Comparative analysis of methods for extracting vessel network on breast MRI images

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Abstract. Digital processing of MRI images aims to provide an automatized diagnostic evaluation of regular health screenings. Cancerous lesions are proven to cause an alteration in the vessel structure of the diseased organ. Currently there are several methods used for extraction of the vessel network in order to quantify its properties. In this work MRI images (Signa HDx 3.0T, GE Healthcare, courtesy of University Hospital of Larissa) of 30 female breasts were subjected to three different vessel extraction algorithms to determine the location of their vascular network. The first method is an experiment to build a graph over known points of the vessel network; the second algorithm aims to determine the direction and diameter of vessels at these points; the third approach is a seed growing algorithm, spreading selection to neighbors of the known vessel pixels. The possibilities shown by the different methods were analyzed, and quantitative measurements were performed. The data provided by these measurements showed no clear correlation with the presence or malignancy of tumors, based on the radiological diagnosis of skilled physicians.

1. Introduction
Cancer is one of the biggest challenges facing the medical industry in the 21th century. Besides researching new treatment options, early diagnosis is the most important key of successfully battling this lethal condition. The aim of this work is to examine the possibilities of autonomic diagnosis of breast cancer, based on digital image processing, which could lead to quicker results, taking the opportunities of breast cancer screening to more people. [1]
2. Datasets
Clinical material processed in this work contains the results of 15 MRI examinations of 15 female patients, alongside with the radiology-based diagnosis of the attending physician. Since tumorous lesions are usually asymmetrical, breasts of the same patients were evaluated separately. Table 1 shows the radiological diagnoses of the 30 cases. All of the datasets were obtained courtesy of the Medical Image and Signal Processing (MEDISP) Lab of the Technological Educational Institute (TEI) of Athens.

| Category of radiological diagnosis | Number of cases |
|-----------------------------------|-----------------|
| Normal (BI-RADS I)                | 17              |
| Benign (BI-RADS II-III)           | 4               |
| Malignant (BI-RADS IV-V)          | 9               |

Patients were subjected to 3T MRI examination (Signa, GE Healthcare). Conventional MRI protocol included:

| MRI Protocols used in image acquirement. |
|------------------------------------------|
| Axial T2-weighted Fast Spin Echo imaging sequence (T2-FSE) | Axial diffusion-weighted echo-planar imaging sequence (DW-EPI) | Axial short T1 recovery imaging sequence (STIR) |
| TR | TE | slice thickness | spacing | TR | TE | slice thickness | spacing |
| 3600 ms | 100 ms | 4 mm | 0 mm | 6000 ms | minimum | 4 mm | 0 mm | 3875 ms | 90 ms | 4 mm | 0 mm |

Prior to the examination, gadolinium contrast material was injected. Two images were taken, the first in TP1, 90 seconds after injecting the contrast material, the second in TP2, 180 seconds after the injection. Both of the scans were rendered with maximum intensity projection (MIP). [2]

3. Pre-processing
The goal of this work was to determine the areas of the images, which represent vessels, and collect quantitative metrics about the vascular network of the breast, which may serve as a support for the diagnosis. For preprocessing of the images several methods for the following subtasks were tested and evaluated in order to obtain the best possible results. After consideration the following methods were chosen:

| Pre-processing subtask | Method used | Parameters |
|------------------------|-------------|------------|
| Noise reduction        | Gauss- filter [3] | $\sigma^2 = 1$ |
| Background correction  | Subtraction of the image subjected to an erosion operator | disk-shaped |
|                        |              | $r = 1$    |
| Contrast enhancement   | Intensity window [4] | 1% saturation on both high and low intensity ends |
Figure 1 shows the result of the entire process.

Figure 1. The original image (left) and the result of the pre-processing (right)

4. Vessel extraction methods

After pre-processing the points of local maxima were determined with the following rules:

- For any pixel $P_0 = I(x, y)$ let $P = \{P_0, P_1, P_2, \ldots, P_N\}$ be the set of all pixels meeting the following conditions:
  - For any $0 \leq i, j \leq N$ $P_i$ and $P_j$ are 8-connected with each other
  - For any $0 \leq i, j \leq N$ $P_i$ and $P_j$ share the same value

- Let $Q = \{Q_1, Q_2, Q_3, \ldots, Q_M\}$ be the set of every pixel meeting the following conditions:
  - None of the elements of $Q$ is also an element of $P$
  - For every $1 \leq i \leq M$ exists a $0 \leq j \leq N$ so, that $Q_i$ is in the 8-connectivity neighbourhood of $P_j$.

- Define $S(x, y)$ as the binary image containing the local maxima:
  $$S(x, y) = \begin{cases} 1, & \text{if for any } 1 \leq i \leq M \text{ } Q_i < P_0 \text{ AND } I_{\text{min}} < P_0 \\ 0, & \text{otherwise} \end{cases}$$
  where $I_{\text{min}}$ represents a minimum pixel value for the local maxima to be detected.

- Note, that in case of any $P_0$ is recognized as local maximum, every element of $P$ are bound to be marked as well, which means appointing areas of local maxima instead of sole points.

For the vessel extraction three different algorithms were tested and compared, described in the following.

4.1. Graph theory approach

Suppose that the local maxima are vertices of a graph. The edge between two vertices represents if there is a vessel connecting the areas corresponding to the pixels. We assign a vector to each pairing of pixels by examining the neighborhood of the line connecting them. The vector consists of four values, serving as a basis for a classification process, deciding about establishing an edge of the pairing.

4.2. Directional vector model

In this approach an attempt is made to determine the directional vector and diameter of vessels at the known pixels. This procedure starts with setting up the map of the local maxima as well. For each peak $P_A$ we do the following: first we locate the closest pixel not belonging to the vessel, call it $P_B$. Locating $P_B$ is achieved by increasing the search radius, starting from 1, checking for the first pixel with intensity below a limit point. Based on manual inspection 30% of the central pixel’s intensity is a rational division value. If more than one of the pixels on a certain radius are below this value, the lowest one is to be chosen. Based on trials performed on several images, it is safe to assume that in most of the time the line segment $P_AP_B$ is a
good approximation for the radius of the vessel. The orthogonal line to this segment is considered as the directional line of the vessel in the point of interest.

4.3. Seed growing method
Define $F$ as the set of pixels identified as foreground pixels. At beginning it contains all of the peaks detected by the local maxima algorithm. The backbone of this algorithm is a loop, which stops after the first iteration without new pixels being added to $F$. The body of the loop does the following:

- For each $P = f(P_x, P_y)$, for which $P \notin F$ stands, define $N = \{N_1, N_2, N_3 \ldots N_M\}$ as the 8-connective neighbourhood of $P$.
- If the subset $B = N \cap F$ is not empty, define $A_B$ as the arithmetical average of its elements.
- For an arbitrary proportional threshold value $0 < c_{\min} < 1$, if $A_B \cdot c_{\min} \leq P$ satisfies, $P$ is added to a temporary set $F_{\text{temp}}$.
- After each $P$ value has been examined, $F_{\text{temp}}$ is added to $F$. If $F_{\text{temp}}$ is empty, we end the loop.

5. Comparative evaluation of experimental results
All of the three approaches of vessel network extraction were tested on several images in order to visually determine their fitness and weaknesses. The results were the following:

5.1. Graph theory approach
Although the algorithm was successful in obtaining most of the major structures, there are several errors made by the classification method. Broadening the set of classification variables, or experimenting with further classification methods may explore the eligibility of this method.

5.2. Directional vector approach
While the results are promising, since the directions of the vectors show considerable consistency with the vessels, apart from the thickest sections, segments are not connected. Connecting these segments would be possible with optimization algorithms, but it exceeds the limits of this work.

Even though extraction of the whole vessel network is not possible using solely the detected direction vectors, this method is perfectly capable of obtaining the diameters of the vessels, which renders this method as a potential expansion of other algorithms.

5.3. Seed growing algorithm
Although there is certainly room for improvement, the algorithm was not only successful in extracting major structures, but also marked a significant amount of the smaller vessels.

6. Conclusion
The seed growing algorithm was successful in extracting the vessel network for further quantitative measurements, while the directional vector model provided valuable measurements about the diameter of vessel segments. Directions of further development were outlined for each of the methods, providing a basis for further work.

References
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