

An example-based system to support the segmentation of stellate lesions

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Abstract. The detection and segmentation of stellate lesions in mammograms is a difficult task in image processing due to the high variances in their appearance. We present the application of an interactive generic system, that is trained to detect and segment stellate lesions based on their local features. The training is done by an expert presenting examples of stellate lesions to the system. With the data available good detection results are achieved, yet the performance of the system can be increased as more examples are presented.

1 Problem

Stellate lesions (or spiculated masses) are important indicators for the most common type of breast cancer ($\sim 75\%$ of all malignancies). They can mostly be characterized as follows: From an ill-defined central mass, strands of tissue (spiculi) are radiating out, producing a stellate appearance [1]. Their automated recognition though is a difficult image processing task. The appearance of the masses and especially the spiculi varies from case to case, because in the mammogram they are overlapped by surrounding tissue. In most cases a human expert is capable of recognizing the lesion and defining at least the central mass. This work is quite time-consuming and depending on the expert the results may differ substantially. But as the spiculi infiltrate healthy tissue even the radiologist cannot always segment appropriately. For an automated analysis the mammogram one would like an automatic segmentation to separate suspicious regions from the rest of the image (i.e. background). As the special properties of spiculated lesions are still unknown, there yet exists no common parameter set for a good segmentation. To derive these parameters, a sufficient number of mammograms has to be manually pre-segmented, which is again time-consuming. Thus a system is preferable that can be trained interactively by the expert to detect and perhaps also to segment stellate lesions.

2 State of the art

There exist many approaches for detection and segmentation of stellate lesions. Li et al. proposed a morphological enhancement and a Maximum Likelihood

approach for the detection of potential lesion sites [2]. In a second step they computed three features (two morphological and one textural) for classifying the detected lesions. Kobatake et al. [3] presented an adaptive filterfinding suspicious regions despite their contrast to the background. They used 9 features (textural and morphological) characterizing malignant tumors. Kupinski et al. [4] described a region growing segmentation combined with a radial gradient function as they assumed the masses to be circular objects. All these methods use fixed segmentation algorithms that can only be applied to stellate lesions. It is unknown if the underlying features of the stellate lesions are appropriate. It is also difficult to adapt these algorithms to the detection of so far unknown shapes of masses. Beller et al. [5] presented a generic approach to segmentation that can be trained by interaction with an expert to segment arbitrary objects. The needed segmentation parameters are derived automatically from a random sample of objects. It is yet unknown whether this method can be applied to the segmentation and detection of stellate lesions.

3 Basic improvement by this contribution

We present how easily our already introduced system [5] could be trained to detect and segment stellate lesions. For the training only examples and little user interaction are needed. It is particularly possible to adapt to hit her to unknown shapes of stellate lesions. A database of manual segmentation – if available – can be used as training examples; but it is also possible to incrementally set up a database during the training. We'd like to emphasize that we apply an existing method of adaptive segmentation to a difficult task, not a specially for this application developed system and not a clinically relevant system.

4 Methods

The adaptive segmentation approach can be described as follows: Starting with the first image of a set of images with similar content, the expert interactively selects an exemplary and a counter-exemplary region. From these two regions 45 local features are automatically extracted, e.g. statistical and textural features. Note that the extracted features do only apply to region elements, e.g. pixels, and not to the whole region. From these features a suitable subset is selected and a classifier is constructed to discriminate between the pixels of the two exemplary regions. In a region growing process this classifier is applied to the whole image resulting in a segmentation based on the given examples. The expert reviews the segmentation result and interactively makes corrections as described in the next paragraph. The classifier is rebuilt to include these changes. If the result is satisfying, the next image will be processed in the same manner. This way the local properties of the objects to be recognized are learned. If the presented images are representative, a set of representative properties can be found to achieve a good generalization. We used the BCRP-Part from the DDSM-Database [6] consisting of digitized mammograms and their manual segmentations. The images are

Table 1. The classification error for the training set was estimated by 10-fold cross-validation on 37823 observations consisting of 7 local features.

Set	Detection rate for lesions	Classification error for pixels	False positives (lesions)	False positives per image	Interactions per image	Iterations per image
Training	91%	3.4%	267	6	3.4	2.7
Test	70%	NA	325	8	NA	NA

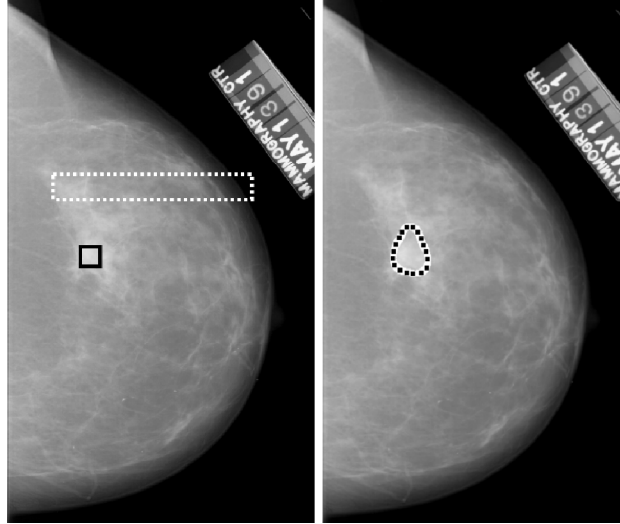
$\sim 4000 \times 8000$ pixel@12bit and $43.5 \frac{\mu m}{pixel}$. The manual segmentations cover parts of the central mass and in some cases as well regions with spiculi. The database is divided into a training and a test set containing 39 and 40 cases respectively, but only 32 cases from the training set could be successfully decompressed. The image size was reduced to 25%. Using the method described above, the images are processed sequentially. On the 1st image, the expert simply drags rectangles with the mouse to mark a stellate lesion and healthy control-tissue. The markers should only cover exemplary areas of the particular tissue. With this information, the algorithm segments all areas that belong to a stellate lesion with high probability. These areas are reviewed by the expert and corrected if necessary: A mis-segmentation is manually assigned to the appropriate object-type (lesion, control-tissue). This is done until the segmentation is satisfying. With the segmentation parameters derived so far, step by step all images are processed, where as we iterate over each image until the segmentation is satisfying. Besides the classification error for assigning pixels to the correct class, we measured the number of interactions and the number of iterations. How often the expert had to interfere with the algorithm, e.g. how many additional rectangles had to be dragged until the resulting segmentation was satisfying, is expressed by the interactions. The number of iterations specifies, how often the algorithm had to adapt and to re-estimate the segmentation parameters, until a good set was found. We also measured the detection rate for the lesions in the training and test case.

5 Results

The used algorithm employed a standard feature selection algorithm (BestFirst-Bidirectional) and a classification tree (J48) [7] to estimate a good parameter set for the detection and segmentation. The time to train the system required 4h of manual work and another 60h on a Pentium IV 1.6GHz with 1GB RAM for the computation of the parameters. The number of interactions per image was 3.4, which means that for each image 2.4 additional rectangles had to be defined. The segmentation parameters had to be recomputed 3 times per image. For further results refer to table 1.

During the sequential processing of the images the number of features used for segmentation varied from 1 to 12, but finally 7 features were selected as most

Fig. 1. Exemplary images. Left: the original mammogram with user defined rectangles for stellate lesion (black) and healthy tissue including background (dotted white). Right: the boundaries of the resulting lesion segmentation.



important: Mean, Variance, Minimum, Maximum, Sum Average, Homogeneity and Runlength-Greyleveldistribution (see [8] for definition).

Processing the images consecutively we achieved an accuracy of 97% during the training. After we processed all the images, we applied the final pixel classifier to all images, resulting in a loss of 2 training masses, which means the accuracy dropped to 91%.

6 Discussion

We presented how a generic system could be trained to the difficult task of detecting and segmenting stellate lesions. The system was guided by an expert but the effort for the expert was very low, since the required form of interaction was to mark exemplary regions on digitized mammograms. The parameters needed to segment were automatically derived and could with little additional effort by the expert be extended to hit her to unknown shapes of masses, showing a good generalization ability. The loss of accuracy (97% to 91%) might be prevented by choosing a better pixel-classifier. An iterative creation of the database is still considered meaningful as the system estimated a good set of segmentation parameters. The detection and segmentation results were subjectively satisfying. A quantitative segmentation analysis is not very meaningful, as only one manual segmentation per image was available for comparison. In some cases the manual

Table 2. Comparison between the true positives in training and test case as well as the average number of false positives per image.

	Our method	Heath [6]	Kobatake [3]	Kupinski [4]	Li [2]
TP train	96%	88%	NA	NA	NA
TP test	70%	86%	92–96%	90.4%	70–90%
avg. FP	8	8	NA	1.3	1.6

segmentations even appeared to be incorrect. 30% of the masses in the testset could not be clearly detected. We observed that those forms were not present in the training set, thus the learning algorithm could never derive a correct generalization that includes those lesions. We therefore state that the training set of 33 mammograms was not sufficiently representative. Compared to others (see tab. 2), our results are similar. But we did not develop a system or an algorithm specifically designed for the detection and segmentation of stellate lesions. In fact our system is not limited to this presented task. We see this as the main advantage of our proposed method. The number of interactions and iterations per image show that the presented results could be achieved with little effort, but the computation time is still relatively high. The algorithm was fixed to a manually chosen feature selector and classifier combination, which might not be the optimum solution. Using a different combination could improve the results. To this time we only used local properties to segment. A subsequent step of classifying the regions according to their global features could reduce the number of false positives and thus improve the overall accuracy.

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