Detection of Microcalcifications using SMF

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Abstract. We have reported previously [10,6] two algorithms for detecting microcalcifications that operate either on Highnam and Brady's [3] h_{int} representation or the latter's presentation as an image: SMF = Standardised Mammogram Form. We introduce a third such method that applies to SMF a model of human foveal image processing. Comparative analysis with [10,6] shows significantly enhanced results for the new method.

1. Introduction

The h_{int} model developed by Highnam and Brady [3] assumes that the attenuation coefficients of normal and cancerous tissue are very similar but that they are both significantly different from fat. The h_{int} generation algorithm then produces a quantitative representation of the amount (in millimetres) of non-fatty tissue at each pixel. It assumes that the percentage of calcifications in a mammogram is insignificantly small. Highnam and Brady [3] show that the h_{int} representation eliminates the specific image acquisition parameters (e.g. exposure time). If "standard" parameters are chosen, the h_{int} representation can be displayed as an image, which is called the Standard Mammogram Form (SMF) of the mammogram. This article compares three algorithms that operate upon the h_{int} representation (or the SMF) to detect microcalcifications. Two of these algorithms have been developed previously in our group [8,10,6]; the third is a refinement of [6] and is introduced here. Using ROC analysis, we demonstrate the superiority of this latter algorithm. First, however, we recall the main features of the two previously published algorithms.

Yam *et al*.'s algorithm [10] aims to find image locations where the assumption of no calcification appears not to hold. It does this by exploiting two ideas: (a) calcifications have an x-ray attenuation that is about 26 times higher than that of normal tissue; so in the h_{int} representation, microcalcifications (interpreted initially as normal tissue) tower above the surrounding landscape; and (b) the estimated volume of the interesting tissue corresponding to the region where a calcification is detected must exceed the estimated volume of the 3-D model of that region. The h_{int} representation is relatively noisy, and so Yam's algorithm incorporates a Wiener filter that smooths the representation as it attempts to assign pixels to noise or calcification. See [10] for details of the algorithm. Yam *et al*. [8,10] initially tested their method on

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isolated macrocalcifications and microcalcifications. They obtained a detection rate of 95% TPs with 0.38 FPs per image for a set of 93 mammogram samples digitised at 50 microns containing 92 isolated microcalcifications. Further tests lead to a rate of 93% TPs with 0.16 FP cluster per image for a set of 83 mammograms with a total of 95 microcalcification clusters.

Of course, the Wiener filter [9] may cause both small spots of noise and very fine microcalcifications to be overlooked. An alternative filtering method should be expected to outperform the existing one. To this end, in our previous work [5,6], we studied filtering the SMF using anisotropic diffusion [7]. In summary, our previous method used three filters in sequence: (i) an adaptive Gaussian derivative filter, which generates a gradient map and, more important, the value of contrast needed for anisotropic diffusion; (ii) an anisotropic diffusion filter, which will enhance certain suspicious regions based on the previously computed contrast value; and (iii) additional statistical analysis to discriminate between microcalcifications and the rest of the image. These three logical steps are in fact integrated into a single computational process. We applied initially the method to a database comprising 35 samples of digital mammograms at a resolution of 50•m with the size of 500x500 pixels. The h_{int} images were in a 32-float format and contained a total of 23 isolated microcalcifications previously labelled by an experienced radiologist. The collection of images was designed to cover a wide range of possible cases of microcalcifications, some subtle, some obvious, some large, and some small. Initially, the overall ratio of detection was 91.3% TPs for a number of 0.32 FPs per image. We noted that a few regions of noise or dense breast tissue were incorrectly detected as microcalcifications. Interestingly, one source of FPs in our detection algorithm are overlaps in CLS. When we removed the CLS from the images with FPs [1] and then applied the algorithm again on the CLS-free h_{int} images. The number of FPs was reduced from the initial number of 0.32 per image to 0.2. Note that in this form, the algorithm does not exploit knowledge of the attenuation characteristics of calcium.

2. "Foveal" Segmentation

In our most recent development, the detection of microcalcifications is completed by a foveal segmentation based on the algorithm of Heucke *et al.* [2]. We initially remove the glare, shot-noise [4] and CLSs [1] from the SMF image. Having the SMF_{noCLS} image, we compute a set of mean values using masks for the inner area, its neighbourhood and background. The histogram of the inner surface provides a mean of the object ($\bullet_O$), while the histogram of the entire image gives the mean of the background ($\bullet_B$). The mean in a neighbourhood ($\bullet_N$) is defined as the weighted sum of intensities depending on the scale of the mask. The perceivable contrast C is:

$$C = \frac{|\mu_o - \mu_N|}{\mu_N} \quad \textbf{(1)}$$

Based on [2] we compute C_{min} (2), where $\bullet_A = 0.923 \cdot \bullet_N + 0.077 \cdot \bullet_B$ [2]. The segmentation parameters are set-up automatically based on the value of k, which is

image-adapted. We found that $c_w = \sqrt{k}/200$ gave stable results. SMF regions whose contrast $C > C_{min}$ an adaptable threshold are marked as microcalcifications:

$$C_{\min} = \begin{cases} \frac{c_w}{\mu_N}\left(0.0808 + \sqrt{\mu_A}\right)^2, & \mu_A \geq \mu_N \\ \frac{c_w}{\mu_N}\left(0.808 + \sqrt{\frac{\mu_N^{\,2}}{\mu_A}}\right)^2, & \mu_N > \mu_A \end{cases} \quad (2)$$

The overall process flow (k is the contrast for anisotropic diffusion) is:

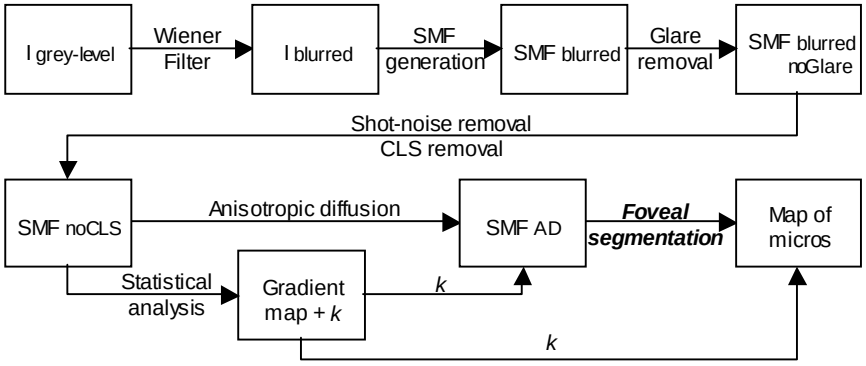

Fig. 1. Process flow to detect microcalcification in Standard Mammogram Format images.

3. Comparative Results

Figure 2 shows a typical result on some mammogram samples containing microcalcification clusters. We present, along the original contrast-enhanced SMF sample, the detection maps of the Physics-based Approach, Statistical Analysis and Foveal Approach. We used a database of 102 samples of digital SMF images, 78 of them contain 1 to 3 clusters per image, while 24 are normal mammogram samples. There are a total of 98 clusters of microcalcification. All images were digitised at a resolution of 50•m and have sizes under 1500x1500. Figure 3 shows the comparative Receiver Operating Characteristic (ROC) curves of the tested detection methods.

4. Conclusion

Adding adaptive contrast segmentation based on human foveal processing significantly enhances the detection of microcalcifications. We continue to develop the algorithm, incorporating additional knowledge of x-ray attenuation.

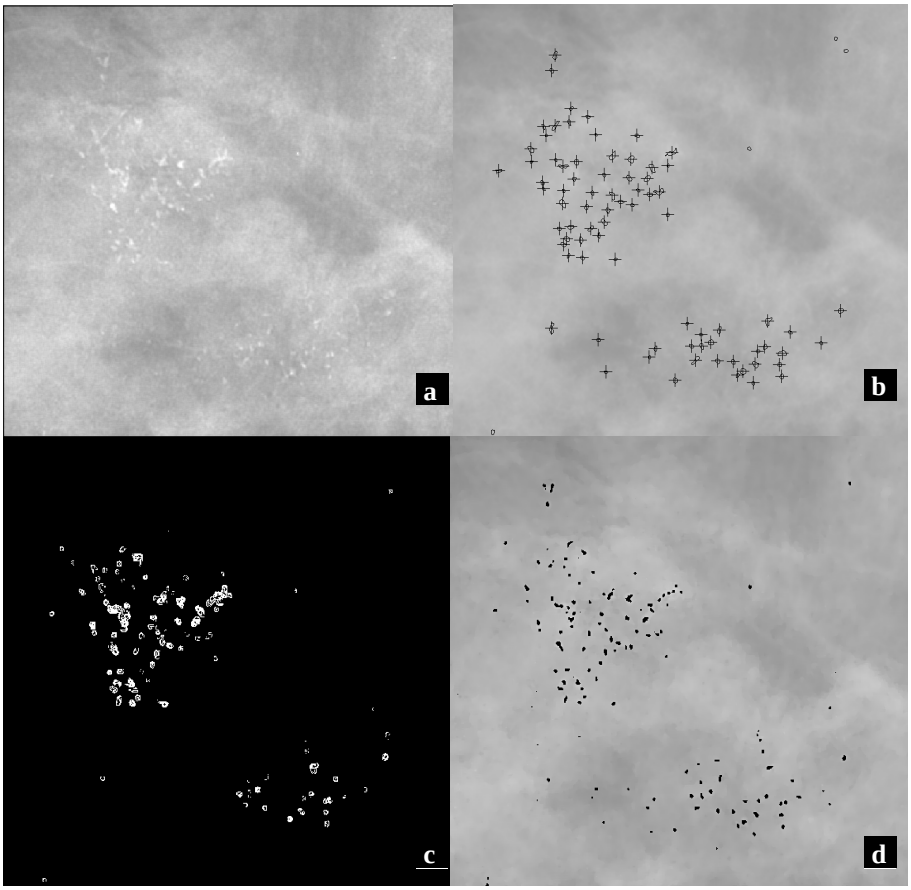

Fig. 2. (a) The original SMF; (b) the detection map of the Physics-based Approach; (c) the BWMD of the Statistical Analysis; (c) the detection map of the Foveal Approach.

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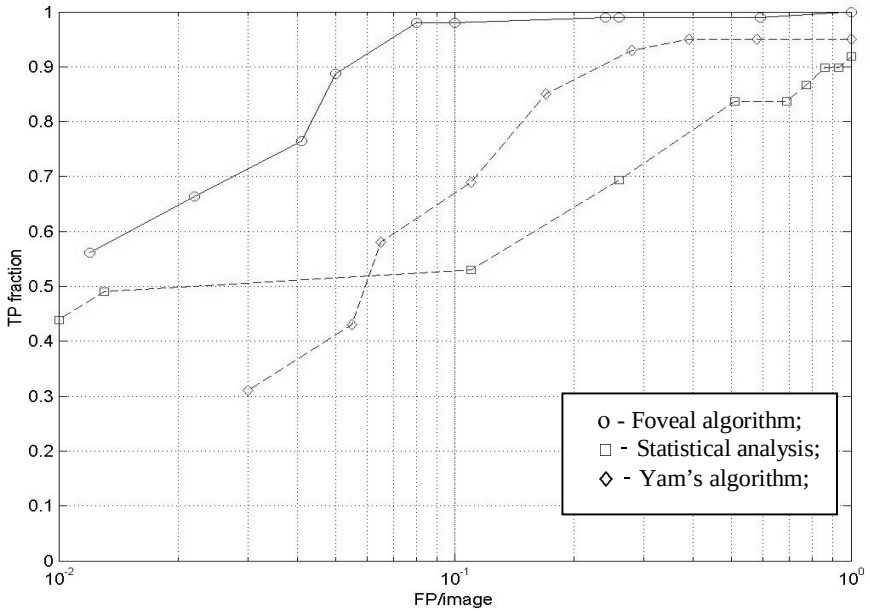

Fig. 3. The ROC curves of the three microcalcification-detection methods, where we notice the better performance of the Foveal Approach.