A Method for Detecting Microcalcifications in Digital Mammograms

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Microcalcification clusters are often an important indicator for the detection of malignancy in mammograms. In many cases, microcalcifications are the only indication of a malignancy. However, the detection of microcalcifications can be a difficult process. They are small and can be embedded in dense tissue. This paper presents a method for automatically detecting microcalcifications. We utilize a high-boost filter to suppress background clutter enabling segmentation even in very dense breast tissue. We then use a threshholding and region growing technique to extract candidate microcalcifications. Likely microcalcifications are then identified by a linear classifier. We apply this method to images selected from the LLNL/UCSF Digital Mammogram Library, and produce a receiver operating characteristic (ROC) curves to detail the trade-off between probability of detection and false alarms. Finally, we exam the ability to properly select a threshold to achieve a desired probability of detection based upon a training set.

KEY WORDS: digital mammography, microcalcifications, high-boost filtering, detection.

MICROCALCIFICATIONS ARE an important early indicator of malignancy in mammography. Clusters of microcalcifications are present in between 30% and 50% of breast cancers, and such clusters are the only visible sign in approximately 36% of these cases.[1] Unfortunately, microcalcifications are often difficult to locate. They are generally smaller than 1.0 mm in diameter, and they are usually in the 0.1 to 0.3 mm range. As few as five small microcalcifications can be an indication of malignancy. Furthermore, microcalcification clusters can occur in dense breast tissue where they are not easily discernible. As a result, it is often necessary for a radiologist to carefully scan a mammogram under magnification.[2] This can be a difficult and tedious process.

One common method of locating likely microcalcifications in digital mammograms is via a locally adaptive threshholding method.[3] The image is binarized on a pixel by pixel basis. A pixel is set if it exceeds the mean pixel value in a local window by some threshold. Typically, the threshold is dependent on the local variance. The end result is a binary image denoting locally bright pixels. A region growing algorithm is then employed to aggregate bright pixels, which are adjacent to form objects, and objects of the proper size are retained as candidate microcalcifications.

This method, unfortunately, does not always work well in the presence of dense breast tissue. Generally, it is the case that the difference between the intensity of the microcalcification and the intensity of the background decreases as the intensity of the background tissue increases. Despite this, it is typically the case that the brighter regions tend to have the highest variance. So, with the above method, it often works out that the threshold is increasing while it should actually be decreasing.

There are a number of other methods for finding likely microcalcifications. Each of these methods have their various strengths and weakness. A sampling of such algorithms can be found in the *Proceedings of the 3rd International Workshop on Digital Mammography.*[4] It is also important to remember that the algorithm described in this paper is meant as an initial scanning or segmentation algorithm meant to find likely microcalcifications for further consideration. Methods such as those compared in Woods et al[3] would then be used to further prune the false alarms.

High-boost filtering is a method for detect small, bright objects in variable backgrounds.[5] It is calculated as follows:

$$\text{High-boost} = (A)\ \text{Original} - \text{Low-pass}$$

where $A > 1$. A is known as the amplification factor. One notes that if $A = 1$, we have a standard high-pass filter. Typical values for A are 1.1, 1.15, and 1.2. The net results of such a filter is a slight added emphasis of intensity differences of the brightest pixels. An example of a high-boost filter

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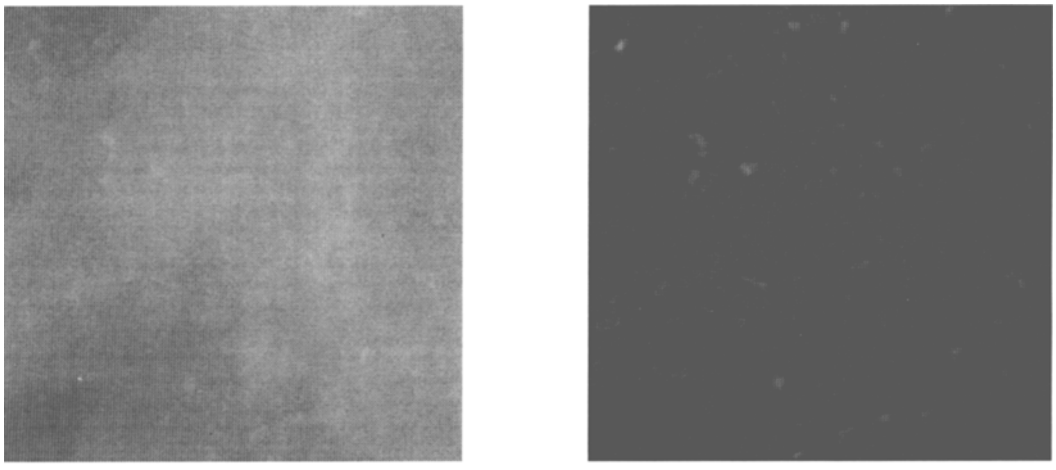

(a) Original Image (b) High-Boost Filtered Image

Fig 1. Example of the application of a high-boost filter to an image of a microcalcification cluster embedded in dense breast tissue. (A) Original Image. (B) High-boost filtered image.

on an image of a microcalcification cluster in dense breast tissue is seen in Fig 1.

APPROACH

We use the high-boost filter as a preprocessing step before using the traditional detection methods. A low-pass filtered image was constructed from the original image via a morphological opening. This was then used to construct a high-boost filtered image. The above described segmentation algorithm was then used to extract candidate microcalcifications. Each candidate microcalcification was then assessed in the high-boost filtered image by its signal strength as defined as follows:

$$\zeta = \frac{I_0 - I_N}{\sigma_N}$$

where ζ is the signal strength, I_0 is the average intensity of the candidate microcalcification, I_N is the average intensity of a neighborhood about the candidate microcalcification, and σ_N is the standard deviation of the values in that same neighborhood. Applying a linear classifier, we then decide the candidate is likely to be a microcalcification for sufficiently large values of ζ.

The major improvement over the adaptive threshold method is the use of the high-boost filter. This allows for more robust performance in dense tissue. Also, use of a linear classifier rather than the common practice of keeping a set number of the most likely microcalcifications. The use of a linear classifier presents some additional questions in the area of selectivity, which we address later.

The above algorithm was then applied to two image patches from the LLNL/UCSF Digital Mammogram Library.[6] Both images contained a microcalcification cluster, as well as scattered microcalcifications. Image 1 contained fifteen microcalcifications, and Image 2 contained fourteen microcalcifications. An example of processing of a subregion of Image 2, which contains a microcalcification cluster is found in Fig 2.

We then studied what happened as the threshold varied. At various threshold settings, we calculated the percent of known microcalcifications detected and the number of false alarms. False alarms were characterized on a per square centimeter basis because the eventual goal is to calculate accumulations of microcalcifications in a cm^2 basis. One notes from the receiver operating characteristic (ROC) curves (Fig 3) that this method is able to achieve a high rate of detection with relatively few false alarms per square centimeter. Some false alarms are allowable, as the goal is generally to detect the presence of five or more microcalcifications within a square centimeter rather than just a single microcalcification.[2] Also, as this is meant as an initial scanning or segmentation routine, more advanced techniques and more computationally intensive techniques could then be used to further reduce the number of false alarms.[3]

Another question of interest is that of selectivity.

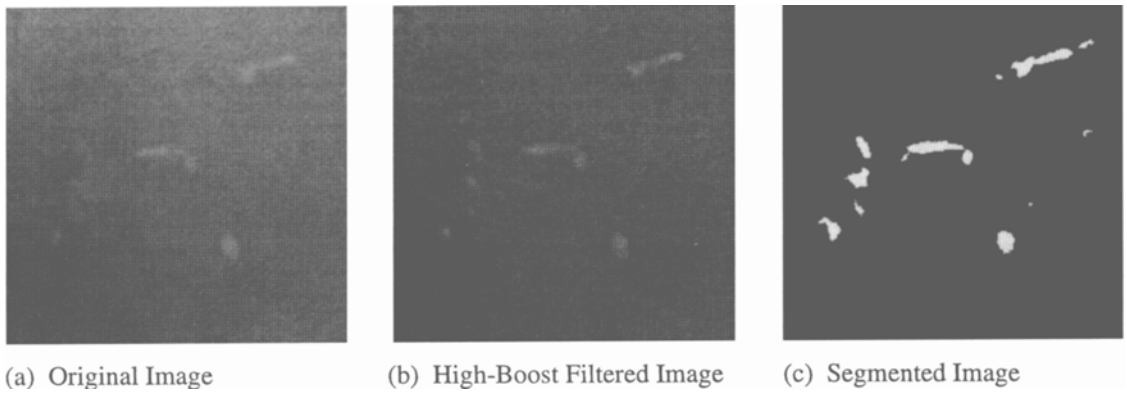

Fig 2. Example of processing on image 2. (A) Original image; (B) high-boost filtered image; (C) segmented image.

To build a useful classifier, it would be necessary to be able to select a threshold based on a given training set and achieve the desired probability of detection in an as yet unseen test set. This was studied by selecting a threshold such that in Image 1, a certain percent of the microcalcifications where detected. This same threshold was then applied to Image 2. Ideally, the threshold chosen from Image 1 would give the same probability of detection in Image 2. This is an issue that is often overlooked and is very important. Otherwise, the process of chosing a probability of detection in a new image automatically loses meaning. We did this process at a number of different thresholds, and the results are found in Fig 4. There appears to be some ability to properly select thresholds, but this is clearly an area that needs further study.

CONCLUSIONS

The method outlined in this report is a simple but effective means of prescanning digital mammograms to find microcalcifications. Specifically, it appears that the use of a high-boost filter greatly improves performance in the segmentation step, although we are still in the process of quantifying this improvement. This would reduce the need for more advanced techniques in detecting microcalcification, while reducing the likelihood of missing the more difficult to detect microcalcifications.

Truth data in relationship to the location of individual microcalcifications is difficult and expensive to acquire. As additional truth data becomes available, we hope to be able to use more sophisticated means of discrimination than a linear classifier.[7] As we do this, we will also expand our study to a much larger image set.

Once we are able to definitely characterize our ability to locate individual microcalcifications, it will be possible to automatically locate excesses of microcalcifications which are an important indicator of malignancy. By combining this ability with our groups experience in textural classification,[7,8] we believe it may be possible to not only locate microcalcification, but also to discriminate between benign and malignant clusters.

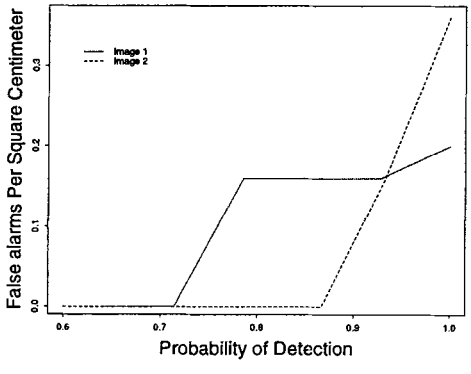

Fig 3. ROC curves for images 1 and 2.

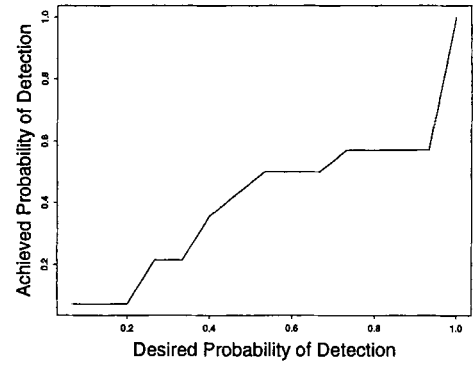

Fig 4. Selectivity analysis using image 1 as training data and image 2 as unseen test data.

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