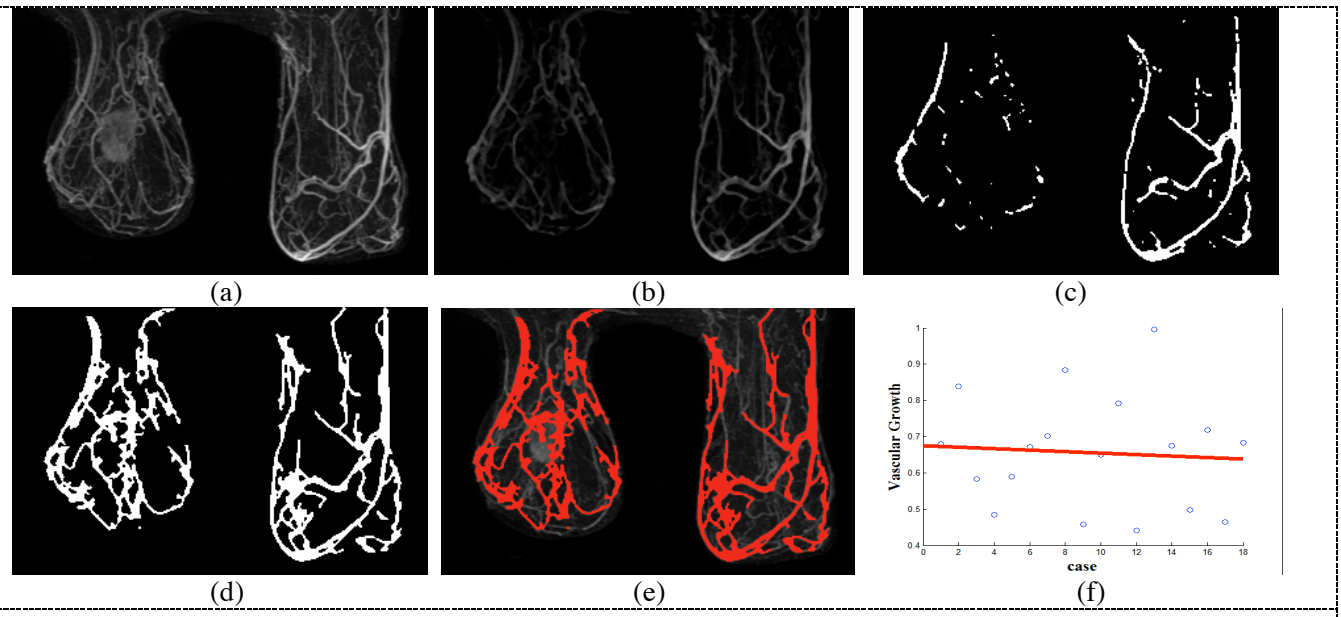

Figure 1. (a) Original Image, (b) Background Corrected Image, (c) Median Filtered Image, (d) Threshold Image, (e) Final SRG Segmented Image, (f) Vascular Growth

The sensitivity of the proposed method (94.4%) is in line with results presented in literature [7] (around 90%), although the proposed methodology investigates the problem from a different point of view focusing on the vascular network of the breast, rather than investigating the TOC curves [7].

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